International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct-2026, PP 01-06

AI Chatbots in Healthcare: A Review Of Conversational Agents For Symptom Checking, Patient Support And Mental Health

Ghare Vaishnavi Shahaji; Prof. C. A. Kolse; Prof. M. C. Kolse; Prof. S. K. Said
Department Of Artificial Intelligence And Data Science Jaihind College Of Engineering Pune, Maharashtra, India;

Abstract—Healthcare systems face long waiting times, shortages of clinicians and limited access to reliable health information, particularly in rural and underserved areas. AI chatbots, conversational agents that interact with patients through text or voice, can answer health questions, check symptoms, remind patients about medication and appointments, and provide basic mental-health support around the clock. This paper reviews AI chatbots in healthcare. It traces their development from rule-based dialogue systems to agents powered by natural language understanding and, most recently, large language models trained or adapted on medical knowledge. Evidence from systematic reviews, randomized trials of mental-health chatbots, audits of online symptom checkers and comparisons of chatbot and physician responses is examined, together with studies of patient acceptance and of how assistants respond to crisis questions. A five-layer architecture comprising the user interface, language understanding, a grounded medical knowledge and reasoning layer, a safety and escalation layer and integration with health records is proposed. Research gaps, objectives, a comparison of chatbot types and challenges including accuracy, hallucination, privacy, liability, language diversity and digital literacy are discussed. The review concludes that healthcare chatbots are valuable as supervised, well-grounded assistants rather than replacements for clinicians.

Index Terms—Healthcare chatbot, conversational agent, symptom checker, large language models, mental health, patient engagement, natural language processing

I. Introduction

Patients often have simple questions: whether a symptom needs a doctor, how to take a medicine, or when their next appointment is. Busy clinics cannot answer every query promptly, and many people, especially in rural India, live far from specialists. Conversational agents can provide immediate, always-available responses through smartphones and messaging apps.

The idea is not new: ELIZA [1] simulated a psychotherapist in the 1960s. Modern chatbots, however, use natural language processing and large language models that can hold fluent, context-aware conversations. Laranjo *et al.* [2] systematically reviewed conversational agents in healthcare and found promising but early evidence, and Thirunavukarasu *et al.* [3] described both the opportunities and the risks of large language models in medicine.

This paper reviews AI chatbots in healthcare, proposes a safety-focused architecture and discusses challenges.

II. Theoretical Background

1. Types of Healthcare Chatbots

Fig. 1 classifies chatbots by function (information, symptom checking, mental-health support, chronic-disease management, administrative tasks) and by technology (rule-based, retrieval-based, generative).

International Journal of Computational Research in Science and Technology
E-ISSN: 3108-0871, Volume 2 Issue 5
Sep-Oct-2026, PP 01-06

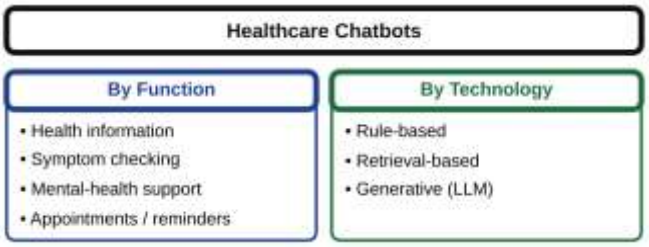


Fig. 1. Classification of healthcare chatbots.

2. How a Chatbot Understands Users

Natural language understanding identifies the user's intent, such as asking about a symptom, and extracts entities such as the symptom name and duration. Biomedical language models such as BioBERT [4] improve recognition of medical terms, and retrieval-augmented generation [5] grounds answers in trusted documents.

III. Survey of Existing Approaches

Laranjo *et al.* [2] reviewed studies of conversational agents for health and found that most used rule-based dialogue, with few randomized trials and limited safety evaluation. Fitzpatrick *et al.* [6] conducted a randomized controlled trial of Woebot, a chatbot delivering cognitive behavioural therapy techniques, and reported reduced depression symptoms among young adults compared with an information-only control.

Semigran *et al.* [7] audited online symptom checkers and found that the correct diagnosis was listed first only in a minority of cases, while triage advice was often appropriate but risk-averse. Miner *et al.* [8] tested smartphone assistants with questions about suicide, violence and physical health and found inconsistent and sometimes inappropriate responses, showing the need for crisis-handling design.With large language models, Singhal *et al.* [9] showed that a medically adapted model could answer medical licensing-style questions at a high level, and Ayers *et al.* [10] found that evaluators preferred chatbot responses to patient questions over physician responses in quality and empathy, although the study did not test clinical outcomes. Nadarzynski *et al.* [11] studied acceptability and found that patients were willing to use chatbots for minor issues but worried about accuracy and the loss of human contact. Table I summarizes these works.

