Integration of Large Language Models in Remote Healthcare: Current Applications, Challenges, and Future Prospects

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ABSTRACT

The integration of Large Language Models (LLMs) into remote healthcare has the potential to revolutionize medication management by enhancing communication, improving medication adherence, and supporting clinical decision-making. This paper aims to explore the role of LLMs in remote healthcare, focusing on their impact. This paper comprehensively reviews existing literature, medical LLMs cases, and commercial applications of LLMs in remote healthcare. It also addresses technical, ethical, and regulatory challenges related to the use of AI in this context. The review methodology includes analyzing studies on LLM applications, comparing their impact, and identifying gaps for future research and development. The review reveals that LLMs have shown significant potential in remote healthcare by improving communication between patients and providers, enhancing medication adherence monitoring, and supporting clinical decision-making in medication management. However, there are notable challenges, including data privacy concerns, system integration issues, and the ethical dilemmas of AI-driven decisions such as bias and transparency. This review offers a comprehensive analysis of LLMs in remote healthcare, identifying both their transformative potential and the key challenges to be addressed. It provides insights for healthcare providers, policymakers, and researchers on optimizing the use of AI in healthcare.

1 Introduction

1.1 Background on Remote Healthcare

Remote healthcare, often referred to as telemedicine or telehealth, has seen significant growth in recent years, driven by advancements in technology and a rising demand for accessible healthcare services[1]. Remote healthcare involves the delivery of medical services and information across distances using telecommunications technologies. This can include a wide range of services, from virtual consultations and remote monitoring to digital diagnostics and online prescription management.

One of the primary motivations for the expansion of remote healthcare is its ability to address the challenges posed by geographic and logistical barriers. For patients in rural or underserved areas, remote healthcare provides access to medical expertise that might otherwise be unavailable. Similarly, for patients with mobility issues or those requiring frequent monitoring, remote healthcare offers a convenient and often more cost-effective alternative to traditional in-person visits[2].

The COVID-19 pandemic has further accelerated the adoption of remote healthcare, as social distancing measures and the need to reduce the burden on healthcare facilities made remote care a necessity[3]. This shift has demonstrated the potential of telehealth to maintain continuity of care while minimizing the risk of virus transmission. The pandemic highlighted not only the advantages of remote healthcare but also the critical need for robust systems capable of supporting it[4].

Despite its benefits, remote healthcare also presents several challenges, particularly in the area of medication management. Ensuring that patients adhere to their medication regimens, managing drug interactions, and providing personalized advice are all areas where traditional remote care methods can fall short. Communication gaps, the inability to perform physical assessments, and the reliance on patient self-reporting can lead to suboptimal outcomes in medication management[5].

As remote healthcare continues to evolve, there is a growing interest in advanced technologies, such as Artificial Intelligence (AI) and, specifically, Large Language Models (LLMs), to overcome these challenges. LLMs, with their ability to process and generate human-like text, offer new possibilities for improving communication, personalizing care, and enhancing the overall effectiveness of remote healthcare.

1.2 Introduction to AI and LLMs

AI has rapidly become a transformative force in many industries, including healthcare[6]. AI refers to the development of computer systems capable of performing tasks that typically require human intelligence, such as understanding natural language, recognizing patterns, making decisions, and solving problems. In healthcare, AI has shown promise in a variety of applications, ranging from diagnostic imaging and predictive analytics to personalized treatment plans and robotic surgery[7].

One of the most significant advancements in AI over recent years is the development of LLMs. LLMs are a subset of AI that focuses on understanding and generating human language at an unprecedented scale and accuracy[8]. These models, such as OpenAI's GPT-4, are trained on vast amounts of text data, enabling them to generate coherent and contextually relevant responses to a wide array of prompts[9].

LLMs operate by processing text input and predicting the next word in a sequence, allowing them to generate text that closely mimics human writing. Their ability to understand context, identify nuances, and provide detailed responses makes them particularly useful in fields that rely heavily on communication and information processing—such as healthcare[10].

LLMs offer a range of potential healthcare applications. They can be used to enhance patient-provider communication, streamline administrative tasks, support clinical decision-making, and personalize patient care[11]. One of the most promising areas where LLMs can have a significant impact is in remote healthcare, specifically in the management of medication.

Medication management is a critical component of healthcare, requiring careful monitoring and communication between patients and providers to ensure adherence, avoid adverse drug interactions, and tailor treatments to individual needs. LLMs, with their advanced language capabilities, can assist in this process by providing personalized reminders, answering patient queries, and even flagging potential medication issues based on patient data[7].

The integration of LLMs into remote healthcare systems holds the potential to address some of the current challenges in medication management, such as the lack of real-time interaction and the difficulty of monitoring adherence remotely. By using LLMs, healthcare providers can offer more responsive, personalized care, ultimately improving patient outcomes in remote settings[6].

1.3 Purpose and Scope of the Review

The rapid expansion of remote healthcare, accelerated by technological advancements and the global necessity highlighted by the COVID-19 pandemic, has created new opportunities and challenges in the delivery of medical services. Among these challenges, effective medication management in remote settings remains a critical concern. Ensuring that patients adhere to their prescribed medication regimens, receive accurate information, and have their unique needs addressed is essential to achieving positive health outcomes.

