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Original Article

# Evaluating Agentic Artificial Intelligence in Healthcare Using a Perceive Reason Act Learn (PRAL) Framework: A Systematic Review

**Jyoti Shendage**[1], **Shital Pashankar**[2]
[1]School of Computer Studies, Sri Balaji University, Pune, India
[2]School of Information Technology, Indira University, Pune

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***Correspondence Address:***
*Jyoti Shendage*
*School Of Computer Studies, Sri Balaji University, Pune, India1 School of Information Technology, Indira University, Pune*
***Email:*** *dangatjyoti@gmail.com*

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***Abstract***

*Recent advances in artificial intelligence have led to increasing interest in agentic systems capable of goal-directed behavior and autonomous tool use. Such systems are proposed in healthcare as an extension beyond traditional generative models. Which primarily function through prompt-based interaction. However, existing studies are varying widely in how autonomy is defined, implemented and evaluated. Which makes it difficult to assess the actual maturity of agentic AI in clinical contexts. In this paper a systematic review of agentic AI applications in healthcare published between 2023 and 2025. The papers are evaluated using the Perceive Reason Act Learn (PRAL) framework. By analyzing systems according to their behavioral capabilities rather than outcome metrics alone. The review highlights substantial heterogeneity in reported autonomy levels. The literature review findings indicates the perception and action components are frequently implemented. Also the reasoning transparency and learning mechanisms are often limited or underreported. The paper is concludes by identifying methodological gaps and also by proposing directions for standardized evaluation of agentic AI in healthcare.*

***Keywords****: Agentic AI, Healthcare AI, Multi-Agent Systems, PRAL Framework, Systematic Review.*

## Introduction

Artificial intelligence has become increasingly embedded in healthcare systems. Particularly through applications such as clinical documentation, decision support and patient engagement tools [19]. Most deployed solutions rely on generative models. These models responds to explicit prompts and also operate within narrowly defined tasks. While these systems have shown efficiency gains. But their dependence on continuous human interaction limits its ability to manage complex, multi-step workflows common in clinical environments [2]. The recent research agentic artificial intelligence has explored by referring to systems designed. It pursues the goals autonomously by decomposing tasks into small chunks, getting help from external tools and updating its results based on feedback system [1], [7]. In healthcare sector such systems are proposed for applications in diagnostic support, administrative workflow automation, and patient monitoring to revenue cycle management and supply chain optimization [8], [17], [18]. It is observed that despite growing interest there is no consensus on what constitutes meaningful autonomy or how agentic behaviour should be evaluated in safety-critical domains [11]. Most existing evaluations focuses on task level performance outcomes. These performance outcomes consist of accuracy or time savings, without examining the underlying behavioural mechanisms that enable autonomy [3][4]. This makes it difficult to distinguish genuinely agentic systems from advanced generative assistants. To address this gap, this paper adopts the Perceive Reason Act Learn (PRAL) framework as an analytical lens for systematically reviewing agentic AI systems in healthcare.

## Agentic Ai as a Computational Paradigm

Agentic artificial intelligence represents a transition from function-centric models to systems that manage sequences of decisions over time. Classical artificial intelligence systems are typically designed to generate single- step responses. Whereas Agentic AI systems operate as stateful processes that track task progression, constraints and intermediate outcomes.



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This shift matches agentic AI more closely with classical intelligent agent theory and distributed systems than with standalone predictive or generative models [1]. AI Agents contain multiple functional components. It also includes modules for ingesting multimodal data, reasoning components for planning and decision-making, action mechanisms for interacting with external toolsand learning processes for adaptation over time [1], [9]. A key characteristic of this paradigm is explicit state management. By maintaining representations of task state agentic systems can condition current actions on prior decisions, enabling continuity across workflows rather than isolated responses. Control flow is therefore conditional instead of linear allowing agents to pause, escalate, or terminate tasks based on contextual factors.In healthcare this computational structure aligns naturally with workflow oriented tasks such as patient triage, longitudinal monitoring and care coordination [8], [24]. However the extent to which agentic components are implemented varies substantially across reported systems. Some multi agent diagnostic frameworks emphasise perception and action while providing limited transparency into internal reasoning processes [3]. Other systems rely on human supervision despite claims of autonomy, effectively constraining agent behaviour through external oversight [6]. Agentic systems also differ in how uncertainty influences behaviour, with some architectures using uncertainty to trigger additional data collection or human review an approach particularly relevant in safety- critical settings [11]. This diversity highlights the need for structured, behaviour-based evaluation approaches. Thus, adaptive AI is best understood not only as an extension of generative modelling but also as a form of autonomous process coordination, motivating evaluation frameworks. Which examine system behaviour, control mechanisms and supervision rather than task accuracy alone.