TABLE I Summary of Literature Survey

Ref.	Author(s) / Year	Technique / Approach	Key Contribution	Limitation / Gap
[2]	Laranjo et al., 2018	Systematic review of health conversational agents	Promising early evidence	Few RCTs; safety rarely assessed
[6]	Fitzpatrick et al., 2017	Woebot RCT (CBT chatbot)	Reduced depression symptoms	Short trial; young adults
[7]	Semigran et al., 2015	Audit of symptom checkers	Triage often appropriate	Diagnosis accuracy low
[8]	Miner et al., 2016	Smartphone assistants and crisis questions	Revealed inconsistent responses	Commercial assistants only
[9]	Singhal et al., 2023	Medical LLM evaluation	High performance on medical questions	Not tested on patient outcomes
[10]	Ayers et al., 2023	Chatbot vs. physician responses	Chatbot rated higher quality and empathy	Online forum questions
[11]	Nadarzynski et al., 2019	Acceptability study	Accepted for minor issues	Concerns about accuracy
[3]	Thirunavukarasu et al., 2023	Review of LLMs in medicine	Mapped opportunities and risks	Rapidly evolving field

IV. Comparative Study

Table II compares chatbot types. Rule-based bots are safe but rigid, retrieval-based bots give accurate answers within their knowledge base, and generative LLM bots are flexible and empathetic but need grounding and safeguards.

TABLE II Comparison of Chatbot Types

Type	Flexibility	Accuracy Control	Risk
Rule-based	Low	High	Low
Retrieval-based	Medium	High	Low–Medium
Generative LLM	Very high	Low without grounding	High
Grounded LLM + rules	High	High	Medium

V. Research Gaps

- Few chatbots have been evaluated in randomized trials with clinical outcomes.
- Generative chatbots can hallucinate medical facts or give unsafe advice.
- Handling of emergencies and mental-health crises is inconsistent.
- Support for Indian languages and low-literacy users is limited.
- Data protection, consent and liability frameworks for chatbot advice are unclear.

1. Aims and Objectives

- **O1:** To review the types, technologies and evidence for healthcare chatbots.
- **O2:** To examine the role of large language models and their risks.
- **O3:** To propose a safe, grounded healthcare chatbot architecture.
- **O4:** To compare rule-based, retrieval-based and generative chatbots.
- **O5:** To identify challenges and future directions.

2. Proposed Architecture

The proposed architecture appears in Fig. 2.

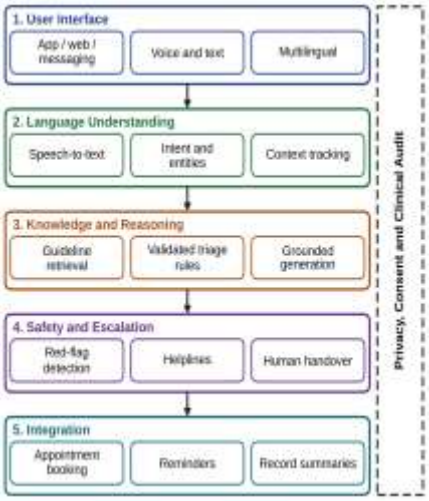


Fig. 2. Proposed safe healthcare chatbot architecture.

3. User Interface Layer

Patients chat through a mobile app, website or messaging platform, by text or voice, in their preferred language.

4. Language Understanding Layer

Speech is converted to text, intents and medical entities are extracted, and the conversation context is tracked.

5. Knowledge and Reasoning Layer

Answers are generated from verified medical guidelines and hospital information using retrieval-augmented generation; symptom triage follows clinically validated rules.

6. Safety and Escalation Layer

Red-flag symptoms such as chest pain or suicidal thoughts trigger immediate advice to seek emergency care and connection to helplines or clinicians. Uncertain answers are routed to human staff.

7. Integration Layer

With consent, the chatbot books appointments, sends medication reminders and records summaries in the hospital system for clinicians to review.

VI. Process Flow and Evaluation

Fig. 3 shows the conversation workflow. Intent classification selects the intent with the highest probability,

$$\hat{\imath} = \operatorname{argmax}_i P(i \mid u) \qquad (1)$$

where u is the user utterance. A response is released only if its grounding score, the fraction of statements supported by retrieved guideline text, exceeds a safety threshold; otherwise the query is escalated.

