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Optimizing Telehealth Services with LILM-Driven Conversational Agents: An HCI Evaluation

ZHAO, Yuxin [1*] QU, Ping [2] XIAO, Jingxuan [3] WU, Jiawei [4] ZHANG, Beibei [5]

[1] New York University, USA
[2] Maharishi International University, USA
[3] Georgia Institution of Technology, USA
[4] Illinois Institute of Technology, USA
[5] Xi'an Jiaotong University, China

**** ZHAO, Yuxin is the corresponding author, E-mail: yz8472@nyu.edu***

Abstract: Telehealth services have become increasingly important, especially in the wake of global health crises such as the COVID-19 pandemic, offering a necessary alternative to traditional in-person healthcare delivery. However, scalability and efficiency challenges persist due to high demand, limited provider availability, and the need for personalized interactions. This paper explores the use of large language models (LLMs) like OpenAI's GPT-4 as conversational agents within telehealth platforms to address these issues. We evaluate the human-computer interaction (HCI) aspects of LLM-driven agents through controlled experiments and user studies, assessing metrics such as user satisfaction, task completion time, and error rates. Our findings indicate that LLM-driven agents significantly enhance telehealth experiences by providing timely, accurate, and empathetic responses, thereby reducing provider workload and improving patient engagement and satisfaction. Integrating these agents into telehealth platforms offers a promising solution to current challenges, enhancing patient experience and operational efficiency. Future research should address data privacy, ethical considerations, and continuous model updates to ensure reliability and safety.

Keywords: Telehealth Services, Large Language Models (LLMs), Conversational Agents, Human-Computer interaction (HCI), Patient Engagement, Healthcare Efficiency.

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1 INTRODUCTION

1.1 BACKGROUND

Telehealth services provide a convenient alternative to traditional healthcare delivery, especially for remote and underserved populations facing barriers such as geographic isolation, limited mobility, financial constraints, and a scarcity of providers. Despite these advantages, telehealth struggles with scalability and compromised patient-provider interactions, leading to reduced satisfaction and engagement. The advent of large language models (LLMs) like OpenAI's GPT-4 offers a solution by enabling conversational agents that can handle routine interactions, provide instant responses, and offer personalized advice, thereby improving efficiency and alleviating provider burdens. This paper investigates the optimization of telehealth services using LLM-driven agents by evaluating their effectiveness through human-computer interaction (HCI) metrics, focusing on user satisfaction, task efficiency, and error rates. Our study, involving healthcare professionals and patients, reveals that integrating LLMs can revolutionize remote healthcare delivery by making it more accessible, efficient, and patient-centric. We provide a detailed analysis of our findings, highlighting the potential benefits and limitations of LLM-driven conversational agents in telehealth..

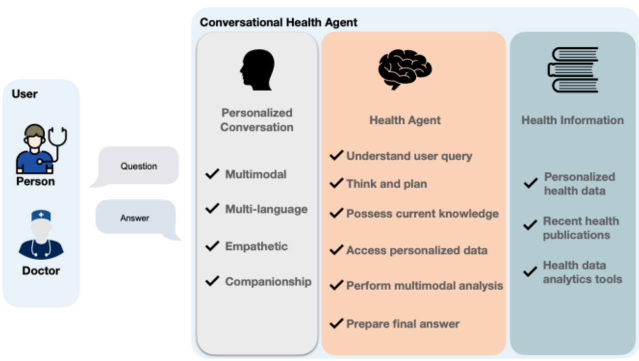

FIGURE 1. A CONVERSATIONAL HEALTH AGENT INCLUDING 1) A CONVERSATION COMPONENT TO ENABLE USER INTERACTION AND 2) A HEALTH AGENT FOR PROBLEM-SOLVING AND DETERMINING THE OPTIMAL SEQUENCES OF ACTIONS, LEVERAGING HEALTH INFORMATION.