**Literature Review**

**Autonomous Diagnostics and Clinical Reasoning**

Early discussions around agentic AI in healthcare are largely concerned with definition rather than deployment. Collaco [1] attempts to draw a clear boundary between prompt-driven language models and systems that act with a degree of independence, particularly through iterative reasoning and external tool use. While this distinction is useful for conceptual clarity, the work stops short of showing how such autonomy behaves under real clinical constraints, where uncertainty and incomplete data are common.More applied efforts focus on diagnostic settings where multiple data sources must be combined. Mishra et al. [2] describe diagnostic agents used in oncology that aggregate imaging and laboratory results, reporting fewer false negatives than conventional workflows. These results are encouraging, but they come from controlled environments with narrowly defined tasks. It remains unclear how such systems perform when diagnostic signals are weak or contradictory. Similar limitations appear in the PathFinder system proposed by Ghezloo et al. [3], where multiple agents collaborate on histopathological analysis. Although performance approaches that of human experts in selected cases, the internal decision process is only partially observable, which may limit clinical confidence.Some work frequently cited as agentic lies outside direct patient care. The AlphaFold-3 update reported by Jumper et al. [4] demonstrates large scale autonomous molecular screening, yet its contribution is primarily upstream in drug discovery instead of clinical decision making. In contrast, applied screening tools such as the FDA cleared Aurora fundus camera operate much closer to patient facing workflows, allowing non specialists to conduct diabetic retinopathy screening under supervised conditions [5]. These systems show that limited autonomy can be useful when the scope of action is tightly constrained.Questions of trust cut across all diagnostic applications. Esmaeilzadeh et al. [6] show that clinicians are less concerned with raw accuracy than with understanding how a system arrives at its conclusions. Their findings suggest that diagnostic independence without some form of reasoning visibility is unexpected to see sustained adoption, regardless of reported performance gains.

**Multi-Agent Systems (MAS) and Infrastructure**

Multi agent architectures are often presented as a natural fit for healthcare workflows, which involve coordination across roles and departments. Yusuf et al. [7] review a range of such systems and report consistent reductions in patient wait times. However the reviewed studies vary widely in what they label as "autonomous" making direct comparison difficult. In many cases agents operate independently only within tightly scripted boundaries.In critical care standards Ode [8] reports that systems monitoring large numbers of physiological variables can identify sepsis risk several hours earlier than standard approaches. While outcome improvements are reported these systems rely on continuous data streams and stable infrastructure conditions that are not guaranteed in all hospitals. As systems scale coordination becomes a problem. Kaur [9] shows that performance degrades beyond a certain number of agents due to communication overhead leading to hierarchical designs that trade flexibility for control.Other applications focus less on reasoning and more on coordination. Jiménez et al. [10] study robotic nursing agents responsible for medication delivery and navigation within hospital wards. These agents perform faithfully within predefined routes and schedules but rarely adapt beyond those constraints. Ethical and governance issues become more pronounced as autonomy increases. Chen et al. [11] propose multi agent agreement mechanisms for high risk decisions. Which reduce erroneous outputs but also slow response times illustrating the tension between safety and efficiency.

A. **Chronic Disease and Remote Monitoring**

Chronic disease management presents a different form of choice which unfolds over long periods instead of discrete decisions. Nimri and Phillip [12] describe insulin titration systems that adjust pump settings based on real time glucose and activity data. These systems respond effectively to immediate changes keeping learning is often restricted to supervise updates instead of continuous adaptation.Clinical trials provide further evidence of benefit under controlled conditions. Ying et al. [13] report improved time in range outcomes for patients with Type 2 Diabetes using AI-assisted insulin adjustment. However these systems operate within clearly defined safety limits. Which raises the question of whether they should be considered fully agentic or advanced control systems. Similar boundaries appear in hypertension management platforms where agents analyse wearable data and offer timely feedback while relying on fixed clinical thresholds [14].The expansion of wearable devices has encouraged more distributed agent based designs. Manickam et al. [15] propose networks of agents that share information across medical devices to prevent adverse drug events. In parallel Fatoum et al.[16] focus on data governance using autonomous agents to manage encryption and access control. These approaches show autonomy in infrastructure management instead of clinical reasoning. Highlighting how agentic behaviour can appear in different layers of healthcare systems.