The purpose of this review is to explore the role of LLMs in enhancing medication management within the context of remote healthcare. Specifically, this review aims to examine how LLMs can be leveraged to address the challenges associated with remote healthcare, such as improving patient communication, monitoring adherence, and providing personalized support.

This review will cover the following key areas:

- Overview of Remote Healthcare: Understanding the current state of remote healthcare practices, including existing challenges and limitations.
- Case Studies: Reviewing medical LLMs cases and where LLMs have been implemented in remote healthcare to improve medication management.
- The Role of LLMs in Medication Management: Analyzing the specific applications of LLMs in enhancing communication, monitoring adherence, and supporting clinical decision-making in remote settings.
- Challenges and Ethical Considerations: Discussing the technical, ethical, and regulatory challenges associated with the integration of LLMs in remote healthcare.
- Future Directions and Research Opportunities: Identifying potential areas for future research and innovation in the use of LLMs for remote healthcare.

By focusing on these areas, this review seeks to provide a comprehensive understanding of the current and potential future impact of LLMs on remote healthcare. We aim to provide useful insights that can guide healthcare providers, researchers, and policymakers in effectively integrating LLM technology into remote healthcare practices to enhance patient outcomes.

2 Overview of Remote Healthcare

Effective healthcare is a cornerstone of patient care, particularly in remote healthcare settings. Ensuring that patients receive the correct medications, adhere to their prescribed regimens, and are monitored for potential side effects or interactions is essential to achieving positive health outcomes. However, the shift to remote healthcare presents unique challenges and necessitates the use of innovative tools and technologies to overcome these obstacles.

2.1 Importance of Medication Management in Remote Healthcare

Medication management plays a critical role in patient outcomes, influencing everything from disease control to overall quality of life. Proper medication adherence ensures that treatments are effective, helps in managing chronic conditions, and reduces the risk of complications or hospitalizations[12]. In remote healthcare settings, where direct patient-provider interactions are limited, medication management becomes even more crucial.

One of the primary challenges in remote healthcare is ensuring adherence. Patients may forget to take their medications, misunderstand instructions, or choose to stop taking them without consulting their healthcare provider. These issues are compounded in remote settings by the lack of face-to-face interactions, making it difficult for providers to monitor adherence and intervene when necessary[13].

Communication barriers are another significant challenge in remote healthcare[14]. Miscommunication can lead to patients receiving incorrect dosage instructions, failing to report side effects, or not understanding the importance of their medication regimen. The absence of in-person consultations means that healthcare providers must rely on digital communication, which can sometimes be less effective in conveying critical information.

Additionally, remote healthcare must address the complexities of polypharmacy, particularly in patients with multiple chronic conditions[15]. Managing multiple medications remotely requires careful coordination and monitoring to avoid harmful drug interactions and ensure that each medication is contributing positively to the patient's health[16].

In summary, medication management is vital for ensuring the success of remote healthcare, but it is fraught with challenges that require suitable solutions to address effectively.

2.2 Current Technologies in Remote Healthcare

Various technologies have been developed and implemented to address medication management challenges in remote settings. These technologies aim to support healthcare providers in monitoring patient adherence, improving communication, and ensuring that patients follow their prescribed medication regimens as shown in Figure 3.

Telemedicine has become a fundamental tool in remote healthcare, allowing patients to consult with their healthcare providers via video calls, phone calls, or secure messaging platforms. Through telemedicine, providers can offer guidance, answer questions, and adjust medications based on patient feedback[17]. However, telemedicine alone is often insufficient for comprehensive medication management, as it typically lacks continuous monitoring capabilities.

Mobile health (mHealth) apps are a popular solution, providing patients with tools to manage their medications more effectively[18]. These apps often include features such as medication reminders, digital pill organizers, and educational resources. Some advanced mHealth apps can also track medication adherence and send reports to healthcare providers, offering a more integrated approach to remote care[19]. Additionally, it also plays a role in medication management, particularly for patients with chronic conditions. These devices can track physiological data (e.g., blood pressure, glucose levels) and provide insights into how well a patient's medication regimen is working. When integrated with healthcare systems, these tools can alert providers to potential issues, such as medication non-adherence or adverse reactions[20].

Automated dispensing systems and smart pillboxes offer additional support by dispensing the correct dosage at the right times and reminding patients to take their medications. These systems can reduce the risk of missed doses and help manage complex medication schedules[21]. However, their cost and complexity may limit their accessibility to a broader patient population.

Despite these tools' availability, current remote healthcare approaches have some limitations. Many technologies rely on patient self-reporting and engagement, which can be inconsistent[22]. Additionally, the lack of real-time monitoring and personalized support means that issues with adherence or medication effectiveness may go unnoticed until they become significant problems. There is a clear need for more advanced solutions that can provide continuous, personalized support to patients in remote settings.

3 Overview of LLMs in Medication

3.1 Medical Large Language Models

There are many LLMs focus on medication field such as Codex 5-shot CoT, Llama 2 5-shot CoT, and GPT-4 with Medprompt. Valentin examed 5 LLMs with three question data base lists (USMLE (United States Medical Licensing Examination),

Figure 1. Overview Technologies in Remote Healthcare from[23–25]

MedMCQA and PubMedQA) in 2023. The result shows that GPT-4 is the highest in MedMCQA and PubMedQA while Med-PaLM 2 is the highest in USMLE. Hongjian conducts a test to show that GPT-4 with Medprompt and Med-Gemini are the highest USMLE in 2024[27]. Therefore, the study focus on GPT-4 with Medprompt, Med-PaLM 2 and Med-Gemini.

