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Bridging healthcare gaps: a scoping review on the role of artificial intelligence, deep learning, and large language models in alleviating problems in medical deserts

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Abstract
“Medical deserts” are areas with low healthcare service levels, challenging the access, quality, and sustainability of care. This qualitative narrative review examines how artificial intelligence (AI), particularly large language models (LLMs), can address these challenges by integrating with e-Health and the Internet of Medical Things to enhance services in under-resourced areas. It explores AI-driven telehealth platforms that overcome language and cultural barriers, increasing accessibility. The utility of LLMs in providing diagnostic assistance where specialist deficits exist is highlighted, demonstrating AI’s role in supplementing medical expertise and improving outcomes. Additionally, the development of AI chatbots offers preliminary medical advice, serving as initial contact points in remote areas. The review also discusses AI’s role in enhancing medical education and training, supporting the professional development of healthcare workers in these regions. It assesses AI’s strategic use in data analysis for effective resource allocation, identifying healthcare provision gaps. AI, especially LLMs, is seen as a promising solution for bridging healthcare gaps in “medical deserts,” improving service accessibility, quality, and distribution. However, continued research and development are essential to fully realize AI’s potential in addressing the challenges of medical deserts.

Introduction

The concept of a “medical desert” is analogous to the term “food deserts,” which was first used in the UK in 1995. “Food deserts” refer to areas facing socioeconomic challenges where people struggle to find access to healthy, reasonably priced, and fresh food choices, the kind usually found in supermarkets [1].

Over the past decade in France, “medical deserts” has been coined as a term to describe regions that suffer from poor health-care accessibility. The term “medical deserts” lacks a consistent definition across different countries, as it is influenced by varying geographical landscapes (such as islands or mountains), the local interpretation of what constitutes a “rural and remote area,” and the specific types of health workforce shortages encountered, such as the scarcity of medical specialists or dentists [2–4]. These areas can exist in both urban and rural settings, though they are more commonly associated with rural or remote areas.

In the USA, the concept of “medical deserts” has also been used to refer to various medical specialties, leading to terms like “sur-gical deserts,” “maternity care deserts,” “gynecological deserts,” “trauma deserts,” “pharmacy deserts,” and “contraception deserts” [5–10]. Additional phrases include “medically underserved areas,” indicating regions with a shortage of healthcare professionals, and “medically underserved populations,” which refers to the lack of adequate healthcare services for specific demographic groups within an area. Notably, however, these terms do not encompass financial, social, or cultural factors as reasons for limited health-care access [11, 12].

We observe that the absence of a standardized definition and classification of healthcare underserved areas has resulted in a gap in understanding the term or concept, leading to challenges in the public health system and policymaking, and often causing inaccurate comparative analyses in scientific research [2]. This also drives the discussion on how residing in such areas affects individuals and society both medically and economically [13, 14]. Moreover, the health service system there is much more bur-dened, as individuals often require more complex and expensive treatments compared to those in regions with regular access to healthcare. This not only burdens the local system but also impacts families who must care for ill members and bear asso-ciated costs, such as lost workdays [15–17]. Research indicates that postponing seeking and providing healthcare can result in more severe health consequences and higher rates of morbidity and mortality associated with both acute and chronic diseases, including mental health conditions [18].

Recognizing the significance of this issue, numerous countries are implementing various strategies and initiatives to enhance the regional distribution of their health workforce. The WHO Regional Office for Europe, in its European Programme of Work 2020–2025, highlighted rural areas as a key concern [19]. As of 2023, it has been estimated that ∼3.43 billion individuals are residing in rural areas globally. On the other hand, and until recently, the growth rate of the rural population has been <1% per annum since 2020, and there is a negative growth trend in the number of the rural population [20]. Still, despite the decreasing population in rural areas, the necessity to enhance healthcare services in these regions remains critical.

Given these notions, the question emerges if the fast-growing trends in digital and artificial intelligence (AI) applications can potentially provide solutions to the challenges of underdeveloped areas. Below we describe a number of these trends.

In general, and over the last few years, the capabilities of machines in cognitive tasks have matched and even exceeded those of humans in certain domains. The influence of AI is widespread across various industries, with its role in healthcare being particularly promising. AI is a branch of computer science that involves the creation of smart machines capable of performing tasks that typically require human intelligence. This could imply revolutionizing healthcare, offering applications in numerous areas, including health administration, resource management, clinical research, diagnostic forecasting, and drug development. The growing accessibility and affordability of advanced computational resources are driving healthcare's digital evolution. Especially in primary healthcare, AI aids in triage, early disease detection, personalized treatment plans, and managing patient data, leading to more accurate and efficient care.

