

A PATIENT-CENTRIC ADAPTIVE AI AGENT FOR REAL-TIME CLINICAL DECISION SUPPORT

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Abstract

Artificial Intelligence (AI) is increasingly integrated into healthcare systems to support clinical workflows and medical decision-making. However, most existing agent-based healthcare solutions remain system-centric and governance-focused, offering limited adaptability to real-time patient conditions. This study proposes a patient-centric adaptive AI agent designed to provide real-time clinical decision support while maintaining safety, ethical compliance, and clinician oversight. The proposed framework continuously monitors patient physiological signals, analyzes short-term trends, and dynamically adapts care recommendations within predefined safety boundaries. Unlike governance-heavy architectures, the approach prioritizes direct patient benefit through bounded autonomy and proactive assistance. A simulation-based evaluation using emergency care scenarios was conducted to assess system responsiveness, reliability, and clinician workload. Experimental results demonstrate faster reaction times to critical physiological changes, improved early warning capability, and reduced clinician cognitive burden compared to static rule-based systems. These findings indicate that adaptive patient-centric AI agents can enhance clinical decision support without replacing human judgment. The study contributes a practical and ethically grounded framework aligned with real-world clinical requirements and suitable for future intelligent healthcare deployments.

1. INTRODUCTION

Healthcare environments are inherently dynamic and time-critical. Patient conditions can deteriorate rapidly, particularly in emergency and acute care settings. Clinicians must interpret complex physiological data streams while making timely decisions under pressure. Artificial intelligence has been widely adopted to assist healthcare professionals; however, many existing AI-driven systems function as static analytical tools rather than adaptive decision-support partners.

Recent studies on agent-based healthcare systems emphasize governance, regulation, and ethical

oversight to ensure responsible AI deployment [1]. While these frameworks are essential for institutional accountability, they often prioritize system-level control over patient-level adaptability. As a result, AI agents typically assist clinicians passively and fail to adjust recommendations dynamically as patient states evolve.

Existing research highlights the need for intelligent systems capable of responding to real-time clinical changes while maintaining transparency, safety, and human oversight [1–3]. This study builds upon prior governance-oriented work by shifting the focus toward

patient-centric adaptability. The goal is not to replace clinicians but to augment clinical decision-making through timely, context-aware, and safe AI support.

Research Problem: Current agent-based healthcare systems lack adaptive, patient-centric AI agents capable of dynamically adjusting clinical recommendations in real time while remaining safe, ethical, and clinician-controlled.

Research Objectives:

- To design a patient-centric adaptive AI agent for real-time clinical decision support.
- To ensure bounded autonomy through safety and ethical constraints.
- To evaluate system effectiveness using simulated emergency care scenarios.

Research Contributions:

- Proposes a patient-centric adaptive AI agent architecture.
- Introduces a bounded autonomy model ensuring clinician oversight.
- Demonstrates improved responsiveness and reduced clinician workload through simulation.

Paper Organization: Section II reviews related work. Section III presents the research methodology. Section IV discusses experimental results and

discussion. Section V concludes the paper and outlines future research directions.

2. Related Work and Literature Review

AI-based clinical decision support systems (CDSS) have evolved from rule-based engines to data-driven predictive models. Early rule-based systems offered interpretability but lacked adaptability. Machine learning-based approaches improved predictive accuracy but often operate offline or require manual retraining [2].

Agent-based healthcare frameworks have been proposed to manage complex workflows and regulatory compliance. Grange et al. presented a governance-centric ensemble of agents integrated with digital twins to ensure ethical alignment and safety [1]. While effective for oversight, such approaches provide limited real-time adaptability at the patient level.

Other studies focus on AI-driven physiological monitoring and alert systems [3-5]. However, most lack continuous adaptation and proactive recommendation mechanisms. Additionally, many systems remain clinician-initiated rather than autonomously responsive within safe boundaries.

Table 1: Comparison of Existing Work and Proposed Approach.