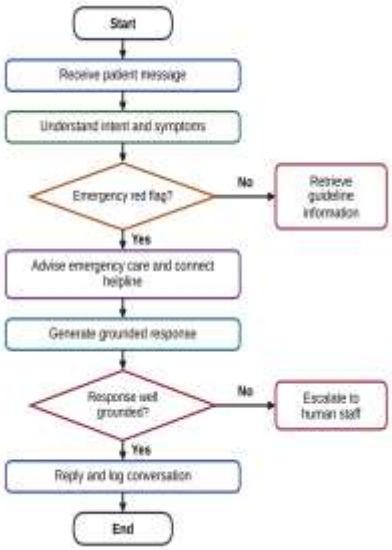


Fig. 3. Conversation workflow of the healthcare chatbot.

Evaluation covers answer accuracy against clinician judgements, appropriate triage, safe crisis handling, user satisfaction and response time.

VII. Limitations and Future Scope

Table III summarizes challenges. Future directions include multilingual voice chatbots for rural India, integration with national digital health records, continuous clinical auditing of chatbot conversations and regulatory guidance on chatbot medical advice [12].

TABLE III Challenges and Mitigation

Challenge	Mitigation
Inaccurate advice	Guideline grounding; clinician review
Emergencies	Red-flag rules; instant escalation
Privacy	Consent, encryption, DPDP compliance
Language diversity	Multilingual voice interfaces
Liability	Clear disclaimers; human oversight

VIII. Conclusion

AI chatbots can make healthcare more accessible by answering questions, checking symptoms, supporting mental health and handling routine tasks at any time. The reviewed literature shows encouraging results but also inaccuracies and safety gaps, especially for emergencies. A grounded, safety-first design with clear escalation to human clinicians allows chatbots to support patients while protecting them.

1. Acknowledgment

The authors express their sincere gratitude to the Department of Artificial Intelligence and Data Science, Jaihind College of Engineering, Pune, for providing the facilities, guidance and encouragement needed to carry out this work. The authors also thank the faculty members and colleagues whose valuable suggestions helped improve the quality of this review.

REFERENCES

1. J. Weizenbaum, “ELIZA—A computer program for the study of natural language communication between man and machine,” Commun. ACM, vol. 9, no. 1, pp. 36–45, 1966.
2. L. Laranjo et al., “Conversational agents in healthcare: A systematic review,” J. Amer. Med. Inform. Assoc., vol. 25, no. 9, pp. 1248–1258, 2018.
3. A. J. Thirunavukarasu et al., “Large language models in medicine,” Nat. Med., vol. 29, pp. 1930–1940, 2023.
4. J. Lee et al., “BioBERT: A pre-trained biomedical language representation model for biomedical text mining,” Bioinformatics, vol. 36, no. 4, pp. 1234–1240, 2020.
5. P. Lewis et al., “Retrieval-augmented generation for knowledge-intensive NLP tasks,” in Proc. NeurIPS, vol. 33, 2020, pp. 9459–9474.
6. K. K. Fitzpatrick, A. Darcy, and M. Vierhile, “Delivering cognitive behavior therapy to young adults with symptoms of depression and anxiety using a fully automated conversational agent (Woebot): A randomized controlled trial,” JMIR Ment. Health, vol. 4, no. 2, Art. no. e19, 2017.
7. H. L. Semigran, J. A. Linder, C. Gidengil, and A. Mehrotra, “Evaluation of symptom checkers for self diagnosis and triage: Audit study,” BMJ, vol. 351, Art. no. h3480, 2015.
8. A. S. Miner et al., “Smartphone-based conversational agents and responses to questions about mental health, interpersonal violence, and physical health,” JAMA Intern. Med., vol. 176, no. 5, pp. 619–625, 2016.

9. K. Singhal et al., “Large language models encode clinical knowledge,” Nature, vol. 620, no. 7972, pp. 172–180, 2023.
10. J. W. Ayers et al., “Comparing physician and artificial intelligence chatbot responses to patient questions posted to a public social media forum,” JAMA Intern. Med., vol. 183, no. 6, pp. 589–596, 2023.
11. T. Nadarzynski, O. Miles, A. Cowie, and D. Ridge, “Acceptability of artificial intelligence (AI)-led chatbot services in healthcare: A mixed-methods study,” Digit. Health, vol. 5, 2019.
12. World Health Organization, Ethics and Governance of Artificial Intelligence for Health: WHO Guidance. Geneva, Switzerland: WHO, 2021.
13. Miryala, M. (2026). A comparative engineering view of Salesforce CI/CD: Copado managed promotion and Jenkins-SFDX orchestrated delivery. International Journal of Research in Commerce and Management Studies, 8(1), 93–117