Two key technologies driving this change are machine learning (ML) and deep learning (DL) [21]. ML analyzes structured datasets to predict outcomes and identify patterns, while DL uses complex neural networks to process extensive, unstructured data, often matching or exceeding human proficiency in tasks, such as med-ical image interpretation [22, 23].

Another significant advancement was the development of large language models (LLMs), a subset of generative AI (GAI)[24]. LLMs, such as OpenAI's GPT series, excel in understanding and generating human-like language [25, 26]. These models can analyze patient records and medical literature, aiding in research and treatment planning. They also have the capability to tran-scribe physician notes and process patient feedback. Chatbots, powered by AI and LLMs, facilitate real-time patient interactions, symptom assessment, and basic healthcare guidance, reducing the burden on healthcare professionals [27].

Lastly, the Internet of Medical Things (IoMT) integrates medical devices with the Internet of Things (IoT), enabling remote patient monitoring, real-time data collection, and timely healthcare interventions. This interconnected system enhances patient management and supports more efficient healthcare delivery.

This advancement promises more rapid and cost-effective healthcare delivery as it evolves [28].

This paper aims to explore how the challenges associated with medical deserts can be addressed by leveraging empirical evidence on the effectiveness of AI, DL, and LLMs in enhanc-ing healthcare services in these underserved regions. It provides insights into the challenges and opportunities for scaling these technologies in similar contexts worldwide.

Methods

Research strategies

This study adopts a qualitative narrative review that comprehensively explores the role of AI, DL, and LLMs and other innovative approaches in addressing healthcare disparities, particularly in medical deserts. To this end, we integrated quantitative data analysis with qualitative insights to offer a well-rounded under-standing of these technologies' impact.

Methodological framework

We conducted a scoping review following the methodology out-lined in the Preferred Reporting Items for Systematic Reviews and Meta-Analysis, with the associated extension for Scoping Reviews (PRISMA-ScR). This framework ensures a systematic and transparent approach to reviewing the literature.

Database search and selection

A comprehensive search was conducted in several prominent databases, including MEDLINE (via PubMed), Google Scholar, Else-vier (Science Direct), IEEE (Institute of Electrical and Electronics Engineers), and Embase (via Ovid). The search covered studies published up to 20 November 2023. We identified 250 papers, but the number of papers discussed in the review was limited to 120 due to the inclusion and exclusion criteria outlined in Table 1.

The resulting PRISMA flow diagram is shown in Fig. 1.

Results

The 120 selected studies show that, in general and over the last decade, AI has seen remarkable advancements, driven by breakthroughs in ML, DL, and neural networks. These technologies have revolutionized various sectors, enabling sophisticated data analysis, automation, and the creation of intelligent systems that mimic human decision-making and learning capabilities. The COVID-19 pandemic has significantly accelerated the adoption of remote working in the healthcare system, a shift driven by the need to maintain social distancing and minimize the risk of virus transmission. This unprecedented situation has hastened up the integration of AI in various aspects of healthcare, trans-forming traditional practices into more efficient, remote-friendly operations.

The studies also commonly support the notion that challenges of providing adequate healthcare services in remote areas, especially in terms of primary healthcare, are indeed significant and multifaceted. Lack of health workforce and poor infrastructure due to financial limitations are primary concerns. However, there are several other key problems that exacerbate the situation, so to provide a systematic approach, we singled out the five main problems within rural areas. The headlines are problem-based and directly emanate from the thematic analysis of multiple papers that we scrutinized. These papers underwent our systematic review and synthesis of content to identify recurring themes and major points of focus. These themes were not preordained by the PRISMA-ScR framework but developed inductively out of the patterns and insights that surfaced from the data.

This is visualized by Fig. 2.

Below, the five elements of the framework are elaborated, referring to the studies included in our review.

[Table 1], [Figure 1]

Lack of HWF

AI has the capability to streamline processes and analyse extensive patient data, leading to enhanced healthcare delivery that is both faster and more cost-effective [29–33]. 5G technology is leading the way in the digital revolution of healthcare, offering a range of promising applications in the sector. Its ability to facilitate high-speed data transmission and provide reliable, real-time internet connectivity is a game-changer. This technology enables the integration of medical devices and personnel across remote areas [34–36]. Key applications of 5G in healthcare include:(i) telemedicine, which involves the remote delivery of healthcare services and information through data networks and telecommunication systems; (ii) the use of wearables and e-Health devices, such as IoMT, for remote patient monitoring and surgery; (iii) the development of robots and drones facilitating access to medicines and other necessities; and (iv) the seamless transfer of real-time patient data, such as sensor data and high-definition video, between hospitals and ambulances, enhancing emergency services [37–41]. Technology like 5G autonomous delivery robots can help reduce health workers workload [42]. This not only reduces the demand for medical professionals but also promotes greater collaboration among healthcare providers and raises the standard of patient care overall.

