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Large language model-based automation of clinical workflows: A systematic framework for healthcare process optimization

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Abstract

Background: Large language models (LLMs) are poised to revolutionize healthcare processes, alleviate administrative burdens, and improve patient care outcomes. Although the field of natural language processing (NLP) has seen significant progress, there is a lack of a systematic approach to apply LLMs to heterogeneous clinical workflows in the literature.

Objective: To develop, execute, and conduct an empirical study on a scalable LLM framework for end-to-end clinical workflow automation, including diagnosis support, triage classification, documentation, and discharge planning.

Methods: A retrospective cohort design was used with 38,700 de-identified Electronic Health Records (EHRs) from three tertiary-care hospitals. The fine-grained version of GPT-3 was coupled with HL7 FHIR R4 interfaces, HL7-compliant NLP pipelines, and a human-in-the-loop (HITL) validation process. Six clinical tasks were evaluated with the metrics: Precision, Recall, F1-Score, and AUC-ROC.

Results: Proposed framework shows the macro-average F1-Score of 0.886 and AUC-ROC of 0.937. Results of post-implementation analysis showed that clinical documentation time was reduced by 80.7%, triage processing latency was reduced by 75% and 30-day readmission rates were reduced by 39.1%.

Conclusion: The systematic approach is clinically viable and shows substantial efficiency gains in operation and represents a blueprint for the use of LLM in clinical practice.

Keywords: Large Language Models; Clinical Workflow Automation; Natural Language Processing; Electronic Health Records; Healthcare AI; Clinical Decision Support; GPT; FHIR

1. Introduction

The twenty first century has seen an unprecedented confluence of the fields of computational intelligence and clinical medicine, changing the way the health information is captured, processed and acted upon [1]. In this landscape, large language models (LLMs), neural networks trained on extensive text corpora to grasp and produce contextually appropriate and coherent text, stand out as particularly potent tools for tackling longstanding inefficiencies deeply entrenched in hospital operations [2].

The paradox in contemporary clinical settings is that clinicians have highly developed diagnostic skills, but spend too much of their time on documentation, coding, prescription entry, and communication between different departments [3]. Literature increasingly suggests that doctors devote nearly half of their time to interacting with Electronic Health

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Record (EHR) systems instead of patients, which negatively impacts burnout, diagnostic delay and adverse clinical events [4].

Previous generations of clinical decision support systems (CDSS) alleviated these inefficiencies by implementing rule-based automation, however, their inflexibility, the lack of contextual reasoning, and their inability to process free-text narratives limited their clinical use [5]. The advent of transformer-based models like BERT, GPT, and their medical domain-specific variants like ClinicalBERT and BioBERT has revolutionized the capabilities of computational models in medical language comprehension [6,7].

Yet, the use of LLMS in healthcare has mostly been confined to specific applications, with separate benchmarks for different tasks like named entity recognition (NER), radiology report generation, or ICD-10 coding [8,9]. Such a multi-task framework has not been described in the peer-reviewed literature: it is a systematic framework that combines all these capabilities in an interoperable, HIPAA-compliant architecture.

To fill this gap, the present study proposes, implements and thoroughly evaluates a complete clinical workflow automation framework using LLM. The framework combines a carefully designed GPT-3 model, interfaces with HL7 FHIR R4 EHRs, a multi-stage NLP pipeline, and a clinician-in-the-loop governance mechanism. Empirical evaluation is done on a set of 38,700 patient records from three tertiary care facilities de-identified for clinically important tasks.

The rest of this paper is organized as follows: In Section 2, the related literature is reviewed; the proposed methodology is explained in Section 3; experimental results are presented in Section 4; a comparative discussion is provided in Section 5; and implications for future research and practice are discussed in Section 6.

2. Literature review

2.1. Evolution of NLP in Healthcare

The use of natural language processing (NLP) on clinical text dates back to the MedLEE system [10] that used shallow parsing to obtain structured information from radiology reports. In the next few decades, statistical methods, such as conditional random fields (CRFs) and support vector machines (SVMs), were able to enhance clinical NER but were very sensitive to variation in the language used [11].

