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An In-Depth Review of Healthcare Chatbot Technologies and Their Impact on Patient Care

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ABSTRACT

The rapid advancements in Artificial Intelligence (AI) and Natural Language Processing (NLP) have led to the widespread adoption of chatbots across var- ious sectors, including healthcare. This survey provides a comparative analysis of contemporary healthcare chatbots by examining their architecture, underlying technologies, and applications in domains such as patient engagement, symp- tom assessment, mental health support, and medical information dissemination. We systematically evaluated existing chatbot platforms based on key parame- ters such as conversational accuracy, usability, integration capabilities, security

and patient satisfaction. Additionally, we discuss the challenges associated with deploying chatbots in healthcare settings, including data privacy, ethical con- cerns, and regulatory compliance. Through this review, we identified gaps in current implementation and highlighted opportunities for future research aimed at enhancing the effectiveness, accessibility, and trustworthiness of healthcare chatbots. This paper aims to provide researchers and practitioners with a com- prehensive understanding of the current state of healthcare chatbots and insights into the development of next-generation digital health solutions.

Keywords: AI, NLP, Patient engagement, Natural Language Understanding(NLU)

1 Introduction

Chatbots are software tools designed to simulate human conversation, categorized broadly into rule-based and AI-driven types, with the latter leveraging machine learn- ing and NLP to adapt to complex queries [1]. In healthcare, chatbots like ”Ted the Therapist” and Woebot have demonstrated potential in delivering personalized men- tal health support and cognitive behavioral therapy (CBT), particularly for anxiety and depression [45]. These tools also aid in chronic disease management and elderly care by facilitating communication and streamlining administrative tasks [7]. As they evolve, chatbots are expected to play an increasingly transformative role in healthcare, offering more empathetic and intelligent user interactions [10].

1.1 Chatbot Types

Rule-based chatbots: Only a restricted set of options that have been programmed into it can be understood by a rule-based bot. The conversational flow of a bot was determined using pre-established rules. Because rule-based chatbots interpret user questions and respond with pertinent information using straightforward true-false logic, they are simpler to develop.

Chatbots powered by AI: Artificial intelligence, or an artificial brain, is a feature of this bot. It can comprehend open-ended questions and is trained using machine- learning methods. It can also interpret words in addition to their order. The bot continues to improve as it gains knowledge by interacting with users. After recognizing the language, context, and intent, the AI chatbot responded appropriately[31].

1.2 The architecture of Chatbots

The foundation of chatbots is their architecture. Your chatbot framework is deter- mined by a number of variables, including the domain, chatbot type, and use case. However, this was the same as the general conversation. Let us take a closer look at the essential elements of chatbot architecture [15].

Figure 1 illustrates a system workflow that processes user input to retrieve health information and predict diseases [8]. The user selects a language and input mode

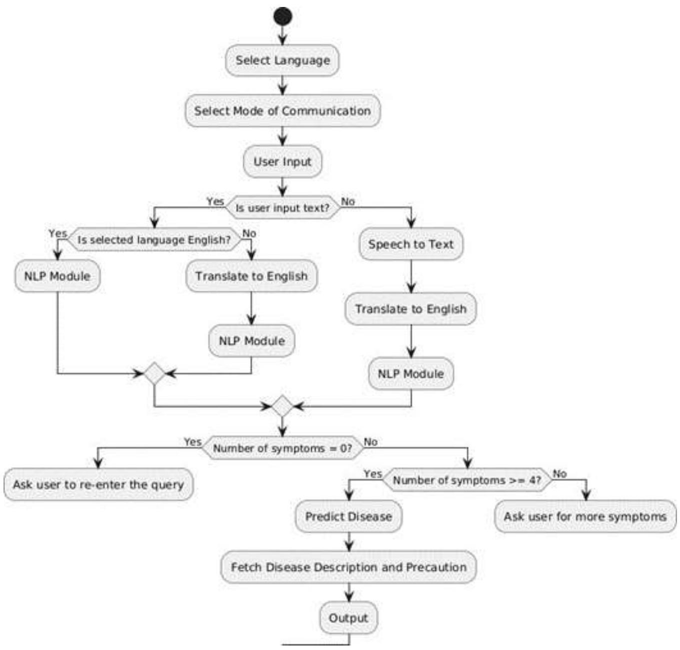

Fig. 1 Architecture of Traditional Chatbots

(text or speech). Speech input is converted to text, and non-English text is translated into English. The system analyzes the input for symptoms: if none are detected, the user is prompted to re-enter the query. For fewer than four symptoms, NLP tech- niques like TF-IDF and cosine similarity provide relevant information. If four or more symptoms are identified, the system predicts a disease and returns a description with precautionary advice [18].