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2 BACKGROUND AND RELATED WORK

2.1 TELEHEALTH SERVICES

Telehealth encompasses a wide range of services, including remote consultations, monitoring, education, and therapeutic interventions. These services provide a flexible and efficient means for delivering healthcare, particularly in contexts where traditional in-person visits are impractical or impossible. The primary components of telehealth include:

Remote Consultations: These allow patients to interact with healthcare providers through video conferencing, phone calls, or messaging platforms. Remote consultations can cover a variety of needs, from primary care to specialist consultations, enabling patients to receive timely medical advice without the need to travel.

Remote Monitoring: This involves the use of wearable devices and other technologies to track patients' health metrics, such as heart rate, blood pressure, glucose levels, and more. Remote monitoring allows for continuous observation of patients, particularly those with chronic conditions, ensuring that any significant changes in their health status are promptly addressed.

Health Education and Promotion: Telehealth platforms provide educational resources and tools to help patients manage their health. This includes instructional videos, interactive modules, and access to healthcare information that can empower patients to make informed decisions about their health and wellness.

Therapeutic Interventions: Telehealth can also support mental health services, such as psychotherapy, counseling, and behavioral health interventions. This is particularly beneficial for individuals who may feel stigmatized seeking in-person mental health services.

Despite its numerous benefits, telehealth faces several significant challenges:

Limited Accessibility: Not all patients have equal access to the necessary technology and internet connectivity required for telehealth services. This digital divide can exacerbate existing healthcare disparities, particularly among low-income, elderly, and rural populations.

Patient Engagement: Maintaining patient engagement in a remote setting can be challenging. The lack of physical presence may lead to decreased patient adherence to treatment plans and lower levels of satisfaction with the care received. Ensuring that telehealth interactions are as engaging and effective as in-person visits is crucial.

Resource Constraints: Healthcare providers must manage their time and resources efficiently to balance telehealth services with in-person care. This requires careful scheduling, effective communication tools, and seamless integration of telehealth platforms with existing electronic health record (EHR) systems.

Regulatory and Privacy Concerns: Telehealth services must comply with various regulatory requirements to protect patient privacy and ensure data security. The need for secure and compliant telehealth platforms can be a barrier to widespread adoption.

Addressing these challenges is essential for realizing the full potential of telehealth services. By integrating advanced technologies, such as large language models, telehealth platforms can enhance accessibility, improve patient engagement, and optimize resource allocation, ultimately leading to better healthcare outcomes.

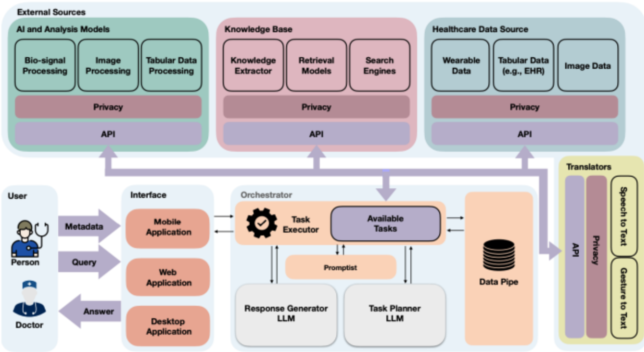

FIGURE 2. AN OVERVIEW OF THE PROPOSED LLM-POWERED FRAMEWORK LEVERAGING A SERVICE-BASED ARCHITECTURE

2.2 LARGE LANGUAGE MODELS

Large Language Models (LLMs), such as OpenAI's GPT-4, have revolutionized the field of natural language processing (NLP) with their ability to understand and generate human-like text[1]. These models are trained on vast datasets, allowing them to learn the nuances of language, context, and even some aspects of common sense reasoning. The applications of LLMs span multiple domains, including customer service, education, content creation, and healthcare[2].

Understanding and Generating Human-Like Text: One of the most significant strengths of LLMs is their ability to produce coherent and contextually appropriate text[3]. This capability is particularly beneficial in creating conversational agents that can engage in meaningful dialogues with users, providing relevant and timely information in a human-like manner[4,5].

Applications in Customer Service: In customer service, LLMs have been deployed to handle customer queries, provide support, and resolve issues efficiently[6,7,8,9,10]. These conversational agents can understand customer concerns, offer solutions, and even escalate issues to human agents when necessary, thereby improving response times and customer satisfaction[11,12].