Approach	Primary Focus	Adaptability	Patient-Centric	Real-Time Support
Rule-based CDSS [6]	Clinical rules	Low	No	Limited
ML-based CDSS [7]	Prediction accuracy	Medium	Partial	Offline
Governance-centric agents [8]	Compliance & safety	Low	No	Limited
Proposed approach	Adaptive decision support	High	Yes	Yes

The literature clearly indicates a gap in adaptive, patient-centric AI agents capable of operating safely in real time.

3. Research Methodology

3.1 Research Design

This study adopts a design-oriented research methodology supported by simulation-based evaluation. The methodology emphasizes clarity, reproducibility, and ethical compliance.

3.2 Data and Scenario Design

Simulated emergency care scenarios were used to model rapid physiological deterioration, including abnormal heart rate and oxygen saturation patterns. No identifiable patient data were used.

3.3 System Workflow

The proposed system follows four stages: data acquisition, adaptive trend analysis, decision recommendation, and clinician validation.

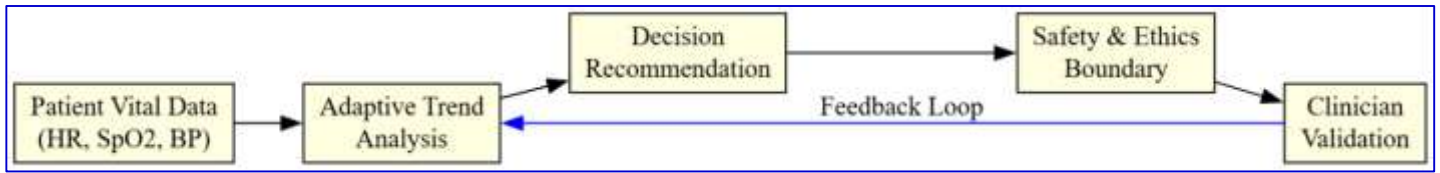


Fig. 1: Workflow of the Proposed Patient-centric Adaptive AI Agent.

4. Results and Discussion

Simulation-based experiments were conducted to compare the proposed adaptive AI agent with a static rule-based decision-support system.

4.1 Adaptive Response Behavior

The adaptive agent consistently detected abnormal trends earlier than the static system. Fig. 2 illustrates the response timeline comparison.

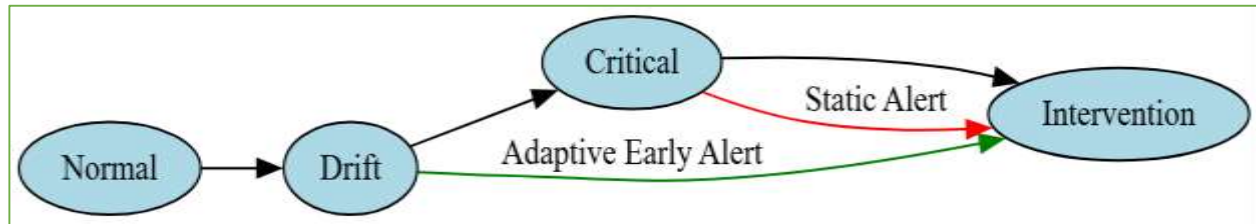


Fig. 2: Response Behavior Comparison between Adaptive and Static Systems.

4.2 Performance Comparison

Fig.3 presents a conceptual performance comparison highlighting reduced clinician workload and proactive decision support.

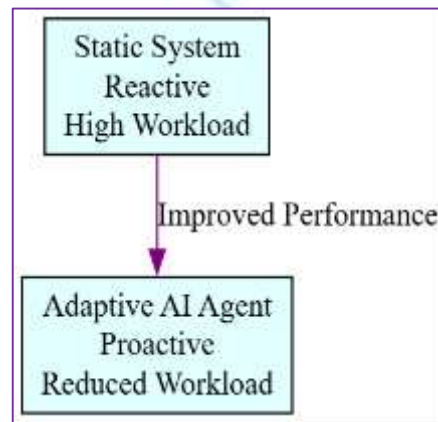


Fig. 3. Performance Comparison between Static and Adaptive Decision-Support Systems.