B. **Operational and Financial Agents**

Administrative workflows are often where agentic systems encounter the least resistance. Revenue cycle management agents described in industry case studies operate with clear objectives and limited ethical risk making them suitable for higher degrees of autonomy [17]. Similar characteristics appear in supply chain forecasting systems that manage surgical inventory with minimal human intervention [18].

Prior authorization agents further illustrate this pattern. Systems described by Tierney et al. [19] assemble clinical documentation and interact with payer systems with little ongoing supervision. At an organizational level Subramanian's autonomy framework [20] places such systems along a gradual progression from simple automation to self-managing infrastructure. While these applications lack clinical reasoning. They provide practical evidence of autonomous behaviour functioning reliably at scale.

C. **Ethics, Triage and Mental Health**

As agentic systems move closer to patient interaction, social and ethical concerns become more visible. A longitudinal study by Youth Leaders for Active Citizenship [21] reports that some users increasingly rely on autonomous agents for mental health triage, raising concerns about isolation and reduced human contact. These findings suggest that autonomy in mental health contexts requires strict boundaries than in administrative settings.

Educational impacts are also reported by The Duke University study on automation bias [22] shows that trainees exposed to opaque systems may lose situational understanding over time. This contrasts with workforce focused deployments such as the Nirmitee nurse agent partnership, where carefully limited automation reduced burnout without removing professional judgment [23].

Emergency triage systems illustrate a similar balance. Vision based agents evaluated by AEYE Health improve prioritization of high risk cases but operate under explicit supervisory protocols [24]. Finally projections for rural healthcare suggest that agentic systems could help address specialist shortages, although infrastructure limitations and bias remain unresolved challenges [25].

**Table I: Comparative Analysis of Literature Findings**

| Feature | Traditional AI / RPA | Generative AI (circa 2023) | Agentic AI (circa 2025) |
|---|---|---|---|
| Primary Function | Rule-based prediction and automation of predefined processes [7], [20] | Text, code, and content generation based on prompts [2], [19] | Goal-directed task execution across multiple steps [1], [9] |
| Human Input | Required at each decision point [7] | Frequent input through prompting and validation [2], [22] | Reduced interaction, with human supervision at defined checkpoints [1], [11] |
| Task Handling | Isolated, rigid tasks with limited context awareness [7], [20] | Single-step or loosely connected responses [19], [22] | Coordinated sequences of tasks within constrained workflows [8], [9] |
| Clinical Role | Pattern recognition and alerting functions [12] | Documentation support and information summarization [19] | Workflow coordination and decision support assistance [6], [23] |
| Adaptability to Errors | Limited tolerance to unseen conditions or data shifts [7] | Susceptible to inconsistent or fabricated output s ("hallucinations") [22] | Partial recovery through monitoring, consensus, or corrective mechanisms [11], [8] |
| Operational Scope | Narrow and highly specific deployments [20] | Broad applicability with shallow task integration [2] | Narrower scope with deeper task integration and coordination [9], [17] |

**Table II: Comparative Matrix of Reviewed Literature**

| Focus Area | Representative Papers | Reported Outcome / Observation | Dominant Architectural Pattern |
|---|---|---|---|
| Diagnostics | [1], [2], [3], [5] | Reported reductions in diagnostic errors under controlled or task-specific settings | Multi-modal reasoning components with tool invocation |
| Critical Care | [8], [9], [24] | Earlier detection of patient deterioration and associated outcome improvements in monitored cohorts | Continuous data-stream monitoring agents |
| Chronic Care | [12], [13], [14] | Improved disease management metrics (e.g., time-in-range) within defined safety constraints | Closed-loop systems integrating IoMT devices |
| Operations | [7], [17], | Reduced administrative processing time and | Workflow orchestration using |

| | | | |
|---|---|---|---|
| | [18], [20] | improved workflow efficiency in pilot deployments | task-specific agents |
| Ethics / Bias | [6], [11], [21], [25] | Increased emphasis on transparency and trust in human–agent interaction | Reasoning trace and consensus-based oversight mechanisms |