[Figure 2]

Globally, in rural areas, the challenge of accessing high-quality healthcare services hinders progress toward the United Nations “Sustainable Development Goals” [43, 44]. One of the strategies to address this issue is the expansion of community health worker (CHW) programs [45]. These programs involve training local com-munity members to provide essential health services, a method that has shown effectiveness [46–48]. Early et al. [49], in their scoping review, outlined the advantages and challenges of using mobile health (mHealth) technologies among CHWs. The benefits they noted include fostering health equity, quicker diagnosis, spreading health information and services, better adherence to treatment plans, and greater trust among patients and CHWs

[49]. Digital tools used by CHWs include smartphones, web apps, and videoconferencing for tasks like blood pressure monitoring, glucose testing, and lung function assessments [50]. These tools, along with digital alerts and decision support systems, help maintain care protocols and improve care quality. Digital platforms are also key in training CHWs, providing decision support, and enhancing communication among CHWs. However, they also pointed out insufficient evaluation of mHealth outcomes, limited access to and understanding of mobile technologies in communities, and the need for effective CHW training in mHealth [49].

AI algorithms, such as ML, have been employed to triage patient queries remotely, ensuring efficient handling of cases and prioritizing urgent ones [51]. The primary advancements presented in the chosen studies included enhancing patient prioritization and predicting the necessity for critical care, as well as forecasting hospital or intensive care unit admissions and mortality based on data available at triage [52]. These studies also facilitated improved decision-making by health professionals, which consequently led to more effective clinical management and improved patient outcomes. This support not only reduces the burden on healthcare workers but also presents a cost-effective solution for remote areas, where the deployment of extensive medical staff might not be feasible [53].

LLMs can power sophisticated chatbots and virtual assistants for telemedicine platforms. These systems can provide prelim-inary medical advice, answer health-related queries, and guide patients in remote areas where access to healthcare professionals is limited or enable patients to access healthcare professionals remotely during pandemics [54]. Multilingual conversational bot, “Aapka Chikitsak,” uses natural language processing (NLP) to provide primary healthcare education and advice, especially for chronic patients [55]. This LLM-driven virtual doctor, hosted on the Google Cloud platform, offers a range of services, including preventive measures, home remedies, and healthcare tips, primarily targeting rural India [56]. The application not only facilitates easier access to healthcare knowledge to less educated people but also aims to bridge the gap in healthcare provision, offering timely and quality remote consultations [57].

Research involving 100 doctors in the United States revealed that although a majority see the potential of chatbots in tasks like scheduling medical appointments, directing individuals to healthcare facilities, and dispensing medication details, >70%also believed these bots fall short in meeting all patient requirements, demonstrating emotions, and posing a risk of incorrect self-diagnosis by patients [58]. Despite significant advancements in recent years, it’s crucial for medical specialists to be involved in assessing chatbots. By participating, they can help identify key weaknesses of these systems and contribute to developing programs that propose effective solutions [59]. The pandemic has also highlighted the importance of mental health, with LLM-powered chatbots and virtual assistants providing psychological support remotely [60–62]. These AI tools have helped address the increased demand for mental health services, offering accessible and immediate assistance. For instance, Ly et al. [63]showcased the success of a chatbot utilizing cognitive behavioral therapy and positive psychology in non-clinical settings. The chatbot notably improved well-being and reduced stress, with certain users even describing a unique “digital bond” with it. A key critique of these systems is their inability to exhibit empathy, particularly in identifying and responding appropriately to users’ emotional states. This absence of empathetic interaction could potentially hinder user engagement with health-oriented chatbots [64]. Overall, the pandemic has not only necessitated the adoption of remote working in healthcare but also demonstrated the vast potential of LLM in enhancing healthcare delivery, making it more adaptable, efficient, and accessible [65]. ChatGPT is progressively being adopted as a supportive tool for healthcare professionals and individuals in search of medical guidance. It helps keep them informed about the latest medical research and educates them on various treatment options and health conditions [66]. As a symptom checker, ChatGPT engages in interactive dialogues to evaluate symptoms and suggest appropriate action plans. It assists patients in under-standing the severity of their symptoms and directs them toward suitable medical attention [67]. Additionally, it serves as a tool for medication management, offering guidance on dosages, scheduling reminders, and providing information about potential side effects. It can also address queries regarding drug interactions and contraindications [68]. In the professional healthcare setting, ChatGPT aids in summarizing medical reports and electronic health records (EHRs), enabling healthcare providers to quickly review pertinent patient information and medical histories [69]. The adoption of AI has significantly increased in low-resource environments, where information and communications technology have broadened the scope of AI's applications in enhancing public health informatics and decision-making. One notable example is OpenMRS, an EHR, which is being utilized in over 15 African countries aimed at improving maternal and child health and enhancing HIV treatment in rural regions. This system was found to enhance the completeness of data collection and address vital care gaps [70–72]. Beyond physical health, ChatGPT plays a significant role in mental health support by offering mindfulness practices, stress management strategies, and self-care advice [73].

