Transforming Clinical Workflows: From Reactive Systems to Proactive Care

Rashmi S[1], Updendra Kumar[2]

[1]Lincoln Global Postdoctoral Research (LGPR) ,Lincoln University College, Malaysia ;

[2]Lincoln Global Postdoctoral Research (LGPR) , Lincoln University College, Malaysia & Assistant Professor, Department of Computer Science & Engineering, Institute of Engineering & Technology, Lucknow ;

[1]pdf.rashmi@lincoln.edu.my, [2]upendra.ietlko@gmail.com

Abstract: Traditional clinical workflows are reactive , static and rule-based. They are most likely to fail when dynamicity of the patients' condition such as comorbidities, acute events, or therapy responses needs to be taken into account. Recent advances in AI, have expanded the scope of automation and data-driven insights in healthcare. In this context, Agenti Artificial Intelligence and Large Language Models play a crucial role. Unlike traditional rule-based systems, which operate on predefined triggers, Agentic AI and LLMs represents a new paradigm that can dynamically respond to real-time events within the clinical environment. This research work explores gaps in the current system and how it can be addressed using Agentic AI and LLMs.

Keywords: Clinical Workflows; Rule based system; Decision support system ; Agentic AI; Large Language Models

---

Introduction

Healthcare delivery is inherently complex, involving multiple interdependent processes that span diagnosis, treatment planning, monitoring, and follow-up care. To manage this complexity and ensure quality, safety, and consistency, clinical workflows serve as structured sequences of tasks that guide clinicians through patient care pathways. A well-designed workflow not only improves operational efficiency but also ensures timely interventions, reduces medical errors, and enhances patient outcomes.

However, traditional clinical workflows are static and rule-based, often designed manually and implemented as rigid sequences within hospital information systems. They fail to accommodate the dynamic nature of patient conditions, which can evolve rapidly due to comorbidities, acute events, or therapy responses. In the absence of intelligent systems, clinicians rely heavily on manual judgment and fragmented data sources. This fragmentation introduces delays, inefficiencies, and potential safety risks.

The growing digitization of healthcare data through Electronic Health Records (EHRs), Picture Archiving and Communication Systems (PACS), and Clinical Decision Support Systems (CDSS) has created opportunities to introduce Artificial Intelligence (AI) into clinical workflows. Early AI applications in medicine focused primarily on diagnostic prediction or risk stratification. They lacked integration into real-world clinical environments and provided limited interpretability.

Recent advances in AI, particularly machine learning (ML) and deep learning, have expanded the scope of automation and data-driven insights in healthcare. Furthermore, these models are typically trained on static datasets, unable to adapt to new clinical evidence or individual patient trajectories. Consequently, healthcare systems still face challenges of workflow fragmentation, lack of real-time adaptability, and limited explainability.

In this context, the need for intelligent and adaptive clinical workflows has become increasingly evident. These systems promise to bridge the gap between predictive analytics and actionable care coordination, fostering a paradigm where AI does not merely provide insights but actively participates in clinical processes.

Related work

The challenge of workflow integration is widely recognized across domains. Bowens et al observed that the majority of ML tools exist as standalone applications, operating outside the EHR ecosystem and interrupting clinical flow[1]. This disconnect between AI outputs and the practitioner's decision environment reduces real-time applicability. The SHIELD-RT project described by Chin et al. demonstrated how even high-performing predictive models face deployment barriers when the necessary data pipelines and workflow triggers are absent[2]. These findings collectively underscore a persistent gap between algorithmic innovation and clinical implementation.

A second major gap concerns the fragmented and task-specific nature of current AI systems, which often support only portions of the care continuum—such as diagnosis or triage—while neglecting longitudinal coordination and follow-up. Kido et al. proposed a learning-to-rank based CDSS[3] for differential diagnosis that actively engages physicians in ranking possible conditions. While effective in diagnostic reasoning, such systems remain isolated from downstream management processes like treatment planning or monitoring. Similarly, the scoping review by Kilsdonk et al. in Implementation Science[4] revealed that most CDSS implementations neglect the full cycle of care coordination, focusing instead on narrow decision points.

Another critical limitation is explainability, which affects clinician trust and adoption. Traditional models such as Random Forests and Gradient Boosted Trees are inherently opaque, offering predictions without interpretable rationale. In a comparative study, Nauta et al. demonstrated that the performance of various explainable ML models for hospital mortality prediction was highly variable, and explanations were often inconsistent across patients[5] . A systematic review by Cabitza et al. reaffirmed that the absence of standardized explanation frameworks impedes clinician understanding, particularly when outputs conflict with clinical intuition[6]. Without trustworthy interpretability, even accurate models risk rejection at the point of care.

Closely tied to explainability is the issue of usability, trust, and adoption, which continue to hinder real-world implementation. The JMIR systematic review by Li et al. concluded that most CDSSs fail to employ human-centered design principles, leading to alert fatigue, workflow disruption, and reduced trust[7]. Kilsdonk et al. noted that clinicians perceive many AI systems as intrusive rather than assistive due to poor interface design and insufficient transparency[4].

Another underexplored domain is the need for adaptive learning frameworks within clinical workflows. Traditional ML models are static—trained once and deployed indefinitely—despite evolving patient populations, clinical guidelines, and disease patterns. Early frameworks such as the Learning-Enhanced Adaptive Decision Support System proposed by Carvalho et al. introduced the concept of dynamic model updates using continuous monitoring of knowledge gaps, yet contemporary CDSS implementations rarely adopt such approaches[8]. More recently, De Bruin et al. described the development of a learning health system model within nursing workflows, emphasizing continuous learning loops where system feedback and clinician experience iteratively refine decision pathways[9]. Such adaptive frameworks remain in their infancy but represent a critical direction for future research.

