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THE EVOLUTION OF AI MEDICAL CONSULTANTS AND THEIR IMPACT ON PATIENT EDUCATION: A LITERATURE REVIEW

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ABSTRACT

Background: The rapid development of Artificial Intelligence (AI) has led to its transition from a theoretical concept in informatics to a functional clinical tool. This study evaluates the impact of AI-based consultants and Large Language Models (LLMs) on patient health literacy and the quality of medical education within the framework of contemporary healthcare standards.
Methods: A systematic literature review was conducted in accordance with PRISMA guidelines. Databases including PubMed, Embase, and the Cochrane Library were searched for peer-reviewed publications from 2021 to 2025. Following a rigorous selection process based on Evidence-Based Medicine (EBM) criteria, 31 key sources were identified and synthesized.
Results: LLMs significantly improve the comprehensibility of clinical terminology by adapting medical content to a 9th-11th-grade literacy level. Digital feedback systems, such as the KidneyOnline platform, demonstrate superior efficacy in improving patient adherence compared with standard protocols. However, several critical limitations were identified, including hallucination bias (fabrication of clinical data), a "readability floor" phenomenon associated with up to 83% content reduction, and the risk of professional deskilling among clinicians. Furthermore, wearable devices such as the Apple Watch show high correlation ($r=0.92$) with medical-grade pulse oximetry, offering new perspectives for real-time health monitoring.
Conclusions: AI represents a transformative yet socially consequential innovation in patient education and health literacy. Its responsible implementation requires a strict human-in-the-loop model to ensure clinical safety, ethical accountability, and equitable access. Systematic verification of AI-generated medical information by qualified healthcare professionals remains essential to maintain both high standards of care and public trust in digital health innovations.

KEYWORDS

Artificial Intelligence, Health Literacy, Patient Education, Social Innovation, Large Language Models

CITATION

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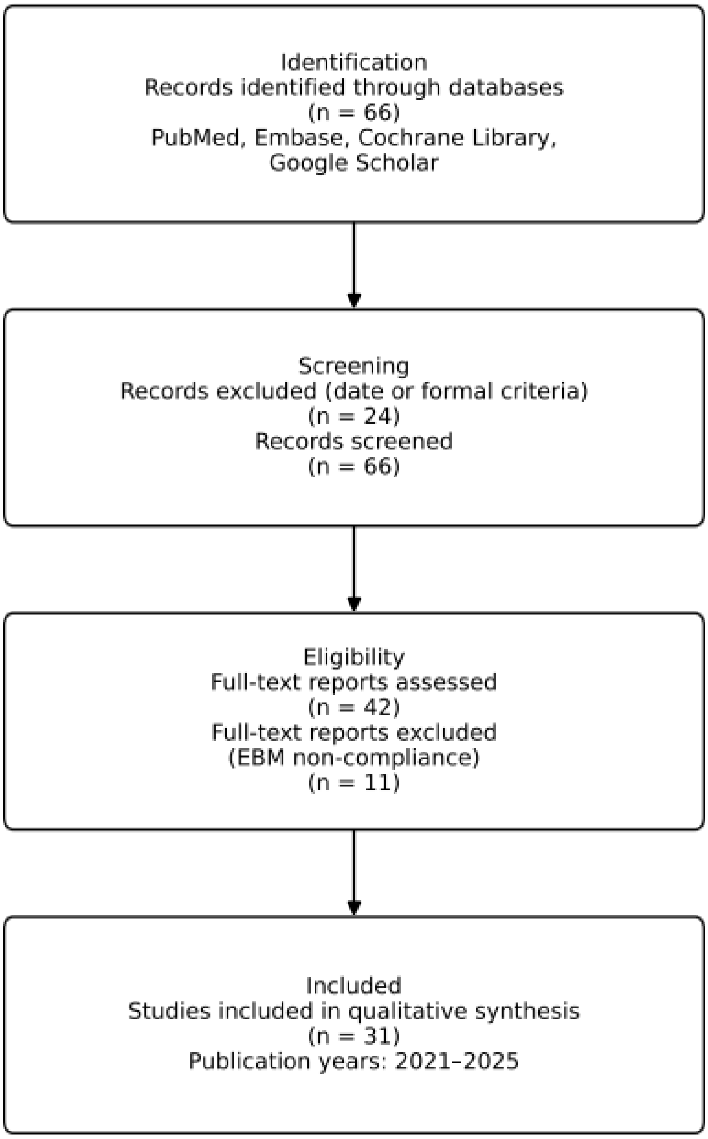
Introduction