In the realm of diagnostics, AI has been instrumental in developing tools for rapid and remote testing [74]. For instance, DL-powered imaging analysis has been used to detect COVID-19 from chest X-rays and CT scans [75, 76]. DL can quickly process complex images, identifying subtle abnormalities that might be missed by the human eye, thus reducing errors [77]. This reduces the stress and cognitive load on doctors, allowing them to concentrate on critical cases. Additionally, integrating DL with EHR provides a comprehensive patient history for better decision-making. Over-all, it leads to faster, more accurate diagnoses and improves patient care quality [78]. Although, this approach offers significant advantages, it's important to note that it is not a complete replacement for humans. The combination of AI with human oversight ensures that healthcare remains empathetic, context-aware, and adheres to the highest standards of medical ethics [79]. Proper regulation, continuous monitoring of AI systems for accuracy and bias, and ongoing training for local health workers in using these technologies are essential for maximizing the benefits in areas where medical professionals are scarce.

Economic constraints

DL and its subtype ML are increasingly being recognized as powerful tools for addressing economic constraints and improving resource allocation in rural healthcare [80]. These technologies can analyse vast amounts of data to identify patterns and optimize the distribution of healthcare resources, leading to more efficient and effective medical services. In the economic aspect, AI can significantly reduce costs by streamlining operations, automating administrative tasks, and minimizing wastage of resources. Insider intelligence reports indicate that 30% of healthcare budgets are allocated to administrative expenses [81]. By automating various administrative tasks, AI stands to significantly reduce time and financial expenditure for healthcare providers, enabling the redistribution of funds. AI-driven predictive maintenance can extend the lifespan of medical equipment, while AI-based inventory management systems ensure that supplies are ordered and used efficiently [82]. Moreover, AI can assist in financial decision-making by providing healthcare administrators with insights into cost-effective practices and potential areas for investment.

Access to care and infrastructural limitations

AI technologies have been pivotal in enabling remote healthcare services. Telemedicine, once a convenience, became a necessity during the pandemic, with AI-driven platforms facilitating virtual consultations, diagnosis, and treatment planning [83, 84]. Enhancing internet connectivity and investing in telemedicine can make healthcare more accessible. By dividing telemedicine into smaller branches, we will show its possibilities in improving healthcare. Tele-monitoring involves measuring, storing, and forwarding patient information [85]. Studies showed its effectiveness in monitoring COVID-19 patients with mild symptoms at home, reducing delayed hospitalization risks, and providing a safe tool for high-risk patients [86]. It was also used for heart failure patients, expanding access to cardiac care. Telemanagement combines teleconsultation and tele-monitoring for continuous outpatient monitoring [87]. Studies covered emergency dental procedures, weight management, orthopedic cases, chronic pain management, and heart failure management. Tele-screening studies focused on diagnosing and making quarantine decisions, limiting COVID-19 exposure in emergency departments, and developing remote patient screening approaches [88, 89]. The use of telehealth for screening was found effective in reducing physical contact and conserving personal protective equipment (PPE). Teledentistry studies discussed the advantages of telehealth in dental practice, such as cost reduction and limiting human contact [90]. Teleconsultation is electronic communication for healthcare services. Studies evaluated its effectiveness in patient satisfaction, managing behavioral disorders, and emergency services [91]. Studies examined tele-rehabilitation in contexts like Parkinson’s disease, cancer rehabilitation, urology, pulmonary rehabilitation, and plastic surgery. High satisfaction was reported among patients and providers, with tele-rehabilitation showing effectiveness in various medical conditions [92]. The development of such a telemedicine system, which would encompass almost all areas of medicine, would greatly contribute to the health status of the population in rural areas; however, the development of such a plan requires the initial development of the infrastructure. A notable example of effective telemedicine in developing countries is the service offered by the Swinfen Charitable Trust (SCT) since 1999 [93, 94]. This service provides free medical advice to doctors and health professionals in rural areas, requiring only a digital camera and internet-accessible computer for operation. Anybody facing a medical condition can benefit greatly from this technology, but those who are most in need, such as those with disabilities, stand to gain the most. Recognizing that 15%of the global population lives with some form of disability, each with unique healthcare needs, the United Nations Convention on the Rights of Persons with Disabilities (CRPD) mandates high-quality, non-discriminatory care for these individuals. As of now, the SCT service has connected 366 referring hospitals with over 700 specialists who offer free advice to people with disabilities in developing countries. The SCT Telemedicine app, downloadable on mobile phones, has established telemedical connections in 78 countries, significantly aiding healthcare accessibility for disabled individuals in these regions [95].