GPT-4 with Medprompt: GPT-4, the latest iteration of OpenAI's language model, demonstrates significant potential in the healthcare domain, particularly when integrated with structured prompting techniques like MedPrompt[28]. This tailored approach enhances GPT-4's performance in generating accurate, relevant, and comprehensible medical content, making it a valuable tool for clinicians, researchers, and patients alike. In benchmark evaluations, GPT-4 with MedPrompt achieved an accuracy rate of 90.2% in diagnosing MedQA dataset, compared to 86.1% without structured prompts[29]. GPT-4 with MedPrompt excels in synthesizing complex medical knowledge, providing differential diagnoses, and simplifying medical jargon for non-expert audiences. While the model effectively delivers context-specific and ethical responses, including emphasizing the importance of consulting healthcare professionals, it occasionally produces outdated or overly technical outputs and relies heavily on the quality of user input[30]. Its applications span clinical decision support, medical education, patient communication, and research summarization, though its limitations—such as the need for verification, dependency on input quality[30], and secure handling of sensitive data—highlight areas for further refinement. Despite these challenges, GPT-4 with MedPrompt represents a transformative step toward using AI in modern medicine, provided its implementation is paired with rigorous oversight and continuous updates to ensure reliability and safety.

Med-PaLM 2: Med-PaLM 2, a medical LLM developed by Google Research, represents a significant advancement in the application of AI for healthcare[31]. Med-PaLM 2 is designed to excel in understanding and generating domain-specific content with exceptional accuracy and contextual relevance through the PaLM 2 architecture and fine-tuned on extensive medical datasets. In benchmark tests, Med-PaLM 2 achieved 86.5% accuracy on the USMLE questions while 60% is the pass line, closely approximating the performance of human medical professionals and surpassing prior models in the domain[32]. The model's ability to generate concise, contextually appropriate responses makes it a valuable tool for clinical decision support, patient education, and medical research. Its integration of advanced reasoning capabilities allows it to provide nuanced answers to complex medical queries, such as differential diagnoses and treatment options. Moreover, the model's ability to translate medical jargon into layperson-friendly explanations positions it as an effective bridge for improving patient communication. Despite these strengths, Med-PaLM 2 is not without limitations; it occasionally exhibits gaps in handling rare or highly specialized cases and depends heavily on the quality[33]. Nonetheless, Med-PaLM 2's contribution to advancing medical AI is undeniable, offering a robust platform for augmenting healthcare delivery and supporting medical professionals through reliable and efficient assistance. With continuous updates and domain-specific refinements, Med-PaLM 2 holds the potential to become a cornerstone in the integration of AI within modern medicine.

Med-Gemini: Med-Gemini, developed as a cutting-edge medical AI model by Google Research, represents a milestone in the intersection of advanced deep learning and healthcare applications[34]. This model refers from Google's foundational Gemini architecture, renowned for its scalability and computational efficiency, and is specifically fine-tuned for medical contexts using an extensive corpus of domain-specific data. In benchmark evaluations, Med-Gemini achieved notable results, including a 91.1% accuracy rate on USMLE[35]. A key strength of Med-Gemini lies in its multimodal integration capabilities[36], enabling it to process and correlate data from textual, visual (medical imaging), and structured sources such as electronic health records (EHRs)[37]. The model's adaptive learning features ensure continuous improvement when exposed to new datasets, enhancing its relevance in rapidly evolving medical scenarios. Additionally, Med-Gemini's advanced natural language understanding enables it to generate patient-friendly explanations[38], making it a powerful tool for bridging the gap between clinicians and patients. Despite these strengths, challenges persist; the model's reliance on high-quality, diverse datasets highlights the need for ongoing curation and validation to prevent biases or inaccuracies. Overall, Med-Gemini showcases remarkable potential to revolutionize healthcare delivery by augmenting clinical decision-making, streamlining diagnostic workflows, and improving patient communication. Its integration of multimodal capabilities positions it as a trailblazer in the AI-powered medical ecosystem, with further refinements promising to solidify its role as an indispensable asset in modern medicine.