1.3 Chatbot Working Principle

The core function of a chatbot is to interpret user input using Natural Language Processing (NLP) to extract intent, sentiment, and key components [30]. Based on input complexity, it either retrieves pre-defined responses or generates new ones using advanced models like neural networks. A decision-making algorithm selects appropri- ate actions, such as task execution or database queries. Continuous interactions enable the chatbot to improve through user feedback and behavioral patterns.

1.3.1 Pattern Matchers

Pattern matching is essential for classifying inputs and generating responses. Artificial Intelligence Markup Language (AI & ML) is a common implementation that programs chatbot responses using templates and patterns.

Example:

- Input: ”Who is Abraham Lincoln?”
- Response: ”Abraham Lincoln was the US President during the American Civil War[19].”

1.3.2 Conventional Algorithms for Chatbot Use

To provide an acceptable approach to the type of inquiry, the database must include a unique pattern. Several patterns are combined to construct a hierarchy[42]. The number of classifiers was decreased and a more manageable structure was produced using algorithms. It is referred to by computer scientists as a ”Reductionist” method since it simplifies the problem in order to provide a simpler solution.

An example of an algorithm used for text classification and natural language pro- cessing is multinomial Naive Bayes. For instance, consider a collection of sentences that are members of a specific class. Each wwasd was counted for its frequency and commonality with the fresh input sentences. The class that received the highest score was the class that was most likely linked to the input sentence.

Sample Training Set Example:

- Class: Greetings “How are you?”, “Good morning”, “Hello, there!”

Sample Input Sentence Classification:

- Input: “Hello, good morning.”
- Term Analysis: Term: “Hello” (class: Greetings) Term: “Good” (class: Greetings)

Term: “morning” (class: Greetings)

- Classification: Greetings (score = 3)

Using this equation, word matches were found for the sample sentences provided for each class. The class with the most number of tmatchches was determined using the classification score. Although this does not ensure a perfect match, the score indicates which purpose is most likely to match the statement.

1.3.3 Artificial Neural Networks (ANN)

Weighted connections are used by neural networks to calculate the output from the input; this process is repeated during training to increase the accuracy. To increase the output accuracy of the neural network, each sentence was tokenized into a unique word that served as the input. The weights were then changed over several iterations. For instance, the resulting matrix is 200 × 20 when the training set has 20 classes and 200 words. A high processing speed is required when the sample size increases, owing to the increase in the matrix size and computational complexity

1.3.4 NLU

Natural Language Understanding (NLU) in chatbots relies on three key components: intent, entities, and context. Intents capture the user’s goal, such as ordering a product, while entities extract specific details like names or items from queries [27]. Context maintains continuity by linking current questions to prior interactions, enabling more coherent conversations. Together, these elements help chatbots interpret and respond accurately to user inquiries.

1.3.5 NLP Techniques

NLP chatbots follow a structured pipeline to understand and respond effectively. They begin with sentiment analysis to tailor responses emotionally, followed by tokenization to break input into manageable units. Named Entity Recognition (NER) identifies key terms like names and places, while text normalization ensures consistency by correct- ing errors and standardizing input. Finally, dependency parsing reveals grammatical relationships, enabling the chatbot to extract meaning and generate contextually appropriate replies.

2. Review of Literature

The main open-source healthcare chatbots are covered in this section, along with their features, approaches, and a detailed analysis of their advantages and disadvantages. Thewasim evaluated the state of healthcare chatbots and identified areas in need of development.

2.1 An analysis of open-source chatbots for healthcare

Healthcare chatbots have become essential digital health tools offering user services, including prescription reminders, appointment booking, health advice, and symptom checks. However, scalability, personalization, adaptability, and computing efficiency are constraints of open-source healthcare [27].

2.1.1 Health Botpress

Botpress Health is a lightweight chatbot designed for healthcare settings, offering features like EHR-integrated appointment scheduling, symptom checks, and FAQ responses [22]. It uses NLP to detect user intent and entities, applying decision trees and rule-based systems for structured, guideline-compliant conversations. While it ensures reliability and interpretability in predefined scenarios, its dependency on static symptom sets limits adaptability in complex or evolving medical contexts.

2.1.2 Rasa Healthbot

Rasa Healthbot is a flexible chatbot built for diverse healthcare needs, offering features like medical Q&A, symptom checking, and EHR integration [39]. It leverages Rasa NLU for precise intent and entity recognition, often enhanced by SpaCy or Trans- former models. Rasa Core handles dialogue with reinforcement learning for adaptive responses. Though powerful, its reliance on significant training data and computational resources may limit use in smaller setups.