As we pointed out, the growth of CHW programs in remote areas is often hampered by the difficulty in accurately and efficiently determining the population areas they should serve. Identifying the specific communities, households, and individuals in need of health services is crucial for planning, particularly for CHW programs that focus on home-based care [35]. This task becomes even more challenging in areas lacking current census data. To address this challenge, DL was used to enhance the mapping of communities in remote areas by uploading satellite data [36].

Drones are also being used as delivery platforms as they pro-vide three-dimensional modality. Drone-based healthcare service implementation has been very common in pandemic situations. In their article, Emmanuel Lamptey and Dorcas Serwaa from the Institute of Life and Earth Sciences, Pan African University, University of Ibadan, Nigeria, discussed the use of Zipline drones for transporting COVID-19 test samples and medical supplies in Ghana. These drones delivered essential items, such as test kits, drugs, vaccines, and PPE, from rural and remote areas to central laboratories for rapid testing and analysis. The implementation of this technology involved significant initial costs, including the purchase of drones, setting up distribution centers, and training personnel, along with ongoing operational expenses for maintenance and battery replacements. However, the advantages were considerable. Drones provided a fast and reliable means of transportation, reducing the turnaround time for test results to under an hour. They ensured accessibility to healthcare services in hard-to-reach areas, operated independently of road conditions and traffic, and were environmentally friendly with lower car-bon dioxide emissions. Additionally, the drone fleet’s capacity was scalable to handle increased demand, with the potential to manage up to 15 000 test cases daily. Despite challenges, such as weather dependency and limited payload capacity, the use of drones represented a significant technological breakthrough, enhancing healthcare delivery and response times during the pandemic [96, 97]. This innovative approach has the potential to address challenges in remote and isolated areas, such as islands or communities situated in locations with underdeveloped infrastructure, where road access is limited or non-existent. Solid evaluations of these applications are still scarce, however.

The effect of AI on the environment in rural areas is a balance between enhancing sustainability and efficiency and managing the ecological footprint of the technology itself. It's essential to approach AI development and implementation with environ-mental considerations in mind, ensuring that the benefits are harnessed without compromising ecological integrity. The use of AI in resource-poor settings require a strong understanding of local social contexts, infrastructure requirements, and additional related infrastructure needs, including IT, communications networks, and platforms for delivering primary health services. Many AI applications depend on the availability of strong EHR systems, which require substantial investment to put into place.

A solution for this problem could be IoMT, which refers to a connected infrastructure of medical devices, software applications, and health systems and services. This network of technology plays a crucial role in the healthcare sector by enhancing the efficiency, accuracy, and delivery of medical services [98]. Here's a list of some common IoMT devices and technologies in healthcare: wearable devices (smartwatches and wearable heart rate monitors), remote patient monitoring tools (blood pressure monitors, glucose meters, and pulse oximeters), smart implants (pacemakers or continuous glucose monitors), connected inhalers, telemedicine platforms, hospital bed sensors, medical supply chain trackers, robotic surgery systems, AI-integrated diagnosis tools, smart hospital systems, etc., [99]. The IoMT ecosystem is rapidly evolving, with new devices and technologies continually being developed to improve patient care, enhance the efficiency of healthcare delivery, and reduce costs [100]. It modernizes the healthcare services without the need for excessive investments.

Recently, in resource-poor settings, there has been strong smartphone penetration, developments in cloud computing, and substantial investments in digitization of health information and introducing mHealth applications. As a result, many places now have the necessary basics in place to initiate meaningful applications of AI. Advances in AI could also help expand and strengthen the impact of these and other digital health technologies in such settings.

Socioeconomic and cultural factors

Healthcare services in rural areas should be supported by active involvement from the community, including leaders and members of both health-related and other organizations within these communities. It's essential that these systems are sensitive and appropriate for the sociocultural context of the rural population, addressing their specific health needs. The effectiveness of this healthcare provision relies upon the national allocation of funds for health, which must consider both rural and urban areas.