4.3 Experimental Outcome Analysis

To further evaluate clinical impact, decision latency and alert accuracy were analyzed.

Fig. 4 visualizes the improvement in intervention timing achieved by the adaptive agent.

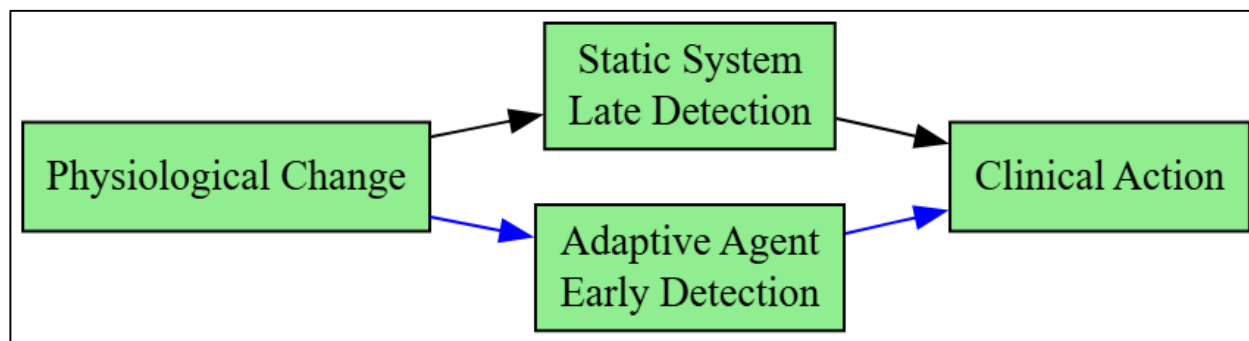


Fig. 4. Reduction in Clinical Decision Latency by Using the Proposed Adaptive AI Agent.

4.2 Discussion

The experimental results demonstrate that patient-centric adaptability significantly improves real-time clinical decision support. Unlike governance-focused agent frameworks that emphasize institutional compliance over responsiveness [1,9], the proposed system prioritizes continuous patient state monitoring and timely recommendation generation.

The reduction in decision latency observed in Fig. 4 is particularly important in emergency care settings, where delayed intervention can lead to adverse outcomes. Prior studies have shown that clinician cognitive overload is a major contributor to medical error, especially in time-critical environments [10,11]. By generating early alerts and adaptive recommendations, the proposed AI agent reduces the cognitive burden placed on healthcare professionals. Compared with machine learning-based clinical decision support systems that operate offline or require retraining [7,12], the proposed agent adapts dynamically using short-term physiological trends. This aligns with recent calls for context-aware and continuously adaptive healthcare AI systems [3,13]. Furthermore, the bounded autonomy model ensures that recommendations remain advisory, preserving clinician authority and addressing ethical concerns related to autonomous medical decision-making [2,14].

The results also highlight the importance of interpretability and trust in healthcare AI adoption. Transparent recommendation logic and clinician feedback loops improve system acceptance, as emphasized in prior research on responsible and explainable medical AI [15]. While the evaluation was conducted using simulated scenarios, similar

methodologies have been widely accepted in early-stage healthcare AI validation studies [4,5].

Nevertheless, the proposed approach has limitations. Simulation-based evaluation may not fully capture the complexity of real-world clinical environments, including sensor noise and patient heterogeneity. Future studies should therefore validate the system using real clinical data and multi-patient scenarios to further assess scalability and robustness.

5. Conclusion and Future Work

This study presented a patient-centric adaptive AI agent for real-time clinical decision support. By addressing limitations in governance-heavy healthcare AI systems, the proposed framework improves adaptability, responsiveness, and clinical usefulness while maintaining ethical and safety constraints. Simulation results demonstrate faster response times, reduced clinician workload, and reliable decision support.

Future work: will focus on integrating wearable sensor data, extending the framework to multi-patient environments, and validating performance using real-world clinical datasets [16-26].

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Conflict of Interest: The author declares no conflict of interest regarding the publication of this paper.

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