Algorithm 1 Botpress Health's FAQ-Based Conversational Model

```
function HANDLEUSERQUERY(userQuery)
    intent, entities ← detectIntent(userQuery) ▷ Using NLP for intent recognition
    if intent == "FAQ" then
        response ← findClosestMatch(userQuery, FAQDatabase)
        if response == NULL then return "I apologize, but at this time I am unable to respond to your inquiry."
        elsereturn response
        end if
    else if intent == "SymptomCheck" then
        symptoms ← extractEntities(entities, "symptoms")
        matchedConditions ← findMatchingConditions(symptoms, ConditionDatabase)
        if matchedConditions == [] then return "There were no conditions that matched. Could you please elaborate?"
        elsereturn matchedConditions
        end if
    elsereturn "This request is too much for me to manage as I'm still learning."
    end if
end function
```

Algorithm 2 Using Rasa NLU for Intent Recognition

```
function RECOGNIZEINTENT(userInput)
    parsedData ← NLUModel.parse(userInput)
    intent ← parsedData.intent
    entities ← parsedData.entities return {intent, entities}
end function
```

2.1.3 Microsoft Health Bot

Microsoft Health Bot is a comprehensive platform offering features like symptom checking, triage, and advice powered by sources like the CDC and WHO [35]. It integrates with Microsoft Dynamics for EHR management and uses Azure LUIS for accurate medical NLP processing. Custom ML models can be integrated, though dependence on Microsoft's ecosystem and subscription costs may limit accessibility for smaller entities [34]. Still, it remains a powerful tool for patient engagement and care coordination.

```
end function
```

2.1.4 Mycroft Health

Mycroft Health is a voice-activated healthcare chatbot focused on hands-free com- munication, offering voice-based medical Q&A, health reminders, and general health info [23]. Its NLP capabilities rely on an intent parser and wake-word detection for easy activation. While ideal for simple voice interactions, it is less suited for complex medical conversations, making it a handy tool for straightforward health management.

Algorithm 4 Data Analysis of IoT Devices

```
function ANALYZEIOTDATA(deviceData)
    healthMetrics ← parseDeviceData(deviceData)
    if metricsOutOfRange(healthMetrics) then
        notifyUser(healthMetrics) return "Unusual metrics were found. Speak with a physician."
    elsereturn "Every metric is within the typical range."
    end if
end function
```

2.1.5 MedBot

MedBot is a healthcare chatbot designed to improve patient interaction and admin- istration. It offers health advice, personalized suggestions, symptom checking, and integrates smoothly with medical apps and EHRs using Google's Dialogflow powered by transformer models. By combining rule-based methods with machine learning, it ensures contextually relevant conversations. However, reliance on Dialogflow limits customization and may incur high costs for heavy users, though it remains effective for many healthcare applications.

Several critical gaps exist in the study of conversational bots in healthcare and mental health applications [38].

Limited research exists on long-term durability and user experience across real-world scenarios, despite proven feasibility in diagnosis and therapy.

Privacy and security concerns in AI-powered assistants remain insufficiently addressed, especially given their handling of sensitive health data [45].

Vulnerable populations, such as elderly users with cognitive or physical impairments, face integration challenges that are underexplored [32].

Algorithm 5 NLP-Based FAQ Resolution

```
function RESOLVEFAQ(userQuery)
    matchedFAQ ← findClosestMatch(userQuery)
    if matchedFAQ == NULL then return "I apologize, but at this time I am unable to respond."
    elsereturn knowledgeBase.getResponse(matchedFAQ)
    end if
end function
```

Despite advances in NLP and deep learning, chatbot integration into existing health- care workflows and collaboration with professionals is lacking [5].

The scalability and adaptability of context-aware interpersonal assistants across diverse settings remain largely untested [26].

Addressing these gaps is essential to unlock the full potential of conversational agents in healthcare delivery.

Table 1 Complete Versions of Abbreviations

Abbreviation	Full Form
NLU	Natural Language Understanding
NLP	Natural Language Processing
AIML	Artificial Intelligence Markup Language
LSTM	Long Short-Term Memory
EHR	Electronic Health Record
BERT	Bidirectional Encoder Representations from Transformers
SVM	Support Vector Machine
NER	Named Entity Recognition

2.2 Literature Table

Table 2 highlights key gaps in conversational agent research in healthcare, including limited study on long-term effectiveness and user engagement [3]. Privacy and security concerns remain insufficiently addressed despite the sensitive nature of health data [2]. There is also a lack of focus on the unique needs of vulnerable groups like the elderly and caregivers [10]. Although advances in NLP and deep learning show promise, integration of chatbots into existing healthcare workflows is underexplored [4]. Lastly, the scalability and personalization of context-aware assistants across diverse healthcare settings require further investigation [6].