In recent years, Artificial Intelligence (AI) has advanced significantly, transitioning from a theoretical computational construct to a pragmatic tool that supports diagnostics, therapeutic process optimization, and personalized patient care. Contemporary AI systems are based primarily on machine learning (ML) and deep learning (DL) technologies [1]. The foundation of these systems lies in the integration and analysis of heterogeneous medical datasets, including laboratory results and high-resolution diagnostic imaging. These algorithms learn from continuously expanding databases. Consequently, the output generated by AI systems does not represent "knowledge" in the human cognitive sense, but rather a statistical inference. These systems estimate the probability of a specific clinical condition based on pattern recognition established during the training phase [2,4,31]. AI technologies can be used by medical professionals for diagnostic and therapeutic support, as well as by patients seeking to better understand their diseases and therapeutic recommendations. Key concerns regarding the implementation of AI in medicine include clinician deskilling, limited usability, lack of algorithmic transparency, and restricted trust in AI-generated content. There is an urgent need to evaluate the extent to which these digital tools effectively enhance patient health literacy and to determine the degree to which they may pose clinical risks resulting from erroneous self-diagnosis and medical hallucinations [3, 30]

Methodology

The methodology was based on a literature review conducted using the PubMed, Embase, Cochrane Library, and Google Scholar databases. The search strategy employed the following terms: Artificial Intelligence, Large Language Models, Patient Education, Health Literacy, and Prompt Engineering. The selection process adhered to PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines. The analysis included studies published between 2021 and 2025, with particular emphasis on meta-analyses and clinical trials. Non-peer-reviewed materials and non-academic documents were excluded. From an initial pool of 66 records, sources failing to meet temporal or formal inclusion criteria were excluded. During full-text eligibility assessment, 11 reports were rejected due to non-compliance with the Evidence-Based Medicine (EBM) paradigm. Ultimately, 31 high-quality publications were included, allowing the formulation of evidence-based conclusions. Identical search strategies were applied across all databases. The analysis was conducted independently by all authors. The quality of the analyzed AI systems was evaluated according to the EBM paradigm, taking into account clinical safety and the reliability of health-related information.



1. The Impact of AI on Patient Health Literacy

1.1 Enhancement of Understanding of Medical Recommendations and Diagnosis

Current scientific reports indicate that the use of Large Language Models (LLMs), such as ChatGPT and Google Gemini, in adapting medical content significantly enhances the health literacy of recipients. Research has demonstrated that these algorithms effectively translate clinical jargon into lay terminology, optimizing readability indices (e.g., Flesch Reading Ease) to approximately a 9th- or 11th-grade reading level [5]. In the cited study, researchers identified a significant technological limitation: these systems encounter a barrier when attempting to simplify content below the high school level. Instead of further linguistic deconstruction, the models employ a strategy of substantial content condensation, reducing text volume by up to 83%. This phenomenon introduces potential clinical risk, as excessive brevity may lead to the omission of critical information, including contraindications or adverse effects.

Simultaneously, clinical evidence confirms that AI-supported personalization can significantly improve patient adherence. A retrospective cohort study of the KidneyOnline system [6] demonstrated that an individualized approach for patients with chronic kidney disease (CKD) in the pre-dialysis stage effectively delayed disease progression. The effectiveness of this intervention was based on a digital feedback loop: AI algorithms analyzed biochemical and hemodynamic parameters in real time, enabling the generation of precise, tailored educational and dietary recommendations. This model of care demonstrated superiority over standard educational protocols by providing support aligned with the patient’s current clinical profile.

1.2 Comparison of Understanding Recommendations: LLMs vs. Traditional Search Engines

Despite technological advancements, there remains a shortage of multicenter prospective studies evaluating AI-based educational tools. Nevertheless, critical analysis suggests that AI models are contributing to a paradigmatic shift in the way patients acquire medical information. These systems provide comprehensive and highly accessible knowledge compendia, demonstrating potential to improve understanding of complex clinical issues [11]. However, their responsiveness is accompanied by the risk of factual inaccuracies, which necessitates that clinicians develop competence in navigating and supervising these technologies. The role of medical professionals increasingly involves not only data verification but also patient education regarding the rational and critical use of digital tools. The lack of infallibility of LLM systems remains a significant barrier to their independent clinical implementation. A comparative study [7], which assessed generative AI technologies (including ChatGPT and Gemini) against traditional search engines in the context of rosacea-related information, demonstrated significant discrepancies in data quality. According to standardized reliability assessment tools such as the DISCERN scale, traditional search engines (Google) provided higher quality and more transparent health information. These findings highlight important limitations of generative systems, including insufficient source transparency and susceptibility to medical hallucinations.

2. Patient Ability to Identify and Name Symptoms

A critical factor determining the clinical safety of AI-based systems is the precision of user-generated inputs (prompts). Although advanced LLMs are capable of generating factually accurate responses, the reliability of the input data provided by patients remains a major risk factor. The literature emphasizes that individuals without medical education are highly susceptible to cognitive bias in identifying subjective symptoms. Mishra [11] underscores the importance of healthcare professional involvement in prompt construction and stresses the need for inclusivity. Prompts should also refer to the most current clinical guidelines applicable within a given country [11]. According to research findings [9], in tasks associated with a moderate clinical risk profile—such as preliminary symptom stratification or interpretation of routine laboratory results—the role of LLMs should be strictly supportive. These authors emphasize that every AI-generated description requires rigorous verification by qualified medical personnel before any therapeutic decision is undertaken. It is also noteworthy, as emphasized by Patil et al. [10], that AI may be utilized by physicians themselves to rapidly extract key information from medical documentation, thereby improving diagnostic efficiency and workflow productivity.