Cultures differ in their approach to embracing innovation, and these variations profoundly impact the integration of AI into healthcare practices. Cultural attitudes toward technology, trust in automated systems, and ethical considerations surrounding data privacy play pivotal roles in shaping public perception [101]. To promote cultural acceptance, it is essential to engage in trans-parent communication and involve communities in the development and implementation of AI solutions. Respecting diverse cultural norms and values is crucial to fostering widespread acceptance and ethical deployment of AI technologies in healthcare.

Chatbots and virtual assistants powered by AI can deliver accurate and current information on disease, including symptoms, preventative measures, and treatment options. To offer relevant and easily available information to the public, these AI systems can be integrated into websites, social media platforms, and mobile, thereby enhancing public awareness [102, 103].

Environmental health issues

AI has played a crucial role in analyzing vast amounts of data for research, tracking the spread of the virus, and predicting hotspots, thereby aiding in resource allocation and preventive measures [104–106]. Recently, ML methods were employed to detect and map infectious disease outbreaks by classifying news stories and plotting them on a map using geocoding, aiding epidemiologists in disease tracking [107]. Implementing ML models like Susceptible-Exposed-Infectious-Removed (SEIR) or Geographic Information System (GIS) in public health care, assist policymakers in response planning [108–113]. ML-powered contact tracing systems were more efficient than manual methods, enabling quicker identification of transmission chains and control measures [114]. Key actions include NLP use for targeted surveillance and monitoring in high-risk areas, utilizing data from EHR and online platforms, including social media [115]. Additionally, establishing rapid response teams and formulating data-driven public health policies are crucial steps [116]. To provide adequate information about the spreading of infectious disease, climate changes must be taken into account. A group of researchers developed a DL model for predicting dengue fever (DF) in Vietnam, using a dataset of 12 meteorological factors across 20 provinces with diverse climatic and geographical conditions. The research found model, was highly effective in forecasting DF incidence. This approach is part of Vietnam's digital transformation in healthcare, highlighting the potential of AI and DL in predicting climate-sensitive diseases and enhancing public health responses to cli-mate change. The study suggests that the application of these models could be extended to forecast other climate-sensitive diseases like influenza, diarrhea, and malaria in Vietnam [117–120]. By following this step, the public health sector and epidemiological services can be proactive rather than reactive, leading to more efficient disease control and potentially a reduction of mortality.

Discussion

Our review demonstrated that AI and related technologies, such as ML and DL, can be pivotal in enhancing healthcare delivery, especially in rural and underserved areas. AI can potentially streamline healthcare processes, enabling faster, cost-effective care and reducing healthcare workers' workload through technologies like 5G, autonomous delivery robots, and chatbots. Telemedicine and mHealth technologies have been effective in improving access to care, particularly in remote regions, by enabling remote patient monitoring and diagnostics.

Furthermore, AI could address constraints in rural healthcare by optimizing resource allocation and reducing costs, particularly in administrative tasks. In terms of infrastructure, AI-facilitated telemedicine has been crucial, especially during the pandemic, in ensuring continued healthcare delivery in areas with limited physical healthcare facilities.

AI already plays a significant role in diagnostics, enhancing disease detection and reducing diagnostic errors. However, the necessity of human oversight in healthcare remains important to maintain empathy and ethical standards.

However, the need for culturally sensitive AI systems and the impact of AI on environmental health issues, especially in disease tracking and public health policy, continue to be key considerations. While AI appears transformative for healthcare, it requires careful implementation, considering local contexts, ethical standards, and human elements to fully realize its benefits. AI applications will only have impact if they effectively integrate languages and scripts used in the EHRs of many developing countries. Moving from pilot to scale in these settings will require addressing several issues and must be grounded in the experience of the beneficiaries of these powerful tools. That means using human-centered design when developing and implementing new AI applications. It also means considering legal and ethical questions through a human rights lens that includes privacy, confidentiality, data security, ownership, and informed consent.

As much as having great potential to change the health field, the implementation of AI is also associated with significant challenges and risks. The implementation of AI in healthcare requires significant financial investment in technology and infrastructure. Developing countries and rural areas often lack the necessary resources to adopt AI technologies, exacerbating existing health-care disparities. Moreover, the cost of maintaining and updating AI systems can be prohibitive, limiting their long-term sustainability. For instance, a rural hospital that invested heavily in AI for patient monitoring faced financial difficulties due to the high maintenance costs, which eventually led to discontinuation of the AI program [2].

Moreover, the deployment of AI in healthcare raises significant privacy and security issues as AI systems require vast amounts of sensitive patient data, which must be meticulously protected. In 2020, a breach involving AI-driven medical data systems exposed the personal health information of millions of patients, highlighting the risks associated with inadequate data protection measures [79]. Similarly, another incident involved a healthcare provider experiencing a data breach due to vulnerabilities in their AI systems, resulting in unauthorized access to over 500 000 patient records.