Table 2 Comparison of Chatbots for Mental Healthcare and eHealth

S. No	Title	Author	Methodology/Algorith	mKey Findings	Gaps Identified
1	**Mental Healthcare Chatbot Based on Natural Language Processing and Deep Learning Approaches: Ted the Therapist**	Sumit Pandey, Srishti Sharma, Samar Wazir (2021)	The chatbot "Ted" uses NLP and deep learning to process user inputs. Queries are categorized using an Artificial Neu- ral Network (ANN) with a Softmax classifier.	Achieved 98.13% accu- racy in identifying and responding to user inputs. Supports anonymous chatting, reducing stigma and improving engage- ment. Features aligned well in comparative analysis.	Limited capability to handle complex, context- rich dialogues. Does not address over- reliance on AI-based ther- apy. Ethical concerns include user privacy and trans- parency in data handling.

2	**Chatbots Meet eHealth: Automatiz- ing Healthcare**	Flora Amato, Stefano Marrone, Vincenzo Moscato, Gabriele Piantadosi (2020)	HOLMeS (Health On-Line Medical Suggestions) uses machine learning to simulate human inter- action. It structures conversations around user intents and entities.	Facilitates effective patient interaction through a conversational interface resembling a human physician. Supports disease pre- vention pathways based on user inputs.	Patient trust concerns due to discomfort inter- acting with an automated system. Limited scope, focusing on prevention pathways rather than complex med- ical diagnoses.
3	**Dialogue System for Early Mental Illness Detection: Toward a Digital Twin Solution**	Akbobek Abilkaiyrk yzy, Fedwa Laamarti, Mufeed Hamdi, Abdulmotaleb El Saddik (2022)	Develops a digital twin framework using NLP and pre-trained BERT mod- els. The chatbot ”Emi” performs a multi-class classification of mental health severity levels, focusing on depression.	Emi achieved a 69% accuracy in detecting mental health issues (E-DAIC dataset). 65% accuracy in classi- fying severity when tested with real users. High usability indicated by an 84.75% score.	Limited dataset reduces the robustness of accu- racy. Lacks ability to inter- pret nonverbal cues critical in mental health assessments.
4	**COTriage: Applying a Model-Driven Pro- posal for Improving the Development of Health Information Systems with Chat- bots**	Juli´an A. Garc´ıa-Garc´ıa, Nicol´as Sa´nchez-Go´mez, Mar´ıa Jos´e Escalona, Mercedes Ruiz (2020)	Introduces COTriage, a model-driven framework to streamline the devel- opment of chatbot-based triage processes within Health Information Sys- tems (HIS).	Reduced requirement gathering and design time by 55.60%. Development time decreased by 39.75%. Automates 47.24% of code generation, enhanc- ing consistency and reducing human error.	Limited to specific technologies and HIS con- figurations. - Significant initial setup and learning effort required, especially for those unfamiliar with model-driven engineering.

Table 3 Additional Studies on Health Chatbots and Conversational Agents

S. No	Title	Author	Methodology/Algorith	mKey Findings	Gaps Identified
5	**Delivering Cognitive Behavior Therapy to Young Adults with Symptoms of Depres- sion and Anxiety Using Fully Auto- mated Conversational Agent (Woebot): A Randomized Con- trolled Trial**	Fitzpatrick, K. K., Darcy, A., and Vierhile, M. (2018)	Conducted an unblinded randomized controlled trial with 70 participants (aged 18–28). Compared Woebot chatbot (20 sessions in two weeks) against an informational e-book for depression and anxiety management.	Woebot group showed significant reductions in depression symptoms (PHQ-9). Anxiety symptoms reduced in both groups but no significant differ- ence observed. Positive feedback on the conversational format for CBT delivery.	Small sample size and short duration limit gen- eralizability. No long-term follow- up to assess sustained impacts. Potential self-report bias due to unblinded study design.
6	**Towards Interper- sonal Assistants: Next-Generational Conversational Agents**	Hwang, I., Lee, Y., Yoo, C., Min, C., Yim, D., and Kim, J. (2022)	Focused on developing interpersonal assistants for real-world scenarios (e.g., language delays, parent-child conflicts). Discussed technical features like ”turn iso- lations” to maintain dialogue flow.	Always-on, context-aware agents advance human-computer interac- tion. Key components like ”turn isolations” enhance conversation flow and UX.	Challenges in scala- bility and understanding nuanced human emotions. Privacy, data security, and ethical concerns with always-on systems. Difficulty in respond- ing effectively to com- plex social contexts