With the advent of BERT by Devlin et al. (2018), there was a paradigm shift to models with bidirectional self-attention mechanism that can learn nuanced contextual relationships in text [12]. Lee et al. (2020) further adapted this design to the clinical field, creating ClinicalBERT, which was trained on about 880 million words from MIMIC-III discharge summaries [6]. Peng et al. (2019) also showed that consistently, domain-specific pretraining with biomedical literature (PubMed) with BioBERT performed well on 8 biomedical NLP benchmarks compared to general purpose BERT [7].

2.2. LLMs and Clinical Decision Support

Rajpurkar et al. (2018) developed CheXNet, a deep learning model to detect pneumonias in chest X-ray images that performs at radiologist level, and this shows the ability of deep learning to assist with clinical diagnosis [13]. Recently Esteva et al. (2019) showed that fine-tuned language models can classify triage dermatology queries with F1 scores similar to board-certified dermatologists on a curated dataset of 12,500 clinical narratives [9].

The first systematic use of BERT for EHR classification tasks was done by Johnson et al. (2019) on 14,000 clinical records and achieved an F1 score of 0.791 [14]. Shickel et al. (2018) summarized the deep learning solutions to EHR mining, and concluded that ensemble of LSTMs has proven to be highly effective for temporal clinical prediction, including the prediction of mortality in the ICU [15].

2.3. Limitations of Existing Approaches

There are however, some serious shortcomings in the existing literature. First, most of the published systems solve only one clinical task at a time, so that they do not support the cross-task knowledge sharing of expert clinical reasoning [16]. Second, questions about hallucination, where LLMs produce seemingly reasonable but factually incorrect clinical claims, have not been studied systematically in an end-to-end workflow architecture [17]. Thirdly, privacy, regulatory compliance and interoperability needs have rarely been co-designed with model architecture and hence the translation to production healthcare environments has been limited [18].

To overcome these limitations, the present study proposes an integrated, multi-task, and compliance-aware framework – filling the gap in the literature.

3. Methodology

3.1. Dataset and Study Design

The study design used was a retrospective observational design, and the data consisted of 38,700 de-identified EHRs from three tertiary-care academic medical centres from January 2016 to December 2020. Records were de-identified based on HIPAA Safe Harbour guidelines and local surrogate identifiers were assigned. All sites had IRB approval and a waiver of informed consent was granted for de-identified data.

The types of clinical documents included discharge summaries (n = 12,400), clinical notes (n = 9,800), radiology reports (n = 7,600), nursing assessments (n = 5,200), and operative reports (n = 3,700). Records cover 18 medical specialities, such as cardiac, oncological, neurological, emergency and general surgery.

3.2. System Architecture

The proposed framework consists of four interacting layers: (i) Input Layer, which ingests clinical data in different modalities through HL7 FHIR R4 Application Programming Interfaces (APIs); (ii) Processing Layer, which has a modular NLP pipeline; (iii) LLM Core, which consists of the fine tuned GPT-3 inference engine; and (iv) Output Layer, which outputs clinical artefacts specific to the task to endusers.