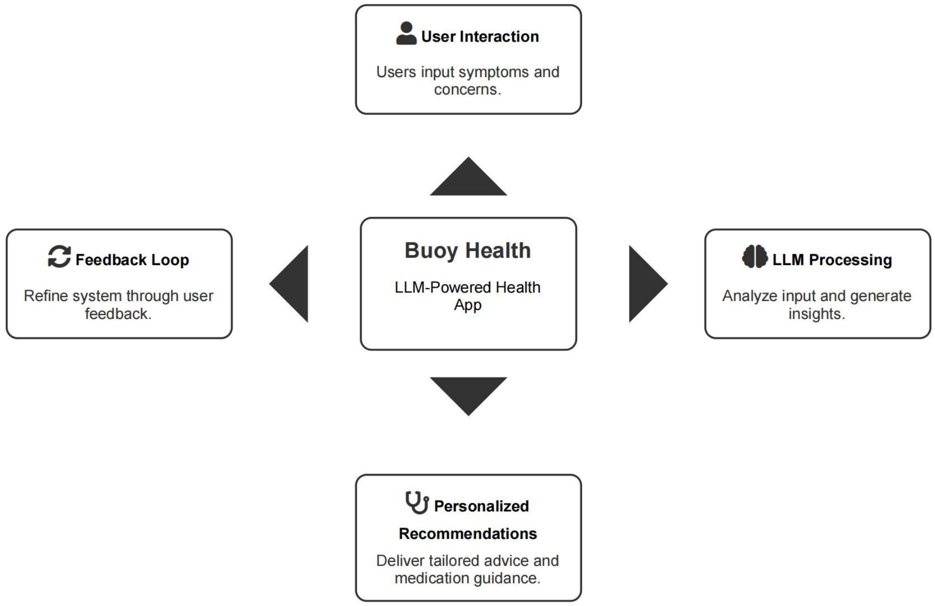

Figure 2. Overview Features of Buoy Health Product

3.2 Applications of LLMs in Remote Healthcare

As the healthcare industry increasingly adopts AI, several platforms and providers have begun to integrate LLMs into their remote healthcare systems. These case studies illustrate the diverse ways in which LLMs can be applied to improve patient care and highlight the lessons learned from these implementations.

Buoy Health: Buoy Health is a digital health company that integrates LLMs and natural language processing (NLP) techniques into its conversational AI chatbot to provide personalized health assessments and medication guidance[39]. Designed to empower users to make informed decisions about their health and navigate the healthcare system more effectively, Buoy Health's tool uses advanced algorithms, including rule-based systems, machine learning models, and medical knowledge graphs, to analyze users' symptoms, medical history, and concerns (Figure 2). It offers tailored recommendations, such as possible conditions, next steps, and self-care advice, while providing information about prescribed medications, including potential side effects and interactions[39,40]. The tool has partnered with several health systems to support remote care initiatives, proving particularly valuable during the COVID-19 pandemic by helping manage chronic conditions and reducing the need for in-person visits[41]. Additionally, it offers reminders to ensure adherence to medication schedules, improving patient engagement and satisfaction[39]. By using AI technology, Buoy Health aims to enhance healthcare access, alleviate patient anxiety, and facilitate early detection and management of medical conditions while reducing the burden on healthcare providers by decreasing routine inquiries.

Ada Health: Ada Health is an AI-driven platform offering personalized health assessments and guidance through conversational interactions[42]. By engaging users in tailored question-and-answer exchanges, it analyzes symptoms and provides detailed explanations and advice to empower proactive health management and timely medical care[43]. With a mission to enhance healthcare accessibility and equity, Ada Health applies advanced NLP techniques, including deep learning, probabilistic reasoning, and medical knowledge bases, to deliver accurate and reliable health insights. Its sophisticated architecture integrates natural language understanding , sentiment analysis, and medical ontologies, ensuring precise, context-aware recommendations that promote early detection, prevention, and improved health literacy.

4 The Role of LLMs in Remote Healthcare

The integration of LLMs into remote healthcare represents a significant advancement in the ability to manage medication more effectively and efficiently. By using the capabilities of LLMs, healthcare providers can address many of the challenges associated with remote healthcare, including communication barriers, adherence issues, and the need for personalized care. This section will summarize the various roles LLMs can play in enhancing remote healthcare (Figure 3), with a focus on patient communication and support, medication adherence monitoring, personalized medication management, and their integration into clinical decision support systems (CDSS).

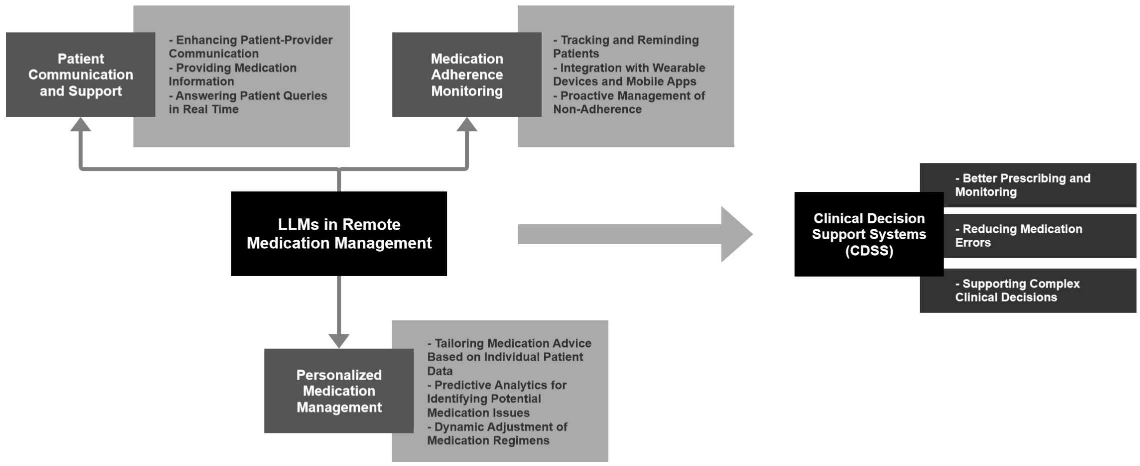

Figure 3. Overall Role of LLMs in Remote Healthcare

4.1 Patient Communication and Support

Effective communication between patients and healthcare providers is essential for ensuring that patients understand their medication regimens[44], adhere to prescribed treatments, and report any side effects or concerns. In remote healthcare settings, where face-to-face interaction is limited or nonexistent, LLMs can play a crucial role in bridging the communication gap.