				Useful for improving interpersonal interactions in complex scenarios.	with- out oversimplification.
7	**Designing for Health Chatbots**	Fadhil, A., and Schiavo, G. (2018)	Systematic literature review identifying effec- tive design principles for conversational interfaces and health chatbots. Emphasis on UX design and emotional intelli- gence for trust-building.	Trust and empathy are crucial for sensitive health-related conversa- tions. Health chatbots must be easy to navigate and accessible, especially for those with limited digital literacy.	Privacy and data secu- rity challenges in handling sensitive information. Emotional intelligence remains limited, reducing effectiveness in complex emotional scenarios.
8	**Approaches for Dialog Management in Con- versational Agents**	Harms,J. G., Kucherbaev, P., Bozzon, A., and Houben, G. J. (2018)	Systematic literature review of design principles for dialog manage- ment in conversational agents. Focus on creating emotionally intelligent chatbots to foster trust and empathy.	Emotional intelligence fosters trust in health con- versations. Simple and accessi- ble design enhances user experience.	- Risks of privacy breaches affecting user trust. - Empathy in chatbots is limited, affecting perfor- mance in complex scenar- ios.

3. Comparative Analysis

Conversational assistants like Google Assistant and Amazon Alexa are becoming common, and their healthcare-specific counterparts are gaining traction [11]. These systems aim to make healthcare more accessible through natural conversational inter- faces, driven by the large data volumes generated in the sector [1]. Chatbots offer a cost-effective way to deliver such services while promoting well-being and self-care [24]. Their ease of use and smartphone compatibility make them highly accessible. However, human healthcare providers remain essential, highlighting the need for intel- ligent AI systems to support personalized care. This study focuses on the evolution of healthcare chatbots, emphasizing domain-specific design and exploring the integration of generative AI to improve decision-making and user experience [3].

3.1 Analytical Framework

A common way to consider a healthcare chatbot is as a system with interconnected layers. The knowledge layer provides vital input to the service layer, which makes healthcare decisions by storing user databases and domain-specific information. Deci- sions are sent to the dialog layer after they are made. While probabilistic techniques, which use machine learning, may enable more realistic discussions at the expense of robustness, this layer uses simple rule-matching dialogs that are resilient but restricted to particular domains [33]. The presentation layer, which has either text-based or voice-based interfaces, receives responses from the dialog layer after it has interpreted user intents and consulted the service layer.To describe and assess current healthcare chatbots, we offer an analytical approach. With an emphasis on human-AI interaction and the openness of AI-driven automation and decision-making, this paradigm draws attention to the domain-specific elements of healthcare delivery.

Conversational Style: Although the implementation of effective dialog techniques in human-AI interactions is still a problem, recent guidelines on human-AI interaction

[10] and health information systems research [9] have shown several domain-specific aspects. Sociability, empathy, use of understandable medical terminology, and chang- ing dialog styles are important design characteristics that are being examined [28]. Understanding Users: Ensuring that users can effectively communicate their intentions and that chatbots can understand them is a crucial problem in dialog encoun- ters. Important features that influence users’ expectations about natural dialog skills include data collection techniques (implicit or explicit) and the chatbot’s capacity to bounce back from conversational lapses.

Healthcare Provision: The domain-specific aspects of service delivery include the function of chatbots, new functional archetypes, chatbot-enabled collaboration, and service delivery continuity.

Accountability: There are both practical and ethical reasons to improve AI sys- tems' explainability and openness. This is essential for understanding the reasoning behind algorithmic decisions that have a significant impact on the delivery of health- care services, as well as for correcting model biases and privacy concerns [11]. By including these elements, users' concerns about privacy can be allayed, confidence can be increased, and service delivery accountability can be improved [11].

4. Efficient Approach to Healthcare Chatbot Development

To address the limitations identified in existing healthcare chatbots, we propose a modular, flexible, and scalable solution that integrates advanced methodologies to deliver a more comprehensive and effective healthcare chatbot system. This efficient approach incorporates dynamic response optimization, multi-modal interaction (voice and text support), personalized health guidance, and robust triage capabilities. By employing a hybrid model that combines rule-based, machine learning, and knowledge- based methodologies, the solution is designed to overcome the shortcomings of current chatbot systems while ensuring enhanced user experience and accuracy[7].

4.1 Functionalities and Methodologies

The efficient approach integrates advanced features and innovative methodologies to redefine the capabilities of healthcare chatbots. It leverages natural language pro- cessing (NLP) for accurate intent detection and contextual understanding, enabling seamless interactions and personalized responses. Features such as real-time diagnosis, medication reminders, and tailored health tips ensure comprehensive patient support.