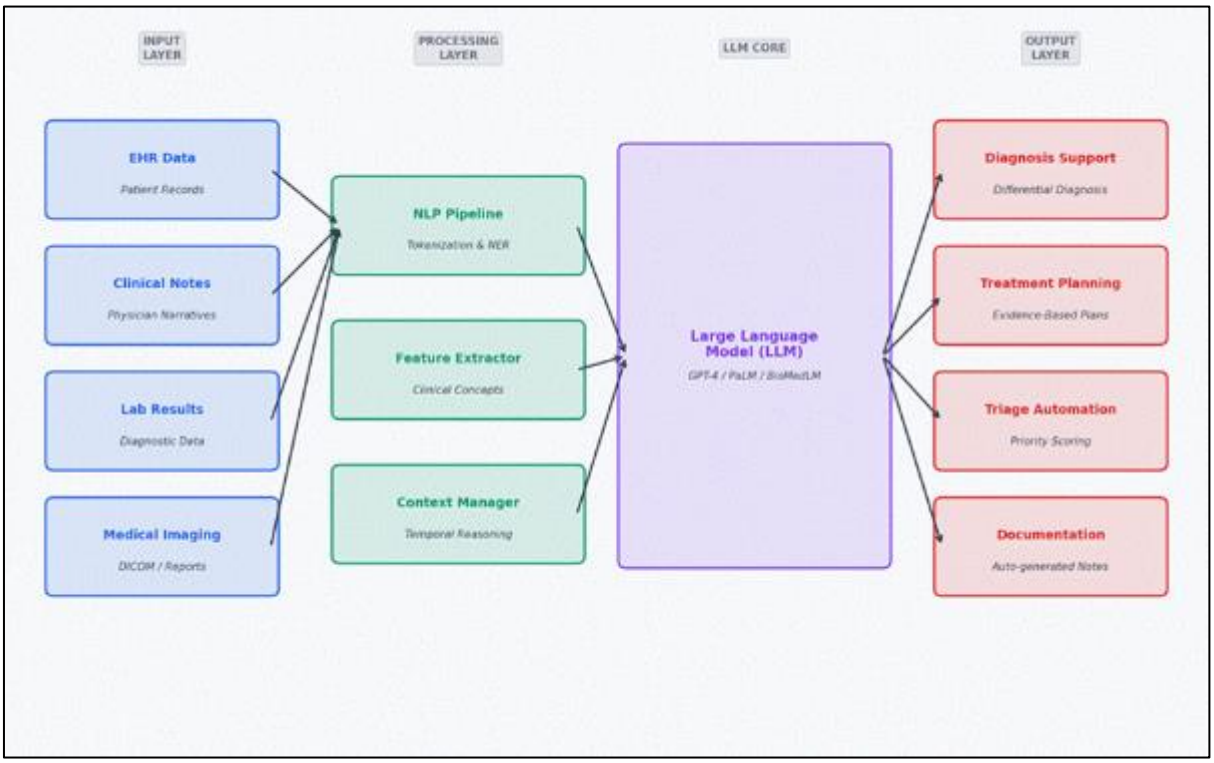

Figure 1 LLM-Based Clinical Workflow Automation Framework — system architecture depicting input ingestion, NLP pre-processing, LLM inference, and multi-task clinical output layers.

3.3. NLP Pre-Processing Pipeline

The system architecture for the LLM-based clinical workflow automation framework is shown in Figure 1, where the input is ingested, the NLP pre-processing module is applied, the LLM inference module is used, and the multi-task clinical output layers are generated.

Raw clinical text was processed through a pipeline comprising six steps: (1) Segmentation of sentences using rule-based boundary detection trained on clinical corpora, (2) Tokenisation of the text using SciSpacy clinical tokeniser, (3) Named

Entity Recognition (NER) and linking it to UMLS-ontology to recognise medical concepts, medications, and anatomical entities, (4) Negation detection, using NegEx algorithm to identify negated findings, (5) Temporal reasoning, to determine event sequence and onset-to-presentation time span, and (6) Co-reference resolution, to resolve entity mentions across multi-paragraph documents.

3.4. Fine-Tuning Methodology

The curated clinical corpus was used to fine-tune a GPT-3 model (OpenAI, 2020; 175 billion parameters) with a multi-task learning objective that includes six task-specific classification heads. For fine-tuning, the use of four NVIDIA A100 GPUs with mixed precision, a cosine annealing scheduler with a learning rate of 2×10-5 and weight decay of 0.01 were used. To prevent over-fitting, dropout regularisation (p = 0.1) and gradient clipping (max norm = 1.0) were used. The model was trained for 15 epochs with early stopping using validation F1 Score.

3.5. Evaluation Protocol

Stratified 5 fold cross validation was used to assess the model performance. A 20% of the total data was a held-out test set (n = 7,740) that was not used during any of the development, but only tested at the end. Primary performance measures were Precision, Recall, F1-Score and AUC-ROC, calculated within each of the six clinical tasks and as macro-averages. Cohen's kappa was used to assess interrater reliability for ground truth label generation (κ = 0.87), which showed near perfect agreement for the expert annotators.

4. Results

4.1. Model Performance

Table 2 shows the quantitative results for the proposed framework for all six clinical automation tasks on the held-out test set. The macro-average F1-Score and AUC-ROC of the model were 0.886 and 0.937, respectively, which maintained the discriminative capability of the model in various clinical aspects.