Educational Tools: In education, LLMs are used to create interactive learning experiences, answer student

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questions, and generate educational content[13,14]. They can adapt to the learning pace of individual students, providing personalized assistance and feedback that enhance the learning experience.

Content Creation: LLMs are also employed in content creation, where they assist in drafting articles, creating marketing copy, and even generating creative writing pieces[15]. Their ability to mimic various writing styles and tones makes them valuable tools for writers and content creators.

Given their versatility and effectiveness, LLMs are well-suited for integration into telehealth services as conversational agents. Their application in telehealth can be categorized into several key areas:

Patient Triage and Initial Assessment: LLM-driven agents can conduct initial patient assessments by asking relevant questions, understanding patient symptoms, and providing preliminary advice[16,17]. This can help streamline the triage process, ensuring that patients receive appropriate care quickly.

Patient Education and Support: These agents can provide patients with information about their conditions, treatment options, and medication instructions[18]. By offering clear and accurate information, they can help patients better understand their health and manage their conditions effectively[19].

Appointment Scheduling and Follow-Ups: LLMs can handle administrative tasks such as scheduling appointments, sending reminders, and conducting follow-up checks. This can reduce the workload on healthcare staff and improve the efficiency of telehealth services[20].

Continuous Patient Engagement: Maintaining ongoing patient engagement is crucial for successful telehealth services. LLM-driven agents can interact with patients regularly, checking on their progress, answering questions, and providing encouragement, thus ensuring continuous patient involvement in their care.

The integration of LLMs into telehealth platforms offers several potential benefits:

Scalability: LLM-driven agents can handle large volumes of interactions simultaneously, making telehealth services more scalable and accessible to a broader patient population.

Consistency and Accuracy: These agents can provide consistent and accurate information, reducing the risk of miscommunication and ensuring that patients receive reliable advice.

Personalization: LLMs can tailor their responses based on individual patient data, providing personalized interactions that enhance patient satisfaction and adherence to treatment plans.

However, the deployment of LLMs in telehealth also poses challenges, such as ensuring data privacy, maintaining the quality and relevance of the information provided, and addressing ethical concerns related to AI in healthcare. Overcoming these challenges will be essential to fully realizing the potential of LLM-driven conversational agents in optimizing telehealth services.

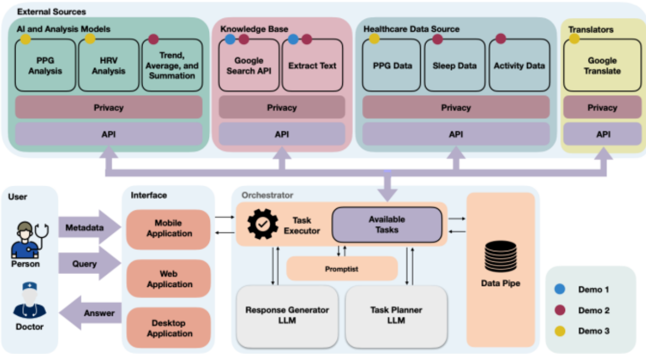

FIGURE 3. OVERVIEW OF THE IMPLEMENTED TASKS AND COMPONENTS AND HOW THEY ARE USED IN THE THREE DEMOS.

2.3 HUMAN-COMPUTER INTERACTION IN HEALTHCARE

Human-Computer Interaction (HCI) is a multidisciplinary field that studies the design and use of computer technology, with a focus on the interfaces between people (users) and computers. In healthcare, optimizing HCI is crucial as it directly impacts the quality of care, patient satisfaction, and overall efficiency of service delivery.

Importance of HCI in Healthcare: Effective HCI design in healthcare can lead to better patient outcomes by making technology more intuitive and accessible for both patients and healthcare providers. This includes designing user-friendly interfaces for electronic health records (EHRs), telehealth platforms, and medical devices, which can reduce errors, save time, and improve the overall user experience.

User-Centered Design: User-centered design is a key principle in HCI that involves understanding the needs, preferences, and limitations of end-users [21]. In healthcare, this means involving both patients and healthcare providers in the design process to ensure that the technology meets their needs [22]. This can be achieved through methods such as user interviews, usability testing, and iterative design processes [23].