Enhancing Patient-Provider Communication: LLMs, such as GPT-4, are designed to process and generate human-like text, making them highly effective tools for enhancing patient-provider communication. These models can be integrated into telemedicine platforms[45], providing patients with instant access to reliable information and support. One of the key advantages of LLMs is their ability to understand and respond to natural language queries from patients. For instance, a patient might ask, "What should I do if I miss a dose of my medication?" or "Are there any side effects I should be aware of?" An LLM can interpret these questions, search relevant databases, and provide accurate, context-specific answers[46]. This capability not only improves patient understanding but also reduces the burden on healthcare providers by automating routine inquiries.

Use Cases in Providing Medication Information: LLMs can be deployed to provide patients with detailed information about their medications, including dosage instructions, potential side effects, interactions with other drugs, and lifestyle considerations[47]. Paris indicated that a patient taking a new medication might receive automated messages generated by an LLM that explain how to take the medication correctly, what foods or activities to avoid, and what symptoms to monitor[48]. The personalization helps patients feel more informed and supported, which can enhance adherence and overall treatment success.

Answering Patient Queries in Real Time: In addition to providing general medication information, LLMs can answer patient queries in real time, offering a particularly valuable interaction level in remote healthcare settings[49]. Amulya indicated that a patient may experience an unexpected side effect or has a question about their medication, they can use a chatbot powered by an LLM to receive immediate assistance[50]. This not only helps alleviate patient concerns but also ensures that potential issues are addressed promptly, reducing the risk of complications. The ability of LLMs to provide consistent, accurate, and timely responses also means that patients are more likely to trust the information they receive. Moreover, because LLMs are available 24/7, they offer accessibility that is particularly beneficial for patients needing assistance outside of regular clinic hours.

4.2 Medication Adherence Monitoring

Medication adherence is one of the most critical factors influencing the success of treatment, especially in chronic conditions where consistent medication intake is essential. Ensuring adherence can be particularly challenging in remote healthcare settings due to the lack of direct oversight. LLMs can play a vital role in monitoring and encouraging adherence, offering both patients and providers valuable tools to manage this aspect of care.

Applications in Tracking and Reminding Patients: LLMs can be integrated into mHealth applications and wearable devices to track medication adherence and remind patients to take their medications on time[51]. Dung indicates that the LLM-powered app can send personalized reminders to patients based on their medication schedules, ensuring that they do not miss doses[52]. These reminders can be customized to include information such as the time of day the medication should be taken, whether it should be taken with food, and any other relevant instructions. Beyond simple reminders, LLMs can engage patients in conversations about their medication routines, asking questions. These interactions can help reinforce adherence by making patients more mindful of their medication regimens and providing a sense of accountability[53].

Integration with Wearable Devices and Mobile Apps: The integration of LLMs with wearable devices and mobile apps offers a powerful combination for monitoring adherence and assessing the effectiveness of medications. Wearable devices can collect data on physiological parameters such as heart rate, blood pressure, or glucose levels[54], while LLMs can analyze this data to provide insights into how well a patient's medication is working. Additionally, LLMs can use data from wearable devices to predict and preemptively address potential adherence issues.

Proactive Management of Non-Adherence: One of the most significant advantages of using LLMs in medication adherence monitoring is their ability to proactively manage non-adherence[55]. By analyzing patterns in patient behavior, Alessandra shows that LLMs can identify early signs of non-adherence and intervene before it becomes a serious problem such as diabetes[56]. This proactive approach can significantly improve adherence rates, as patients receive timely support and intervention. Moreover, by reducing the number of missed doses, LLMs help ensure that treatments are more effective, leading to better health outcomes.

4.3 Personalized Medication Management

Personalized medicine is increasingly recognized as a critical component of effective healthcare, particularly in the management of chronic diseases and complex medication regimens. LLMs offer unique capabilities in tailoring medication management to the individual needs of patients, taking into account their medical history, current conditions, and personal preferences.

Tailoring Medication Advice Based on Individual Patient Data: LLMs can process and analyze vast amounts of patient data, including EHRs, genetic information, lifestyle factors, and medication history, as described in the previous subsection. This enables them to provide highly personalized medication advice that is tailored to the specific needs of each patient. In remote healthcare settings, where providers may have limited time and resources to review extensive patient records, LLMs can serve as valuable assistants. They can quickly generate summaries of relevant patient data, highlight potential issues, and suggest personalized medication plans[57]. The personalization not only improves the effectiveness of treatment but also enhances patient satisfaction by ensuring that their unique needs and preferences are considered[58].

Predictive Analytics for Identifying Potential Medication Issues: Another powerful application of LLMs in personalized medication management is predictive analytics. By analyzing patterns in patient data, LLMs can predict potential issues such as adverse drug reactions, non-adherence, or the need for dosage adjustments[59]. In remote settings, where regular in-person monitoring is not feasible, predictive analytics can be particularly valuable. LLMs can continuously analyze patient data in the background, providing real-time alerts to both patients and providers when potential issues are detected. This proactive approach helps to prevent problems before they arise, leading to safer and more effective medication management[60].