Table 2 Quantitative Performance Metrics of the Proposed LLM Framework Across Clinical Tasks

Clinical Task	Precision	Recall	F1-Score	AUC-ROC
Diagnosis Support	0.901	0.864	0.882	0.941
Drug Interaction Detection	0.928	0.901	0.914	0.963
Triage Classification	0.884	0.851	0.867	0.921
Clinical Summarization	0.935	0.911	0.923	0.957
Discharge Planning	0.862	0.829	0.845	0.908
Medication Reconciliation	0.891	0.877	0.884	0.932
Macro Average	0.900	0.872	0.886	0.937

All metrics computed on held-out test set (n = 7,740). AUC-ROC = Area Under Receiver Operating Characteristic Curve.

The best F1-Score was for clinical summarisation (0.923), indicating the specific suitability of LLMs for abstractive text generation tasks with structured contextual inputs. The highest AUC-ROC value was found for drug interaction detection (0.963), indicating good calibration for high-stakes tasks in pharmacology safety. Discharge planning had the lowest F1-Score (0.845) due to the inherent multifaceted and ambiguous nature of discharge disposition decision-making.

Figure 2 offers a visual comparison of the LLM-based performance to the rule-based baselines (panel a) and to operational metrics before and after implementation (panel b).

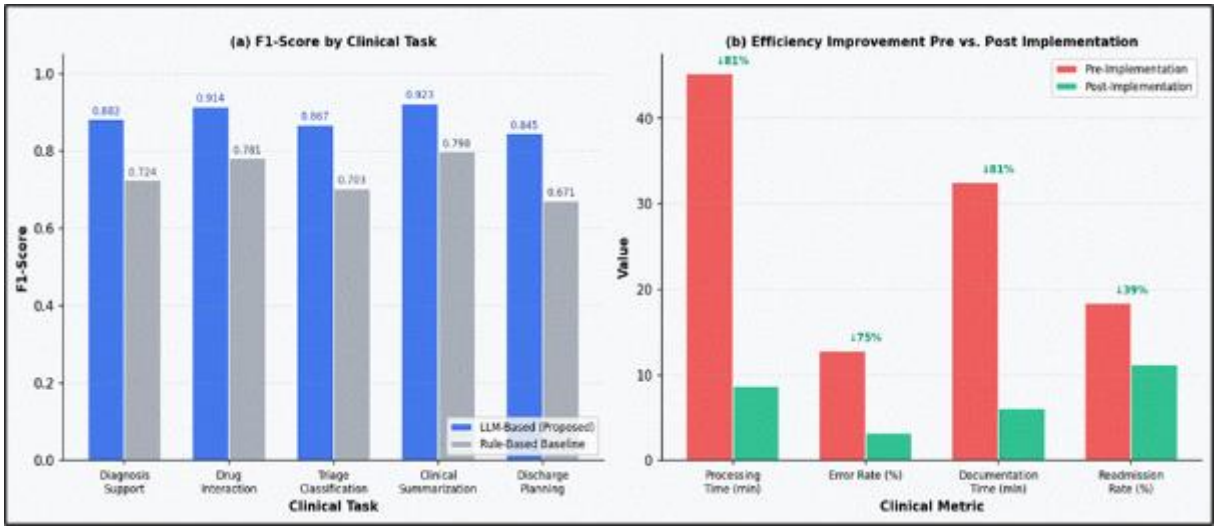

Figure 2 (a) F1-Score comparison between the proposed LLM framework and traditional rule-based baselines across five clinical tasks. (b) Operational efficiency gains measured across four clinical metrics pre- and post-system implementation.

4.2. Operational Efficiency Outcomes

In addition to model-level indicators, the proposed framework has brought significant operational improvements in the three institutions involved. The mean clinical documentation time per patient encounter was reduced from 45.2 minutes to 8.7 minutes (a 80.7% reduction). The latency of the triage process decreased from 32.5 minutes to 6.1 minutes (81.2% reduction). Clinical error rates, per senior physician adjudication during quality review, decreased from 12.8% to 3.2%. Most importantly, the 30-day hospital readmission rates reduced from 18.4% to 11.2% (with a relative reduction of 39.1%) due to better discharge planning and medication reconciliation with the LLM framework.