**Table III.Literature Review of Agentic AI in Healthcare (2023–2025)**

| Category | Study / Author (Year) | Core Contribution | Reported Outcome / Observation |
|---|---|---|---|
| **A. Autonomous Diagnostics** | Collaco (2025) [1] | Conceptual definition of Agentic AI using iterative reasoning and tool invocation. | Provided a taxonomy distinguishing prompt-driven LLMs from systems with limited autonomous behaviour. |
| | Mishra et al. (2025) [2] | Diagnostic agents integrating imaging and laboratory data in oncology. | Reported reduction in false negatives under controlled trial conditions (9.4%). |
| | Ghezloo et al. (2025) [3] | Multi-agent histopathology framework ("PathFinder"). | Improved diagnostic agreement in selected rare biopsy cases. |
| | Google DeepMind (2024) [4] | Autonomous molecular screening pipeline (AlphaFold-3). | Reduced candidate screening time in drug discovery workflows. |
| | Optomed & AEYE (2024) [5] | Autonomous handheld retinal screening system. | Enabled supervised diabetic retinopathy screening within short examination timeframes. |
| | Esmaeilzadeh et al. (2025) [6] | Study on explainability in clinical AI systems. | Found clinician trust correlated with availability of reasoning explanations. |
| **B. Multi-Agent Systems (MAS)** | Yusuf et al. (2025) [7] | Review of decentralized MAS deployments in healthcare. | Reported reductions in patient waiting time across high-volume settings. |
| | Ode et al. (2025) [8] | MAS-based critical care monitoring for sepsis. | Earlier detection of sepsis risk in monitored patient cohorts. |
| | Kaur (2025) [9] | Scalability analysis of large-scale MAS architectures. | Identified communication overhead beyond ~50 agents, motivating hierarchical designs. |
| | Jiménez et al. (2025) [10] | Robotic nursing coordination using MAS. | Improved efficiency in medication delivery and ward navigation tasks. |
| | Chen et al. (2025) [11] | Ethical governance mechanisms for MAS. | Reduced erroneous outputs through consensus-based decision protocols. |
| **C. Chronic Disease & IoMT** | Nimri & Phillip (2025) [12] | Autonomous insulin titration systems for Type 1 Diabetes. | Demonstrated responsive adjustment to real-time glucose and activity data. |
| | Ying et al. (2025) [13] | Randomized trial of AI-assisted insulin titration (Type 2 Diabetes). | Improved time-in-range metrics compared **to manual** adjustment. |
| | Barrett et al. (2025) [14] | Agent-based hypertension management platforms. | Provided timely feedback using wearable blood pressure data. |
| | Manickam et al. (2025) [15] | IoMT-enabled agent networks for medication safety. | Reduced adverse drug events through cross-device coordination. |
| | Fatoum et al. (2025) [16] | Blockchain-based autonomous data-sharing agents. | Improved management of data access permissions in distributed settings. |
| **D. Operations & Finance** | Flobotics RCM Study (2025) [17] | Autonomous revenue cycle management agents. | Reduced accounts receivable processing time in pilot deployments. |
| | ERP Modernization (2025) [18] | Predictive supply-chain agents for surgical inventory. | Lowered frequency of inventory stock-outs in tertiary hospitals. |
| | Prior-Authorization Pilot [19] | Agents for automated payer documentation and evidence retrieval. | Decreased manual administrative workload in prior-authorization tasks. |
| | TCS Autonomy Framework (2025) [20] | Maturity framework for autonomous healthcare IT systems. | Described progression from task automation to self-managing infrastructure. |
| **E. Ethics & Workforce** | YLAC (2025) [21] | Social analysis of autonomous mental health triage tools. | Reported increased reliance on agents among a subset of young users. |
| | Duke University Study (2024) [22] | Study on automation bias in clinical education. | Observed reduced task comprehension with opaque AI systems. |

| | | | |
|---|---|---|---|
| | Nirmitee Case Study (2025) [23] | Nurse–agent collaboration in hospital operations. | Reported reduction in burnout associated with reduced documentation load. |
| | AEYE Health Pilot (2024) [24] | Vision-based autonomous emergency triage agents. | Improved prioritization of high-risk patients under supervision. |
| | Piette et al. (2025) [25] | Forecast of agentic systems in rural healthcare delivery. | Suggested potential role in addressing specialist shortages, subject to infrastructure constraints. |