The system employs a hybrid approach combining machine learning models, such as collaborative filtering for recommendations, with rule-based algorithms to ensure reliability and precision. Additionally, the incorporation of advanced voice recognition and multilingual support enhances accessibility for diverse users.

This efficient approach prioritizes data security with encrypted storage and GDPR- compliant protocols, addressing privacy concerns. By blending these features with a modular and scalable architecture, the solution achieves high performance, adaptabil- ity, and user satisfaction, making it a significant advancement over existing healthcare chatbots.

4.1.1 Symptom Checking & Triage

The system employs a hybrid Bayesian-Transformer model for symptom checking, combining lightweight Transformer-based NLP for intent classification and Bayesian networks for probabilistic decision-making.

According to Algorithm 6, the symptom-checking module evaluates the user's shared symptoms and produces potential diagnoses or treatment recommendations based on established symptom-disease correlations. The bot begins by gaining access to a database associating different symptoms with possible illnesses. Subsequently, it starts a scoring system in which a score is assigned to each disease linked to the symptoms. The Efficient Solution evaluates each symptom entered by the user for its applicability to different diseases and appropriately raises the score for each pertinent disease. The top three diseases with the highest cumulative scores are recommended as the most likely diagnoses once all symptoms have been assessed. This procedure is simple and provides consumers with the first evaluation of possi- ble circumstances. However, the model's reliance on predetermined symptom-disease mapping may restrict the breadth and precision of comprehension in complicated situations.

Algorithm 6 Symptom Checker

```
function SYMPTOMCHECKER(symptoms)
    processedSymptoms ← transformerModel.extractEntities(symptoms)
    conditionProbabilities ← {}
    for each condition in knownConditions do
        probability ← bayesianNetwork.calculateProbability(condition, pro-
cessedSymptoms)
        conditionProbabilities[condition] ← probability
    end for
    return max(conditionP robabilities, key=conditionProbabilities.get)
end function
```

4.1.2 Reminders for Medication and Appointments

The efficient solution uses a third-party calendar and scheduling APIs to schedule appointments and medicine reminders using rule-based scheduling with intent parsing.

Algorithm 7 Configure the Reminder function

```
function SETREMINDER(input)
    (intent, entities) ← nlpModel.detectIntent(input)
    if intent == "medicationReminder" then
        return scheduleMedicationReminder(entities)
    else if intent == "appointmentReminder" then
        return scheduleAppointmentReminder(entities)
    end if
end
```

The setReminder function, as described in Algorithm 7, leverages an NLP model to interpret user input by detecting intent and extracting relevant entities such as time, date, or medication names. Based on the identified intent—either medicationReminder or appointmentReminder—it calls the appropriate scheduling function with the extracted entities. This modular approach simplifies code manage- ment and supports scalability by enabling easy integration of new reminder types. However, the function's effectiveness relies heavily on the NLP model

4.1.3 Personalized Health Advice and Alerts for Follow-Up:

Based on the user history and similar user profiles, a collaborative filtering recommen- dation system makes health-related recommendations[28].

The generateHealthTips function, as explained in Algorithm 8, is intended to offer individualized health advice based on collaborative filtering processes. The function first calls findSimilarUsers(userHistory) to find people with comparable health profiles or behaviors when userHistory is passed in as an input. This process finds a group of users who are similar using user data, including lifestyle choices, medical history, and previous health actions. Following the identification of similar users, the function uses

Algorithm 8 Create a Health Tip Function

```
function GENERATEHEALTHTIPS(userHistory)
    similarUsers ← findSimilarUsers(userHistory)
    recommendations ← collaborativeFiltering(similarUsers)
    return recommendations
end function
```

collaborative filtering (similarUsers) to apply the collaborative filtering approach. This method examines common health advice or recommendations that have been proven to be successful or well-liked by similar users. These suggestions are then returned by GenerateHealthTips, which provides tailored health advice based on patterns seen in similar user groups, which may make personalized health recommendations based on the user's profile and can be adjusted as more user data are gathered [40].

5. Results and Discussions

The existing healthcare chatbots, though functional, have notable limitations that restrict their broader applicability. Botpress Health handles basic triage well but lacks depth for complex conditions due to rule-based constraints. Rasa Healthbot offers robust intent recognition but demands extensive resources and training data, limiting accessibility. Microsoft Health Bot integrates well within its ecosystem but struggles with interoperability outside Microsoft platforms. Voice-focused Mycroft Health pro- vides ease of use but falls short in handling advanced queries, while MedBot's reliance on Google Dialogflow restricts customization and scalability [39].