Dynamic Adjustment of Medication Regimens: One of the most promising aspects of using LLMs in personalized medication management is their ability to support the dynamic adjustment of medication regimens[61]. Kannan indicates that as patient conditions change or new data becomes available, LLMs can help healthcare providers quickly adapt treatment plans to ensure they remain effective[61]. In remote healthcare settings, where patients may not have regular face-to-face contact with their providers, this ability to dynamically adjust medication regimens is particularly important. It ensures that patients continue to receive optimal care even as their needs change, reducing the risk of complications and improving overall health outcomes[62].

4.4 Overall Contribution to CDSS

Better Prescribing and Monitoring: Rajashekar shows that LLMs can enhance CDSS by providing real-time recommendations based on the latest medical research, clinical guidelines, and patient-specific data[63]. The support is particularly valuable in remote settings, where providers may need to make quick decisions without immediate access to a full range of resources. Moreover, LLMs can continuously monitor patient data and provide ongoing recommendations for adjustments to treatment plans[59]. The dynamic and data-driven approach helps to ensure that patients receive the most effective and safe treatments possible[64].

Reducing Medication Errors: Medication errors are a significant concern in healthcare, particularly in remote settings where communication and monitoring are more challenging. LLMs can help reduce these errors by providing AI-driven insights at critical decision points[48]. Cristobal shows it can reduced near-miss events by 33% (confidence interval (CI) 26%, 40%) in pharmacy medication[48]. Additionally, LLMs can assist in ensuring that prescriptions are accurately communicated to patients, reducing the risk of misinterpretation or misunderstanding. By generating clear, concise instructions tailored to each patient's needs, LLMs help to ensure that medications are taken correctly and as intended[65].

Supporting Complex Clinical Decisions: LLMs can also support more complex clinical decisions that involve multiple factors, such as balancing the benefits and risks of a particular medication or choosing between different treatment options. In these cases, the LLM can analyze a wide range of data, including clinical guidelines, patient preferences, and potential outcomes, to provide evidence-based recommendations[59,63]. The decision support is particularly valuable in remote healthcare settings, where providers may have limited access to specialist consultations or other resources[66].

By integrating LLMs into CDSS, healthcare providers can significantly improve patient outcomes, particularly in remote settings where timely, accurate decision-making is critical. LLMs provide the ability to synthesize vast amounts of data quickly, offer personalized recommendations, and reduce the likelihood of errors, all of which contribute to more effective and safer medication management. The use of LLMs in CDSS also facilitates continuous learning and improvement. As LLMs are exposed to more data and outcomes, they can refine their recommendations over time, becoming increasingly accurate and effective. This ongoing improvement helps to ensure that patients receive the best possible care, even as medical knowledge and practices evolve[67].

5 Comparative Analysis of LLM-Based and Traditional Approaches

While the previous section reviewed the current/potential role of LLMs, comparing these AI-driven approaches with traditional medication management methods is important to fully understand their benefits.

Effectiveness in Improving Patient Outcomes: Traditional approaches to remote healthcare often rely on periodic check-ins via telemedicine, phone calls, or the use of mobile health apps[17]. These methods, while effective to some extent, are limited by their reliance on patient-initiated interactions and the availability of healthcare providers[68]. LLM-based approaches, on the other hand, offer continuous support and real-time interaction, which can lead to more consistent medication adherence and better management of chronic conditions. Aaron tested that conversational AI reminder systems significantly improved adherence rates (92%) when compared against traditional reminder systems (78%)[69]. Moreover, LLMs can provide personalized insights and recommendations that are often beyond the capacity of traditional methods[63]. By analyzing patient data in real-time, LLMs can identify potential issues early and suggest proactive measures, leading to improved patient outcomes. This predictive capability is particularly valuable in preventing adverse drug events and ensuring that treatments are adjusted promptly in response to changes in a patient's condition.

Efficiency and Scalability: Traditional methods of remote healthcare can be time-consuming for both patients and providers. Healthcare providers may spend considerable time answering routine questions or manually tracking patient adherence[70]. This can be particularly challenging in large practices or rural areas where resources are limited. LLM-based approaches, however, offer a scalable solution that can handle a high volume of patient interactions without additional strain on healthcare providers. The use of AI-driven chatbots and virtual assistants allows for the automation of routine tasks, freeing up providers to focus on more complex cases[39,50]. In terms of scalability, LLMs can be deployed across large populations with minimal additional cost, making them an attractive option for healthcare systems looking to expand their remote care capabilities. The ability to provide consistent, high-quality support to patients regardless of geographic location is a significant advantage over traditional methods, which the availability of healthcare resources may limit.

Patient Satisfaction and Engagement: Patient satisfaction is a critical metric in evaluating the success of any healthcare intervention[71]. Traditional methods of remote healthcare often suffer from limited patient engagement, particularly when interactions are infrequent or impersonal. Cheng indicated that the AI-assisted human doctors tended to increase patient satisfaction while recalling social information[72]. Thus, The ability of LLMs to engage patients in natural language conversations contributes to a more user-friendly experience. Patients are more likely to engage with a system that understands their concerns and provides helpful, context-specific advice. This increased engagement can lead to better adherence and overall satisfaction with the treatment process.