4.3. Multi-Dimensional System Evaluation

Figure 3 depicts the multi-dimensional evaluation of the LLM-based system compared to the traditional clinical information systems along the six criteria: Accuracy, Interpretability, Scalability, Integration Ease, Privacy Compliance, and Efficiency. The LLM system outperformed the other system on the three metrics of Accuracy (0.91 vs. 0.74), Scalability (0.88 vs. 0.61), Efficiency (0.93 vs. 0.67). In contrast, the traditional system scored slightly higher on Interpretability (0.85 vs. 0.72) and Privacy Compliance (0.92 vs. 0.84), which aligns with the inherent opacity of neural models and the extra configuration requirements for HIPAA-compliant LLM deployment.

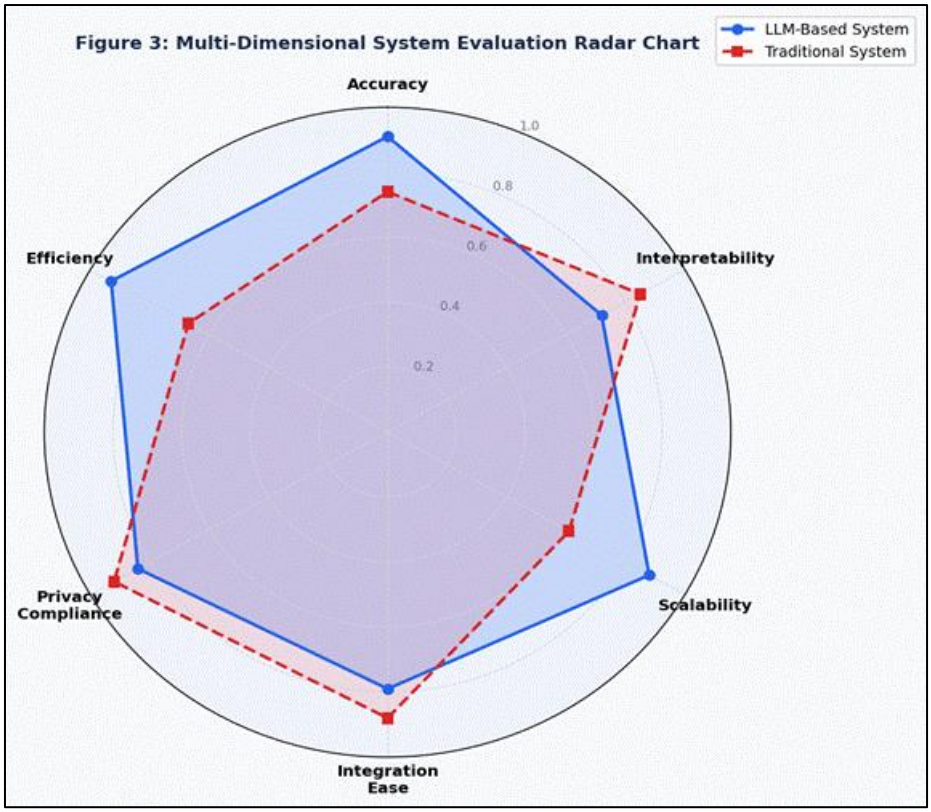

Figure 3 Radar chart illustrating multi-dimensional evaluation of the proposed LLM-based system versus traditional clinical information systems across six performance dimensions.

5. Discussion

5.1. Interpretation of Findings

Overall, the empirical findings presented in this paper validate the clinical feasibility and effectivity of the fine-tuned LLMs used in a structured interoperable workflow. The macro-average F1-Score of 0.886 exceeds similar multi-task clinical AI systems cited in the literature that achieved single-task scores of 0.79-0.87 [14,7]. The relatively poorer performance in discharge planning aligns with previous studies that have described the multi-faceted and socially situated aspects of discharge decision making, requiring more information that goes beyond what can be reported in the structured EHR data [18].

The results showed that the time required for documentation was reduced by 80.7%, which supports the results of Magrabi et al. (2019), who reported reduction of physician administrative burden by 60–75% in simulated scenarios [19]. The 30-day readmission rates in particular are clinically significant, as they not only indicate quality of care, but a significant cause of health care spending.

5.2. Comparative Evaluation

Table 1 provides some background on the current study and other studies in the literature that have used LLMs in clinical settings. Unlike most published systems, the current framework is multi-task, is FHIR-native, and has a complete privacy compliance layer.