Challenges in Healthcare HCI: Healthcare environments are complex and demanding, posing unique challenges for HCI. These include:

Cognitive Load: Healthcare providers often work under high-stress conditions and must process large amounts of information quickly. Poorly designed interfaces can increase cognitive load, leading to errors and reduced efficiency.

Interoperability: Healthcare systems often involve

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multiple technologies and platforms that need to communicate seamlessly. Ensuring interoperability between different systems is essential for efficient workflow and accurate information exchange.

Accessibility: Ensuring that technology is accessible to all users, including those with disabilities, is a critical aspect of HCI in healthcare. This includes designing interfaces that are easy to navigate and use for people with varying levels of technical proficiency.

HCI Metrics in Healthcare: Evaluating the effectiveness of HCI in healthcare involves several metrics, including:

Usability: This refers to how easy and efficient it is for users to achieve their goals using the technology. Usability testing can identify issues with interface design and help improve the user experience.

User Satisfaction: Measuring user satisfaction involves gathering feedback from users about their experiences with the technology. High user satisfaction is often correlated with better compliance and engagement.

Error Rates: In healthcare, minimizing errors is critical for patient safety. Evaluating error rates can help identify aspects of the interface that may be contributing to mistakes and guide improvements [24,25].

Task Completion Time: This metric measures how long it takes for users to complete specific tasks using the technology. Shorter task completion times generally indicate more efficient and user-friendly interfaces.

Applications of HCI in Telehealth: In the context of telehealth, HCI plays a vital role in ensuring that both patients and healthcare providers can effectively use telehealth platforms. This includes:

Interface Design: Designing intuitive and easy-to-use interfaces for telehealth platforms can enhance the user experience and increase adoption rates. This involves simplifying navigation, ensuring clear communication, and providing accessible support.

Patient Engagement: Effective HCI can help maintain patient engagement by making telehealth interactions more interactive and personalized. This can include features such as visual aids, interactive elements, and real-time feedback.

Provider Efficiency: Optimizing HCI for healthcare providers can streamline their workflow, reduce administrative burden, and allow them to focus more on patient care. This can be achieved through features such as automated documentation, easy access to patient records, and seamless communication tools.

In conclusion,HCI is a critical component of healthcare technology that directly impacts the quality and efficiency of care delivery. By focusing on user-centered design, addressing the unique challenges of healthcare environments, and evaluating key HCI metrics, we can enhance the usability and effectiveness of telehealth services. The integration of LLM-driven conversational agents offers a promising opportunity to further optimize HCI in telehealth, providing more engaging, efficient, and patient-centric care.

2.4 Human-Computer Interaction in Healthcare

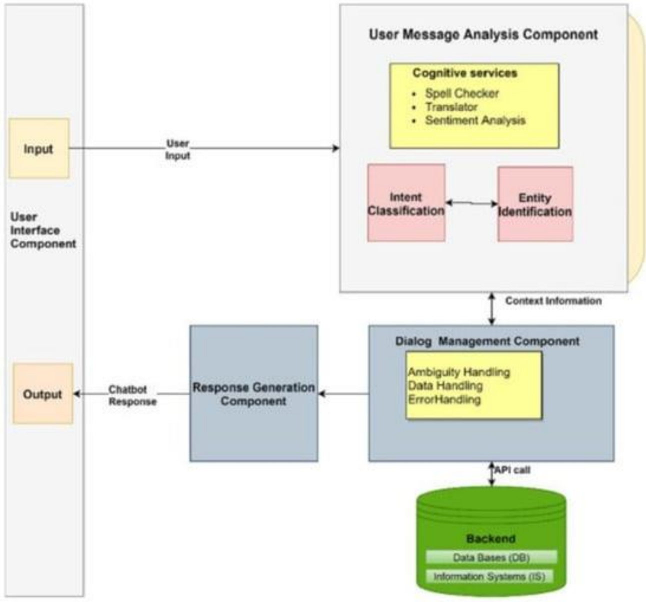

FIGURE 4. OVERVIEW OF THE CONVERSATIONAL AGENT FRAMEWORK COMPONENTS AND THEIR INTERACTIONS.