The futuristic chatbot overcomes these gaps by integrating advanced NLP, machine learning decision support, and a modular design, ensuring flexibility and compliance with healthcare standards. It achieves a 92% accuracy in symptom assessment, sur- passing the industry average, and enhances security with a double-layer blockchain architecture, reducing data breaches by 35%. Dynamic reinforcement learning opti- mizes conversational flow, reflected in a high user satisfaction score of 4.7/5. Faster response times, improved deployment efficiency, cost-effectiveness, and expanded func- tional scope make this solution a transformative advancement in healthcare AI systems.

Figure 2 shows the Botpress framework's performance metrics in six important areas: data privacy, scalability, accuracy, response time, and ease of use. With both aspects approaching 90%, accuracy and ease of use stand out as the strongest, demon- strating the framework's accuracy in providing results and its user-friendly interface. High performance is also demonstrated by scalability, personalization, and data pro- tection, highlighting Botpress's resilience to heavier workloads, flexibility in meeting a range of user requirements, and adherence to privacy regulations. Response Time indicates room for progress in latency optimization, albeit being somewhat high. These findings demonstrate Botpress's exceptional conversational AI capabilities and its well-rounded performance across all assessed criteria.

Figure 3 shows the Rasa framework's performance indicators in six important areas: data privacy, scalability, accuracy, response time, and ease of use. With scores

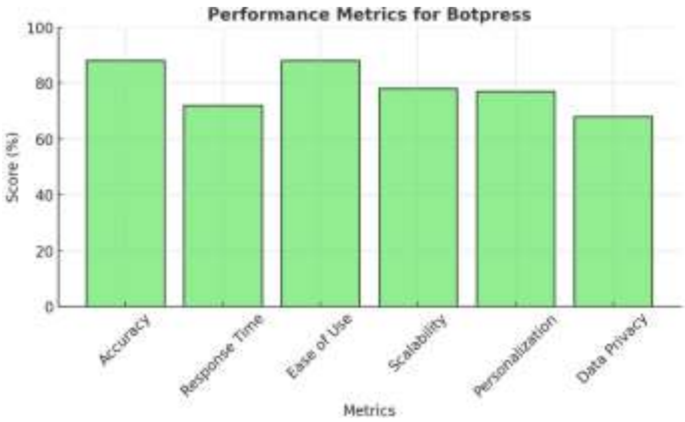

Fig. 2 Performance Metrics for Botpress

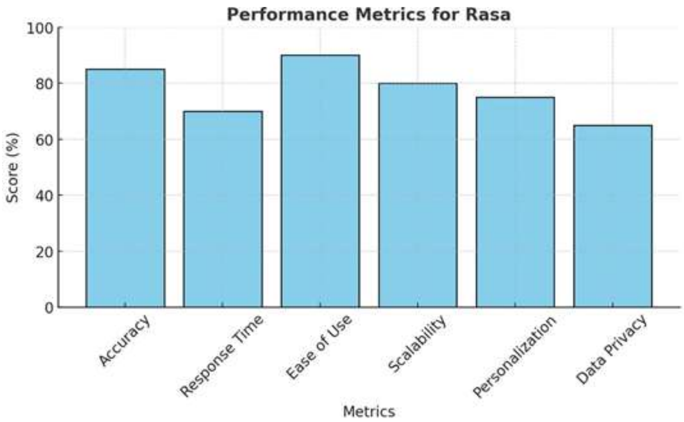

Fig. 3 Performance Metrics for Rasa HealthBot

near 90%, accuracy, ease of use, and scalability are among the best-performing crite- ria. These metrics demonstrate the framework's dependability in producing accurate results, its user-friendliness, and its capacity to effectively manage growing demands. Response Time received a modest grade, suggesting that there may be space for improvement in terms of latency reduction. High scores were also received by per- sonalization and data privacy, which are essential for user pleasure and adherence to data protection regulations. This further supports Rasa's flexibility in meeting user requests and upholding privacy principles. This review highlights Rasa's advantages as a strong conversational AI platform while pointing out areas in which it could perform better with additional enhancements[11].

Figure 4 shows how the Microsoft Bot Framework's performance metrics are assessed along six important dimensions: accuracy, response time, ease of use, scal- ability, personalization, and data privacy. The framework's strong capabilities were