3. Translation of Databases into the Patient's Native Language

A significant challenge remains the translation of natural patient language into precise medical terminology. As demonstrated in available analyses [16], although AI provides support in linguistic translation, it does not yet fully replace human clinical interpretation. AI systems demonstrate satisfactory performance in translating simple medical statements; however, errors remain frequent in the context of complex clinical descriptions [12]. Attention should also be given to the phenomenon of "safe generality" in LLM outputs. These systems often employ imprecise expressions, such as "certain medicinal preparations," which may appear coherent and professionally formulated but fail to provide specific, actionable medical information. This may lead to a misleading sense of being adequately informed.

4. Real-Time Patient Monitoring

Khushhal et al. [17] evaluated the accuracy of heart rate and oxygen saturation measurements obtained using the Apple Watch. The study demonstrated a strong correlation between SpO2 measurements via the watch and standard pulse oximetry at rest ($r=0.92$, $p<0.001$) and after exercise ($r=0.86$, $p<0.001$) across all patients. These findings suggest potential applicability of such devices in daily medical practice and continuous health monitoring, particularly when integrated with AI systems. However, their utility in patients with advanced chronic diseases remains uncertain, and further research involving additional wrist-worn devices is warranted.

5. AI Medical Consultants as a Social Innovation in Patient Empowerment

Patient empowerment plays a crucial role in contemporary healthcare delivery, as it enables individuals to better understand their health conditions and actively participate in their own care. The fundamental pillar of this process is patient education [23]. AI-mediated patient education has the potential to democratize access to medical knowledge, particularly for individuals who encounter barriers to traditional healthcare services, such as prolonged waiting times, geographical limitations, or disability-related constraints. One of the groups that has benefited substantially from the integration of artificial intelligence into everyday life is people with visual impairments [23].

A wide range of assistive technologies has been introduced to support this population, including multisensory robots deployed in educational settings to facilitate learning and social integration, as well as voice assistant systems that enable users to receive auditory descriptions of their surroundings and the objects within them [24,26]. Importantly, voice assistant systems are increasingly utilized to read prescriptions, medical recommendations, and medication labels, thereby reducing dependence on third parties and strengthening patients' sense of agency within the therapeutic process. By improving access to critical health information, these technologies may positively influence treatment adherence, patient safety, and overall engagement in care, positioning AI-driven voice interfaces as a key component of inclusive, patient-centered healthcare innovation.

6. Clinical Deskilling and the Erosion of Professional Competence

A significant challenge associated with AI implementation, highlighted by researchers including Natali et al. [13], is the phenomenon of deskilling. This process refers to the gradual loss of specialized expertise resulting from the delegation of complex cognitive and analytical tasks to AI algorithms. The mechanism underlying deskilling involves the progressive disappearance of decision-making pathways due to insufficient activation of cognitive resources in routine clinical practice. Excessive reliance on AI outputs may lead to irreversible degradation of clinical competencies [14,15]. Ultimately, this phenomenon poses a potential risk to patient safety, particularly if human substantive supervision over AI-generated recommendations is reduced.

7. Ethical Issues and Hallucination Bias

Transparency regarding the data used by AI systems is essential, as is obtaining informed consent from patients for the use of their data. Periodic audits are recommended to identify and mitigate potential biases [4]. It is also crucial to ensure that patients understand the nature of the technology and the scope of their consent [11]. Implementation of AI must comply strictly with legal regulations and data protection standards [2]. Hallucinations refer to factually plausible but fabricated information generated by LLMs. Such outputs may form the basis of clinical errors if therapeutic decisions rely on them [11,13]. For patients with limited health literacy, the professional tone of AI responses may be misinterpreted as factual accuracy. In some cases, AI systems may also underestimate symptoms requiring urgent medical attention.

Aljamaan et al. [17] conducted a study demonstrating that chatbots, even when explicitly asked to provide reliable references, generated fabricated citations that appeared authentic but were incorrect upon verification. This phenomenon is particularly concerning in the context of medicine and patient safety.

Summary

The conducted literature review indicates that the integration of AI into daily medical practice and patient education may provide both benefits and risks. LLM systems can facilitate comprehension of specialized terminology and improve patient adherence. Wearable devices such as the Apple Watch may support continuous health monitoring.

However, limitations, including hallucination bias and clinician deskilling, underscore the necessity of maintaining a strict human-in-the-loop model. The future of digital health education requires not only algorithmic optimization but also systematic implementation of standards for verifying AI-generated content by qualified healthcare professionals. Ultimately, AI should be regarded as a decision-support tool that, without rigorous substantive and ethical oversight, may generate clinical risks exceeding its potential educational benefits, thereby conflicting with the fundamental principles of Evidence-Based Medicine (EBM).

Conclusions for Clinical Practice

- Physicians should actively inquire about AI-derived information obtained by patients and verify it against current clinical guidelines.
- Standardized query templates (prompts) should be developed to assist patients in accurately describing symptoms.
- AI implementation should always follow a human-in-the-loop model, in which algorithms provide support but do not independently authorize clinical decision-making.

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