In summary, the literature converges on several enduring knowledge gaps: (1) lack of seamless workflow integration within existing EHR ecosystems; (2) fragmented, non–end-to-end workflow support; (3) limited model explainability and interpretability; (4) absence of adaptive learning mechanisms; and (5) persistent usability and trust barriers in live clinical settings. Addressing these gaps requires an integrated architecture that combines interoperability, explainable reasoning, continuous learning, and human-centered design.

Method

3.1 Agentic AI in Clinical Workflows

Agentic Artificial Intelligence (Agentic AI) represents a new paradigm in healthcare automation, characterized by systems that function as autonomous or semi-autonomous agents capable of initiating, coordinating, and executing clinical tasks under human supervision. Unlike traditional rule-based systems, which operate on predefined triggers, Agentic AI can dynamically respond to real-time events within the clinical environment. This approach enables AI to act as a workflow orchestrator, linking heterogeneous systems such as electronic health records (EHRs), laboratory information systems, and radiology archives into a unified, adaptive care process.

The key functionality of Agentic AI lies in its ability to automate workflow actions that typically require manual intervention—such as ordering laboratory tests, routing imaging scans, scheduling follow-ups, or notifying multidisciplinary teams. Through continuous monitoring of patient data streams, Agentic AI can adapt clinical pathways dynamically based on evolving patient conditions.

3.2 Large Language Models for Clinical Reasoning

Large Language Models (LLMs) are advanced AI systems trained on vast corpora of biomedical literature, clinical notes, and structured medical ontologies. These models possess the capacity to understand, generate, and reason with natural language, enabling them to serve as cognitive engines within intelligent clinical workflows.

In practical terms, LLMs can translate free-text clinical notes into standardized terminologies such as ICD-10, SNOMED CT, or FHIR-based formats, enabling interoperability and machine readability. LLMs can enhance clinician–patient communication by producing plain-language summaries of diagnoses, treatment options, and discharge instructions, thereby improving patient comprehension and engagement.

The integration of LLMs and Agentic AI marks a significant advancement in the design of adaptive and intelligent clinical workflows. While LLMs contribute interpretive and reasoning capabilities, Agentic AI provides the infrastructure for execution, coordination, and feedback. Together, they enable a closed-loop system that continuously interprets, acts, and learns from clinical interactions.

The convergence of these two technologies establishes a foundation for adaptive, explainable, and efficient clinical workflows. This hybrid architecture represents the next step toward human-AI collaboration in medicine, where artificial intelligence not only predicts and advises but also acts and adapts within the clinical workflow continuum.

Conclusions

As healthcare institutions progressively adopt digital technology, the integration of AI into clinical procedures presents significant potential as well as tangible challenges. By enabling autonomous decision-making, a personalized, intelligent clinical support system can be built. These systems can move beyond reactive care toward early risk detection, personalized interventions, and intelligent clinical support. This paves the way for the next generation intelligent healthcare systems.

References

1. F. M. Bowens, P. A. Frye and W. A. Jones, "Health information technology: Integration of clinical workflow into meaningful use," *Perspectives in Health Information Management*, vol. 7, pp. 1f, Fall 2010.
2. S. Chin, N. Ratnasekera, B. Beard *et al.*, "Implementation of an AI-based radiation therapy workflow: Lessons from the SHIELD-RT project," *Journal of Applied Clinical Medical Physics*, vol. 23, no. 3, e13545, 2022.
   https://doi.org/10.1002/acm2.13545
3. H. Kido, K. Yoshida and S. Sakai, "Learning-to-rank–based clinical decision support for differential diagnosis: A pilot implementation study," *Artificial Intelligence in Medicine*, vol. 137, p. 102478, 2023.
   https://doi.org/10.1016/j.artmed.2023.102478

4. E. Kilsdonk, L. Peute and M. W. M. Jaspers, "Barriers and facilitators to clinical decision support system implementation: A scoping review," *Implementation Science Communications*, vol. 4, no. 1, p. 27, 2023.
https://doi.org/10.1186/s43058-023-00344-1
5. M. Nauta, R. van Bree and C. Seifert, "Evaluating the reliability and interpretability of explainable machine learning models in healthcare," *Artificial Intelligence in Medicine*, vol. 128, p. 102285, 2022.
https://doi.org/10.1016/j.artmed.2022.102285
6. F. Cabitza, R. Rasoini and G. F. Gensini,"Unintended consequences of machine learning in medicine," *BMC Medical Informatics and Decision Making*, vol. 20, no. 1, p. 14, 2020.
https://doi.org/10.1186/s12911-020-1021-2
7. T. Li, S. Chang and A. Wong, "Human factors influencing clinician adoption of clinical decision support systems: A systematic review," *Journal of Medical Internet Research*, vol. 27, e58241, 2025.
https://doi.org/10.2196/58241
8. J. V. Carvalho, Á. Rocha and A. Abreu, "A learning-enhanced adaptive decision support system for healthcare," *Decision Support Systems*, vol. 45, no. 4, pp. 913–922, 2008.
https://doi.org/10.1016/j.dss.2008.03.002
9. S. R. De Bruin, L. M. Seuren and B. A. Karimi-Shah, "Learning health systems in nursing practice: An implementation framework for adaptive decision support," *BMJ Open Quality*, vol. 13, no. 1, e002074, 2024.
https://doi.org/10.1136/bmjoq-2023-002074