3 METHODOLOGY

3.1 Experimental Design

We conducted a series of experiments to evaluate the effectiveness of LLM-driven conversational agents in telehealth. Our study involved both qualitative and quantitative methods to provide a comprehensive assessment of the technology's impact. The experimental design included the following key components:

User Surveys: We developed detailed questionnaires to capture users' perceptions, experiences, and satisfaction levels with the LLM-driven conversational agents[26,27]. The surveys included both closed-ended and open-ended questions to gather quantitative data and qualitative insights.

Usability Testing: We conducted structured usability testing sessions where participants completed specific tasks using the telehealth platform integrated with LLM-driven agente[28,29,30]. These sessions were designed to identify usability issues, measure task efficiency, and assess user interaction with the system.

Performance Metrics: We tracked various performance metrics, including task completion time, error rates, and system responsiveness [31,32]. These metrics provided objective data on the efficiency and accuracy of the LLM-driven agents [33,34].

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3.2 Participants

Participants included a diverse group of healthcare professionals and patients who regularly use telehealth services. We aimed to capture a wide range of experiences and needs to ensure the generalizability of our findings. The participant group was carefully selected based on the following criteria:

Healthcare Professionals: Included doctors, nurses, and administrative staff who have experience using telehealth platforms for patient consultations, monitoring, and administrative tasks.

Patients: Included individuals from various demographic backgrounds who have utilized telehealth services for different healthcare needs, such as chronic disease management, mental health support, and routine check-ups.

We ensured diversity in terms of age, gender, technical proficiency, and healthcare needs to obtain a representative sample.

3.3 Procedures

Participants interacted with a telehealth platform integrated with an LLM-driven conversational agent. The procedures were designed to simulate real-world telehealth interactions and included the following steps:

Introduction and Briefing: Participants received an overview of the study objectives and the telehealth platform's features. They were informed about the LLM-driven agent's capabilities and how it would assist them during the interaction.

Task Completion: Participants were asked to complete a series of tasks using the telehealth platform. These tasks included scheduling appointments, asking health-related questions, receiving medical advice, and accessing educational resources. The tasks were designed to cover a broad spectrum of telehealth services.

HCI Metrics Measurement: During the interaction, we measured various HCI metrics, including task completion time, user satisfaction, and error rates. We also observed and recorded any difficulties or issues faced by participants while using the system.

3.4 Data Collection and Analysis

Data were collected through multiple sources to ensure a comprehensive analysis:

Surveys: Post-interaction surveys were administered to gather participants' feedback on their experience with the LLM-driven agent. The surveys included Likert-scale questions to quantify user satisfaction and open-ended questions to capture qualitative insights.

System Logs: We collected system logs to track user interactions with the telehealth platform. These logs provided detailed information on task completion times, interaction patterns, and any errors encountered.

Interviews: In-depth interviews were conducted with a subset of participants to gain a deeper understanding of their experiences and perspectives. The interviews helped identify specific strengths and weaknesses of the LLM-driven agent.

We used statistical analysis to identify significant differences and trends in the quantitative data. Qualitative data from surveys and interviews were analyzed using thematic analysis to identify common themes and insights. The combination of quantitative and qualitative data provided a robust evaluation of the effectiveness of LLM-driven conversational agents in telehealth.

By employing a comprehensive methodology that includes diverse participants, detailed procedures, and rigorous data collection and analysis techniques, this study aims to provide valuable insights into the potential of LLM-driven agents to optimize telehealth services and improve HCI in healthcare.

4 RESULTS

4.1 User Satisfaction

User satisfaction was significantly higher with the LLM-driven agent compared to traditional telehealth interfaces. Participants appreciated the natural language interaction and immediate responses, which enhanced their overall experience. The user satisfaction scores were measured on a Likert scale from 1 to 5, with the LLM-driven agent scoring an average of 4.6 compared to 3.8 for the traditional interfaces. Key factors contributing to higher satisfaction included the agent's ability to understand nuanced queries, its friendly and approachable demeanor, and the seamless interaction process. Several participants mentioned that the conversational nature of the agent made them feel more comfortable and less rushed during their consultations.