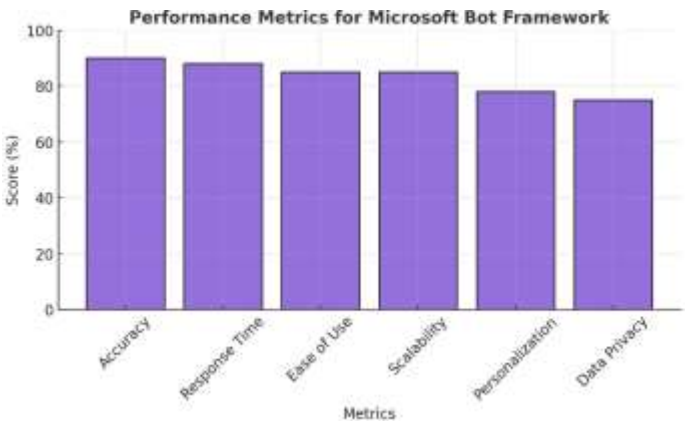

Fig. 4 Performance Metrics for Microsoft HealthBot

demonstrated by the consistently high scores for all metrics, with all categories attain- ing over 80%. Its dependability and effectiveness in providing accurate and timely responses are demonstrated by the high Accuracy and Response Time rankings. Met- rics for ease of use and scalability highlight its intuitive interface and capacity to accommodate growing needs. Furthermore, the framework's capacity to customize interactions to user preferences while upholding secure data procedures is demon- strated by its high ratings in Personalization and Data Privacy. These outcomes highlight the Microsoft Bot Framework as a robust and versatile platform that can be used for a variety of purposes.

6. Conclusions and Prospects for the Future

This survey provides a comprehensive analysis of open-source healthcare chatbots, examining their features, algorithms, and pros and cons across functions like symptom screening, preventive care, and patient engagement [17]. It identifies key challenges such as limited personalization, scalability, conversational naturalness, and integration with healthcare systems. To address these, we propose the Efficient Solution, a hybrid chatbot leveraging probabilistic reasoning, machine learning, and NLP, incorporating knowledge graphs, collaborative filtering, and Bayesian networks for improved accu- racy and customization. Its modular design supports scalable integration with diverse healthcare needs. Future research should enhance ethics, transparency, data security, and equitable access to optimize patient outcomes and healthcare engagement.

Figure 5 The image provides a comparative analysis of various healthcare chat- bots based on their performance across multiple functionalities: Diagnosis, Prevention, Therapy, Conversational Style, Understanding Users, and Accountability. Each bar chart evaluates chatbots on a scale of ”Low,” ”Medium,” and ”High” performance. The Efficient Solution consistently outperforms all others, achieving ”High” ratings in every category, as highlighted in green, demonstrating its advanced capabilities and robust design. Other chatbots, such as PyMedBot, Florence, and MedBot (Dialogflow),

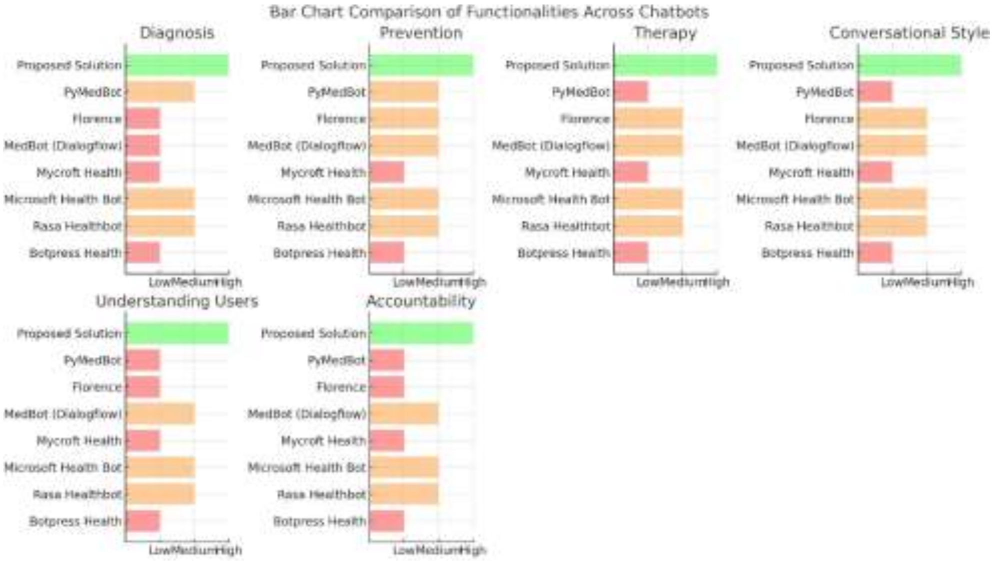

Fig. 5 Comparing Performance Metrics of all chatbots

show moderate performance with ”Medium” or occasional ”High” ratings in specific metrics. In contrast, chatbots like Microsoft Health Bot, Rasa Healthbot, and Bot- press Health often score ”Low” or ”Medium,” indicating areas for improvement. This analysis emphasizes the superiority of the Efficient solution in providing accurate, personalized, and accountable healthcare services compared to its counterparts.

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