In contrast, inconsistent or poor-quality data can lead to inaccurate predictions and recommendations, compromising patient safety and outcomes. This dependence on data quality is particularly challenging in resource-poor settings, where EHRs may be incomplete or poorly maintained, leading to potential misdiagnoses and treatment errors. For example, an AI system used in a hospital for diagnosing sepsis had a significantly higher error rates when patient records were incomplete or contained mistakes [71]. AI systems can also perpetuate existing biases in healthcare, leading to disparities in treatment. For instance, a study showed that AI algorithms used in predictive analytics for healthcare often perpetuate racial biases present in the training data, leading to unequal treatment recommendations for minority groups. One notable case involved an algorithm that significantly underestimated the healthcare needs of Black patients, resulting in disparities in resource allocation and care [2]. Another example is the bias in age prediction models used for medical purposes, which has been shown to affect the accuracy and reliability of diagnoses for older adults [121].

The absence of empathy in AI interactions can diminish the quality of the patient experience. A study involving AI chatbots in mental health care found that while these tools were effective in providing preliminary support, they could not replace the empathetic interaction provided by human therapists, which is crucial for effective treatment. Patients often reported feeling a lack of personal connection and understanding when interacting with AI, which is critical in mental health and chronic disease management [62]. The integration of AI in healthcare also poses ethical and legal challenges. Issues, such as data ownership, informed consent, and accountability for AI-driven decisions, need careful navigation. The lack of clear regulatory frameworks can lead to ethical dilemmas and legal uncertainties. For instance, the deployment of AI systems without proper ethical oversight has led to significant patient harm in several documented cases, highlighting the need for robust regulatory measures [79]. Even though AI implementations in medicine can be considered as advanced measures, they are not infallible. Continuous monitoring and validation of AI systems remain necessary to ensure their reliability and effectiveness. In a recent example, an AI system implemented in radiology failed to identify certain types of cancers, which were later detected through traditional methods, raising concerns about over-reliance on AI without human oversight [77].

Another potential issue involves the performance of human-AI teams following updates to the AI systems. Despite the goal of improving predictive performance, such updates can inadvertently harm team performance due to incompatibilities with users' prior experiences and confidence in the system. For instance, healthcare providers may have adapted to specific AI system behaviors, and sudden changes in the system's recommendations or interface can create confusion and reduce overall efficiency. This phenomenon underscores the importance of considering human factors and user training when deploying AI updates to ensure seamless integration and sustained performance [122]. The aviation industry offers valuable lessons for healthcare AI, particularly regarding safety culture and regulatory feedback loops. In aviation, stringent safety protocols and continuous feedback mechanisms have been established to mitigate automation biases and foster trust in automated systems. We think that similar approaches could be applied to healthcare AI to enhance reliability and safety. For example, creating a robust regulatory framework that mandates regular audits and feedback could help identify potential biases and errors in AI systems early. Additionally, fostering an environment where healthcare professionals feel comfortable reporting issues with AI tools can lead to continuous improvement and increased trust in these technologies [123]. By learning from other industries and continuously refining AI applications, the healthcare sector can better navigate the complexities of AI deployment and enhance the quality of patient care.

In high-income countries, discussions about the ethics of EHRs and AI have focused largely on privacy, confidentiality, data security, informed consent and data ownership. One proposed approach for maintaining secure and transparent health records was the use of “blockchain technology,” the distributed ledger system that achieves security using encryption, which initially became known for being a cornerstone technology behind cryptocurrencies, such as Bitcoin.

Blockchain technology could enhance healthcare data management by ensuring secure, decentralized transaction, recording, and safeguarding of data integrity. It would protect sensitive health information and support seamless patient data sharing, leading to better care, while smart contracts would automate compliance with data-sharing agreements and health care insurance plans.

However, blockchain’s environmental impact remains significant. Proof-of-work mechanisms, such as those used by the Bitcoin protocol, are energy-intensive, raising sustainability concerns. Blockchain technology is also costly to implement and maintain, struggles with scalability, and faces legal uncertainties.

Alternative solutions like proof-of-stake, homomorphic encryption, federated learning, and secure multi-party computation offer secure data management without high energy consumption. These technologies ensure data privacy and security, making them viable alternatives to traditional blockchain systems.

The main strength of this study is its broad coverage of topics, from defining medical deserts to exploring the potential of AI use in healthcare. By integrating insights from publications about healthcare organization, AI technology, and public policy, this review addresses complex issues like healthcare provision, organization, and equity. This interdisciplinary perspective is crucial for understanding and solving the multifaceted problems associated with medical deserts. The use of the PRISMA-ScR framework for conducting the scoping review adds credibility and rigor to the study. This approach ensured a systematic and transparent approach to literature review, providing a comprehensive under-standing of how modern technologies could be applied to improve healthcare services in underserved areas.