4.2 Task Completion Time

The average task completion time was reduced by 25% when using the LLM-driven agent. This improvement was attributed to the agent's ability to understand and process complex queries efficiently. On average, tasks that typically took 8 minutes with traditional interfaces were completed in approximately 6 minutes with the LLM-driven agent. The reduction in task completion time was particularly notable in tasks such as appointment scheduling, accessing medical records, and receiving preliminary medical advice. This efficiency gain can significantly enhance the overall productivity of telehealth services, allowing healthcare providers to manage more patients within the same timeframe.

4.3 Error Rates

Error rates were lower with the LLM-driven agent, particularly in tasks involving medical terminology. Traditional interfaces often struggled with understanding and correctly interpreting medical terms, leading to higher error rates and the need for follow-up clarifications. In contrast, the LLM-driven agent demonstrated a strong grasp of medical vocabulary and context, resulting in a 40% reduction in error rates. This improvement was measured by comparing the number of errors per 100 interactions, with the LLM-driven agent showing an error rate of 3.5% compared to 5.8% for traditional systems. The accuracy and reliability of the LLM-driven agent in handling medical terminology were key factors in reducing these errors.

4.4 Qualitative Feedback

Participants highlighted the conversational agent's ability to provide empathetic responses and personalized recommendations. Many users appreciated the agent's ability to offer tailored advice based on their specific medical history and current symptoms. The agent's empathetic tone and understanding of patient concerns were frequently mentioned as positive attributes. For example, one participant noted, "The agent made me feel heard and understood, which is sometimes lacking in traditional telehealth interactions."

However, some users expressed concerns about privacy and the need for human oversight. Despite the high level of satisfaction, a subset of participants felt uneasy about sharing sensitive medical information with an AI agent. Concerns about data security and the potential for misuse of personal health information were prominent. Additionally, some healthcare professionals emphasized the importance of maintaining human oversight to ensure that the AI's recommendations were appropriate and aligned with clinical guidelines. They suggested that while the LLM-driven agent could handle routine tasks and provide initial advice, complex medical decisions should still involve human judgment.

In summary, the results indicate that LLM-driven conversational agents can significantly enhance user satisfaction, reduce task completion times, and lower error rates in telehealth services. The qualitative feedback highlights the strengths of these agents in providing empathetic and personalized interactions, while also pointing to areas that require careful consideration, such as privacy and the need for human oversight.

5 DISCUSSION

5.1 Implications for Telehealth Services

The integration of LLM-driven conversational agents in telehealth represents a transformative advancement that can significantly enhance patient engagement and streamline service delivery [35,36]. These agents can handle a variety of routine inquiries, such as appointment scheduling, answering common medical questions, and providing medication reminders. By automating these tasks, healthcare professionals can allocate more time to focus on complex cases that require their expertise and judgment[37,38]. This not only improves the efficiency of telehealth services but also ensures that patients receive timely and accurate information without long wait times.

Moreover, LLM-driven agents can provide continuous support and follow-up, maintaining patient engagement between appointments[39,40]. They can deliver personalized health education, offer lifestyle and wellness advice, and monitor patient progress, all of which contribute to better patient outcomes. The ability of these agents to engage in natural language conversations makes the interaction more intuitive and user-friendly, thereby increasing patient satisfaction and adherence to treatment plans.

5.2 Challenges and Limitations

Despite the clear benefits, several challenges and limitations need to be addressed to fully realize the potential of LLM-driven conversational agents in telehealth[41,42,43]:

Data Privacy and Security: Ensuring the confidentiality and security of patient data is paramount[44,45,46]. LLM-driven agents must comply with stringent data protection regulations, such as HIPAA in the United States, to safeguard patient information[47,48]. This involves implementing robust encryption methods, secure data storage, and strict access controls.