The comparative analysis of LLM-based and traditional approaches to remote healthcare reveals that LLMs offer significant advantages in terms of patient outcomes, efficiency, and satisfaction. However, these benefits must be weighed against the potential challenges and limitations associated with AI-driven healthcare. LLMs provide a scalable and effective solution for many of the challenges inherent in remote healthcare, particularly in improving adherence, reducing errors, and enhancing patient engagement.

6 Challenges and Ethical Considerations

While the integration of LLMs into remote healthcare offers significant potential for improving healthcare delivery, it also presents a number of challenges and raises important ethical considerations. These issues must be carefully addressed to ensure that the benefits of LLMs are fully realized while minimizing potential risks. This section explores the technical, operational, ethical, and regulatory challenges associated with LLMs in remote healthcare.

6.1 Technical and Operational Challenges

The implementation of LLMs in remote healthcare is not without technical and operational hurdles. These challenges can impact the effectiveness of LLM-based solutions and must be navigated to ensure successful integration into healthcare systems.

Data Privacy and Security Concerns: One of the most significant technical challenges in the deployment of LLMs in healthcare is ensuring data privacy and security. LLMs require access to vast amounts of sensitive patient data to function effectively, including medical records, medication histories, and real-time health information[73]. The collection, storage, and processing of this data pose substantial risks, especially in the event of data breaches or unauthorized access. Healthcare data is a prime target for cyberattacks[74], and the integration of LLMs introduces additional points of vulnerability[75]. Ensuring that

LLM-based systems are designed with robust security protocols is critical to protecting patient data. This includes encryption, secure data transmission, and regular security audits[76]. Moreover, compliance with regulations such as the Health Insurance Portability and Accountability Act (HIPAA) in the U.S., or the General Data Protection Regulation (GDPR) in Europe, is essential to maintain patient trust and legal compliance[77].

Integration Challenges with Existing Healthcare Systems: Another significant challenge is the integration of LLMs with existing healthcare systems. Healthcare infrastructure is often complex and fragmented, with different providers using various EHR systems, telemedicine platforms, and patient management tools[78]. Integrating LLMs into these systems requires seamless interoperability, which can be difficult to achieve. LLMs must be able to access and process data from multiple sources, including EHRs, wearable devices, and mobile health apps, without disrupting existing workflows. This requires sophisticated data integration capabilities and the ability to work within the constraints of existing healthcare IT infrastructures. Additionally, LLMs must be designed to interact with a wide range of healthcare software[79] and hardware[80], which may have varying degrees of compatibility. The operational challenge also extends to ensuring that healthcare providers are adequately trained to use LLM-based tools[81]. The success of these technologies depends not only on their technical capabilities but also on the willingness and ability of healthcare professionals to incorporate them into their daily practices. This requires ongoing education and support to ensure that providers can effectively leverage LLMs in remote healthcare.

6.2 Ethical Considerations

The use of LLMs in healthcare raises important ethical questions, particularly regarding fairness, transparency, and accountability. These considerations are crucial in ensuring that AI-driven healthcare technologies are used responsibly and equitably.

Bias in AI and Its Impact on Healthcare Equity: One of the most pressing ethical concerns surrounding LLMs is the potential for bias in AI algorithms[82]. Bias can arise from the data used to train LLMs, which may not represent the diverse populations they are intended to serve. Ferrara indicated that if an LLM is trained predominantly on data from a specific demographic group, its recommendations may be less accurate or even harmful when applied to users from different backgrounds[83]. This bias may lead to disparities in care, where certain groups of patients may receive suboptimal treatment or be excluded from the benefits of AI-driven healthcare[84]. This could exacerbate existing health disparities and undermine efforts to achieve healthcare equity. Addressing bias in LLMs requires a concerted effort to ensure that training data is diverse and representative of the broader patient population. Additionally, ongoing monitoring and evaluation of LLM performance across different demographic groups are essential to identify and mitigate any biases that may arise.

Ensuring Transparency and Explainability in LLM-Driven Decisions: Another ethical challenge is ensuring transparency and explainability in the decisions made by LLMs[85]. Healthcare providers and patients need to understand how and why an LLM arrives at a particular recommendation or decision, especially when it concerns critical aspects of medication management[86]. The "black box" nature of many AI algorithms, including LLMs, can make it difficult to trace the reasoning behind specific outputs[87]. This lack of transparency can lead to mistrust and hesitation in adopting LLM-based solutions, particularly in high-stakes environments like healthcare. To address this issue, there is a growing emphasis on developing explainable AI (XAI) models that provide insights into the decision-making processes of LLMs[88]. XAI models aim to make AI outputs more interpretable, allowing healthcare providers to understand the factors influencing recommendations and make informed decisions[89]. Ensuring that LLMs are transparent and explainable is crucial for maintaining trust and accountability in AI-driven healthcare.

6.3 Regulatory and Compliance Issues

LLMs in remote healthcare also presents regulatory and compliance challenges. Navigating the complex landscape of healthcare regulations and ensuring that AI technologies meet legal and ethical standards is essential for their safe and effective deployment.