**Pral Based Evaluation Methodology**

**Review Design**

This study follows a systematic evidence review methodology adapted from PRISMA guidelines, focusing on behavioural evaluation rather than outcome metrics alone. The revie includes peer reviewed articles and high-quality preprints published between January 2023 and December 2025 affirm autonomous or agentic capabilities [1], [7].

D. **Data Sources and Search Strategy**

Databases searched include IEEE Xplore, PubMed, Scopus, and Web of Science. Search strings combined terms such as agentic AI, autonomous agents, multi-agent systems and healthcare. Additional high impact preprints were identified through citation chaining where relevant [3], [8].

E. **Inclusion Criteria**

Studies were included if they Described AI systems applied within healthcare contexts, claimed some degree of goal-directed or autonomous behaviour, provided sufficient technical detail to enable PRAL based analysis, Studies focusing solely on predictive modelling or static decision support were excluded [12], [13].

F. **PRAL Dimensions**

Each included study was evaluated across four dimensions Perception- Ability to ingest and integrate multimodal clinical data (e.g., vitals, imaging, text) [15]. Reasoning - Presence of explicit decision-making, planning or coordination logic [6]. Action - Autonomous interaction with external systems such as EHRs, devices or scheduling tools [5], [24]. Learning - Evidence of adaptation based on feedback or outcomes either online or offline [4], [16]

**Study Classification and Analysis**

The analysis revealed that most systems demonstrated strong perception and action capabilities particularly in administrative workflows such as billing, scheduling and supply chain management [17], [18]. In contrast reasoning processes were frequently opaque or implicitly embedded within model architectures, limiting auditability and clinician trust [6], [11].
Multi agent systems showed improved coordination as well as task decomposition in diagnostic and monitoring contexts [3], [8]. The scalability challenges and communication overhead were reported in larger deployments often necessitating hierarchical or manager worker architectures [9]. Few studies explicitly documented system failures or negative outcomes suggesting potential publication bias.

**Threats to Validity**

This review is subject to several limitations. First reliance on published literature may overrepresent successful or industry supported deployments [17], [18]. Second heterogeneity in reporting standards limited direct comparison across systems and PRAL dimensions. Third some studies provided insufficient technical detail, requiring conservative interpretation of claimed autonomy. Finally, while PRAL enables behavioural analysis, it does not fully capture ethical, legal and organizational factors that influence real-world adoption [11], [21].

**Discussion**

The findings suggest that many systems labelled as agentic exhibit partial autonomy rather than fully realized agentic behaviour. Learning and adaptive components are often constrained to offline updates or rule-based adjustments [4], [16]. This raises concerns regarding long term system robustness and the ability to respond to evolving clinical contexts. In clinical training settings increased independence raises concerns about automation bias and over-reliance [22]. These observations focuses on the importance of transparent reasoning and well-defined human supervision procedures as well as the significance of differentiating automation from autonomy.

**Conclusion and Future Work**

This paper presented a PRAL based systematic review of agentic AI systems in healthcare. Which emphasizing behavioural evaluation over task level performance metrics. The analysis revealed substantial variability in how autonomy is implemented and reported with many systems lacking explicit reasoning transparency or adaptive learning mechanisms. These findings suggested that claims of agentic behaviour should be interpreted cautiously in safety- critical clinical domains. By applying a structured evaluation framework this work contributes a methodological approach for assessing agentic AI beyond surface-level functionality. This approach can support clearer comparisons across studies and promote more responsible system design and reporting practices. Future research should focus on empirically validating PRAL dimensions through prospective system evaluations and expert consensus. Developing standardized reporting guidelines for agentic behaviour would improve reproducibility and comparability across studies.

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The authors declare that there are no conflicts of interest regarding the publication of this paper.

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