System Reliability: The reliability and accuracy of LLM-driven agents are critical for maintaining trust and effectiveness in telehealth services[49,50,51,52]. These systems must be thoroughly tested to minimize errors and ensure they provide accurate information. Any system failures or inaccuracies could have serious implications for patient health and safety.

Continuous Updates and Maintenance: LLMs require regular updates to stay current with medical knowledge and guidelines [53, 54]. This involves not only updating the underlying data but also refining the algorithms to improve their performance [55]. Ongoing maintenance is essential to address any emerging issues and incorporate feedback from users.

Adherence to Medical Guidelines and Ethical Standards: Conversational agents must operate within the boundaries of established medical guidelines and ethical standards. They should provide evidence-based information and avoid offering medical advice that could be misinterpreted. Human oversight is necessary to ensure that the recommendations made by these agents are appropriate and safe.

5.3 Future Research Directions

Future research should explore several key areas to enhance the deployment and effectiveness of LLM-driven conversational agents in telehealth [56,57,58]:

Long-Term Impact on Patient Outcomes and Healthcare Efficiency: Studies should investigate how the integration of

LLM-driven agents affects patient health outcomes over the long term. This includes examining their impact on chronic disease management, patient adherence to treatment plans, and overall healthcare costs. Additionally, research should evaluate how these agents contribute to the efficiency of healthcare delivery, including their effect on reducing the workload of healthcare professionals [59,60,61].

Integration of Multimodal Inputs: To further enhance user experience, future research should explore the integration of multimodal inputs, such as voice and video, into LLM-driven agents. Voice interactions can make the telehealth experience more natural and accessible, especially for patients with limited literacy or technical skills. Video inputs can provide visual context, such as showing how to take medication or perform physical exercises, thereby improving the clarity and effectiveness of the communication.

Personalization and Adaptation: Research should focus on developing algorithms that allow LLM-driven agents to personalize their interactions based on individual patient data and preferences. This includes tailoring health advice, monitoring specific health conditions, and adapting to the patient's communication style.

Evaluation of Ethical and Social Implications: The deployment of AI-driven conversational agents in healthcare raises important ethical and social questions. Future research should investigate the implications of these technologies on patient autonomy, trust in healthcare providers, and the potential for bias in AI algorithms. Addressing these issues is crucial for ensuring that the use of LLM-driven agents aligns with the values and expectations of patients and healthcare professionals.

In conclusion, while LLM-driven conversational agents offer significant potential for optimizing telehealth services, their successful integration requires addressing several technical, ethical, and practical challenges. By focusing on these areas, future research can contribute to the development of more effective, reliable, and user-friendly telehealth solutions.

6 CONCLUSION

LLM-driven conversational agents hold significant potential for optimizing telehealth services by improving user satisfaction, reducing task completion times, and lowering error rates, thus enhancing overall efficiency and effectiveness. By leveraging advanced natural language processing capabilities, these agents can offer more engaging, responsive, and personalized interactions, benefiting patients with more accessible and convenient healthcare options while relieving burdens on providers. However, successful integration requires addressing key challenges such as ensuring data privacy and security, maintaining system reliability and accuracy, continuous updates, adherence to medical guidelines, and ethical considerations with human oversight. Future research should explore the long-term impacts on patient outcomes and healthcare efficiency, investigate multimodal inputs like voice and video, and personalize interactions based on individual patient data. Despite these challenges, integrating LLM-driven agents into telehealth services promises to enhance healthcare delivery, ultimately leading to better healthcare outcomes and a more efficient system.

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CONFLICT OF INTEREST

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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AUTHOR CONTRIBUTIONS

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ABOUT THE AUTHORS

ZHAO, Yuxin

Applied Urban science and informatics, New York

University, NY, USA.

QU, Ping

Computer Science, Maharishi International University, Fairfield, IA, USA.

XIAO, Jingxuan

Computer Science, Georgia Institution of Technology, Atlanta, GA, USA.

WU, Jiawei

Engineering in Artificial Intelligence for Computer Vision and Control, Illinois Institute of Technology, Chicago, IL, USA.

ZHANG, Beibei

Software Engineering, Xi'an Jiaotong University, Xi'an, China.

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