Navigating Healthcare Regulations with AI Technologies: Healthcare is one of the most heavily regulated industries, with stringent requirements governing patient safety, data privacy, and clinical efficacy[90]. The integration of LLMs into healthcare practices must comply with these regulations to avoid legal risks and ensure patient protection. Palaniappan indicated that the regulatory framework for AI in healthcare is still evolving in global[91]. This creates uncertainty for healthcare providers and technology developers, who must navigate a complex and sometimes ambiguous regulatory environment. Ensuring that LLMs meet regulatory requirements involves rigorous testing, validation, and certification processes, which can be time-consuming and costly. Regulatory bodies are increasingly recognizing the need for specific guidelines governing the use of AI in healthcare[91]. These guidelines may include requirements for transparency, bias mitigation, and data privacy, as well as standards for the validation and certification of AI algorithms. Staying abreast of these developments and ensuring compliance with emerging regulations is critical for the successful implementation of LLMs in remote healthcare.

The Role of Oversight in LLM Applications: Given the potential risks associated with LLMs, there is a strong case for robust oversight mechanisms to ensure that these technologies are used responsibly. Oversight can take various forms, including regulatory reviews, independent audits, and the establishment of ethical review boards[92]. Regulatory oversight is essential for ensuring that LLMs adhere to safety and efficacy standards. In addition to formal oversight mechanisms, there is a need for ongoing dialogue between stakeholders, including healthcare providers, technology developers, regulators, and patients. This dialogue can help to identify emerging issues, share best practices, and ensure that the deployment of LLMs is aligned with the broader goals of healthcare equity and patient safety.

7 Future Directions and Research Opportunities

As LLMs continue to evolve, their potential to transform remote healthcare becomes increasingly apparent. However, to fully realize their capabilities, it is essential to explore the future directions and research opportunities that will drive the next generation of LLM-based solutions in healthcare. This section discusses the advancements in LLM technology and identifies key research gaps and opportunities that need to be addressed to optimize the use of LLMs in remote healthcare.

7.1 Advancements in LLM Technology

One of the most exciting advancements in LLM technology is the development of multimodal models, which can process and integrate information from multiple sources, such as text, images, and audio[93]. In the context of remote healthcare, multimodal LLMs could enable more comprehensive patient assessments by combining data from various inputs, including patient questionnaires, medical images, and voice interactions[94]. This could lead to more accurate diagnoses, personalized treatment plans, and better patient outcomes. Another significant trend is the improvement in contextual understanding by LLMs[95]. Future LLMs are expected to have enhanced capabilities for understanding complex medical language, including nuances, idiomatic expressions, and patient-specific context. This would allow LLMs to provide more precise and relevant information, improving their utility in remote consultations and medication management. The development of more efficient and scalable LLMs is also on the horizon.

7.2 Research Gaps and Opportunities

While the potential of LLMs in remote healthcare is immense, several research gaps and opportunities must be addressed to ensure their successful implementation and optimization.

One critical area that requires further research is the long-term impact of LLMs on patient outcomes[96]. While LLMs show promise in improving medication adherence and patient engagement in the short term, their long-term effects on health outcomes remain largely unstudied. Research is needed to understand how the continuous use of LLMs influences chronic disease management, patient satisfaction, and healthcare costs over extended periods.

Another area where research is needed is the effectiveness of LLMs across diverse populations[97]. LLMs are trained on large datasets, but these datasets may not always represent the diversity of the global patient population. Research should focus on evaluating the performance of LLMs in different demographic groups, including those with varying cultural, linguistic, and socioeconomic backgrounds. This will help to identify and mitigate any biases that may exist in LLM algorithms, ensuring that they provide equitable care to all patients.

8 Conclusion

This review has highlighted the transformative potential of LLMs in remote healthcare, showcasing how these advanced AI technologies can enhance patient-provider communication, improve medication adherence, and support personalized care. While the benefits of LLMs are substantial, including the ability to reduce errors and provide timely, accurate information, significant challenges remain. These challenges include technical hurdles related to data privacy and system integration, as well as ethical concerns such as bias and transparency in AI-driven decisions.

For healthcare providers, the integration of LLMs offers an opportunity to streamline operations and improve patient outcomes. However, it is essential that providers receive adequate training and that AI tools are implemented in a way that complements existing workflows. Policymakers play a crucial role in facilitating the responsible adoption of AI in healthcare by establishing clear guidelines and regulations that address data security, algorithmic bias, and the transparency of AI systems. Ensuring that these frameworks are robust and adaptive will be key to maximizing the benefits of LLMs while safeguarding patient rights and equity.

As LLM technology continues to advance, its potential to reshape remote healthcare becomes increasingly evident. The successful deployment of LLMs will depend not only on technological innovation but also on a commitment to ongoing research and the ethical application of AI. By addressing the challenges identified in this review and fostering collaboration among stakeholders, LLMs can play a pivotal role in making remote healthcare more effective, accessible, and equitable for all patients.

Data availability

The datasets used and analyzed during the current study are available from the corresponding author upon reasonable request.

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Acknowledgments

This work was partly supported by Department of Education of Guangdong Province (Grant no. 2023KQNCX117), and Humanities and Social Sciences Planning Fund Project of the Ministry of Education of China (Grant no. 23YJA760014).

Author contributions statement

Y.X. and H.K. conceived the experiment(s), Y.X. and H.K. conducted the experiment(s), Y.X. and J.S. analyzed the results, Y.X. and J.S. and C.F. and S.Y. worked on writing—review and Editing. All authors reviewed the manuscript.