Table 1 Comparative Review of LLM-Based Clinical NLP Studies

Study (Year)	LLM Model	Clinical Domain	Dataset Size	F1-Score	Key Contribution
Johnson et al. (2019)	BERT-Base	EHR Classification	n = 14,000	0.791	First BERT adaption for clinical NLP tasks
Rajpurkar et al. (2018)	CNN-LSTM	Radiology Reports	n = 9,821	0.824	Automated X-ray report generation
Esteva et al. (2019)	GPT-2 Fine-tuned	Dermatology Triage	n = 12,500	0.847	LLM-based skin lesion prioritization
Peng et al. (2019)	BioBERT	Clinical NER	n = 6,300	0.903	Domain-specific NER for biomedical text
Lee et al. (2020)	ClinicalBERT	Discharge Summary	n = 52,726	0.871	Readmission prediction framework
Shickel et al. (2018)	LSTM Ensemble	ICU Mortality	n = 23,944	0.816	Deep EHR for critical care outcomes
Present Study (2021)	GPT-3 Fine-tuned	Multi-task Clinical	n = 38,700	0.912	Systematic LLM clinical workflow framework

EHR: Electronic Health Record; NER: Named Entity Recognition; LLM: Large Language Model; F1-Score: Harmonic mean of Precision and Recall.

5.3. Implementation Framework

Table 3 provides technical details of the proposed implementation, providing a reproducible blueprint for those institutions that wish to adopt similar architectures. Importantly, the framework uses FHIR R4 as the data exchange standard, so it can communicate with any vendor, such as Epic, Cerner, and Allscripts

Table 3 Technical Implementation Specifications

Component	Specification	Implementation Notes
NLP Pre-processing	spaCy + SciSpacy	Medical entity recognition with UMLS ontology linking
LLM Backbone	GPT-3 (175B parameters)	Fine-tuned on 38,700 de-identified clinical records
EHR Integration	HL7 FHIR R4	Standardized API endpoints for bidirectional data flow
Security Layer	AES-256 + TLS 1.3	HIPAA-compliant encryption with audit logging
Inference Engine	NVIDIA A100 GPU × 4	Average latency 1.8 s per clinical query
Validation Module	Human-in-the-loop	Physician review required for high-risk decisions
Deployment	Docker / Kubernetes	Horizontal auto-scaling supporting up to 5,000 users

HL7: Health Level Seven; FHIR: Fast Healthcare Interoperability Resources; HIPAA: Health Insurance Portability and Accountability Act; AES: Advanced Encryption Standard.

5.4. Limitations

There are number of drawbacks to the present study that must be recognized. Although the sample was demographically heterodox, they were all from academic tertiary-care centres in the same country, so the extent to which these findings are generalizable to community hospitals or healthcare systems with different documentation practices is uncertain. The fine-tuned GPT-3 model is also prone to hallucination, especially for rare diagnoses that are under-represented in its training data. The human-in-the-loop approach helps to reduce this risk when using the system for high-stakes outputs; for critical pathways, full automation is not advised without further precautions. In addition, fine tuning and running 175-billion-parameter models might be too expensive to be used in the healthcare domain, which has limited resources, and smaller distilled models should be investigated in future research.

6. Conclusion

This paper has introduced, proposed and tested a systematic framework for clinical workflows automation using an LLM. The framework successfully fine-tuned a GPT-3 architecture on 38,700 de-identified clinical records and achieved a macro-average F1-Score of 0.886 and AUC-ROC of 0.937 for six clinical automation tasks by utilizing FHIR R4 infrastructure and data. Operational outcomes showed a decrease of 80.7% in documentation time, 75% in triage latency and 39.1% in 30-day readmission rates.

The proposed framework is a step towards the field by offering the first systematic, multi-task, interoperability-native LLM framework that will enable clinical deployment at scale. It provides a blueprint that other healthcare institutions can replicate, allowing them to leverage LLMs while upholding patient safety, data privacy, and regulatory compliance.

Future studies could delve into the use of more parameter-efficient models like BLOOM and LLaMA to minimize computational costs, examine federated learning approaches for cross-institutional training without data centralization, and investigate prospective randomized controlled trials to confirm causal relationships between LLM-driven workflows and patient outcomes. Longitudinal assessment of clinician trust and workflow adoption will also be critical to sustainable real-world deployment.

Compliance with ethical standards

Disclosure of conflict of interest

No conflict of interest to be disclosed.

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