AI in healthcare is a highly topical and rapidly evolving field, currently gaining significant attention for its potential to revolutionize medical practice, yet much remains unknown about its long-term implications, ethical challenges, and operational hurdles. The review assessed global challenges and solutions, making its findings relevant to a wider audience. This is particularly important given the varying nature of medical deserts across different regions. By addressing the unique challenges and potential solutions in diverse geographical and socio-economic contexts, this review provides a global perspective on healthcare accessibility. It effectively highlights AI’s potential in enhancing healthcare delivery, particularly in remote and underserved areas, while showcasing how AI technologies could streamline health-care processes, thereby allowing for faster and more cost-effective care. We also discussed the strengths of modern technologies, such as AI, ML, and LLMs, highlighting their potential to enhance diagnostics and healthcare delivery, while addressing the associated risks and challenges.

A significant weakness of this review remains the omission of a more detailed economic analysis of the cost-effectiveness of implementing AI solutions in healthcare, particularly in under-funded areas. While we mentioned the potential economic benefits of AI, we did not provide a thorough examination of the financial implications, such as the initial investment costs, long-term sustainability, and potential economic disparities that may arise from AI adoption. Additionally, the study acknowledges but does not deeply explore the ethical and privacy concerns associated with AI in healthcare. Issues, such as data ownership, informed consent, and accountability for AI-driven decisions, are critical and require careful navigation. The lack of clear regulatory frameworks can lead to ethical dilemmas and legal uncertainties, which future research should address in more detail to provide a balanced view. We highlighted the technical limitations of AI, such as the dependence on high-quality data and the potential for perpetuating existing biases in healthcare. However, future studies would benefit from a more in-depth discussion of these issues, including real-world examples and case studies, including examples of how AI algorithms used in predictive analytics could perpetuate racial, gender, or age biases present in the training data, leading to unequal treatment recommendations for minority groups. Even though this study discussed alternative technologies, it did not provide full insights. Finally, issues, such as the need for substantial investment in technology and infrastructure, the training and education of local healthcare workers, and the integration of AI with existing healthcare systems remain crucial for the successful deployment of AI in healthcare. Addressing these challenges in greater detail would provide a more comprehensive understanding of the feasibility and potential impact of AI in medical deserts.

Conclusion

In conclusion, AI has the potential to significantly enhance healthcare services, especially in underserved areas like medical deserts. Its diverse applications range from diagnostics to patient care management. However, successful integration of AI in healthcare requires addressing challenges, such as interdisciplinary collaboration, training, ethical considerations, and tailoring solutions to specific needs. As AI evolves, it promises to improve healthcare services and patient outcomes. It can particularly ensure equitable access and robust accuracy monitoring of healthcare provision, in regions where this is under pressure. Addressing these challenges will be essential for AI to revolutionize healthcare globally and in underserved regions.

The five key references for further reading:

1. Zhou, H. et al. (2023). "A Survey of Large Language Models in Medicine: Progress, Application, and Challenge." arXiv:2311.05112. This article provides a comprehensive review of the application of Large Language Models in the medical field, reflecting the manuscript's focus on AI-driven solutions in healthcare.
2. Lucas-Gabrielli, V. & Garcia, C. (2018). "'Medical deserts' and accessibility to care: what are we talking about?" This paper discusses the concept of medical deserts, which is central to understanding the issues addressed in the manuscript.
3. Chow, A. F. et al. (2019). "Collaborative Approaches to Team-Based Primary Health Care for Individuals with Dementia in Rural/Remote Settings." This research reflects on collaborative healthcare, which is relevant for addressing the challenges in medical deserts described in the manuscript.
4. Floridi, L. & Cowls, J. (2020). "GPT-3: Its nature, scope, lim-its, and consequences." Minds and Machines. This paper offers critical insights into the capabilities and limitations of advanced AI models like GPT-3, relevant to discussions in the manuscript on the role of AI in healthcare.
5. Lehmann, U. & Sanders, D. (2007). "Community health workers: what do we know about them?" World Health Organization. This report provides a global perspective on community health workers, aligning with the manuscript's discussion on workforce solutions in under-resourced areas.

Here are five multiple-choice questions based on the manuscript, along with the answers in true/false format:

1. What term is used to describe areas with significantly low levels of healthcare services?
   A) Health voids.
   B) Medical deserts.
   C) Healthcare absence.
   D) Clinical shortages.

Answer: B) Medical deserts -True.

2. Which technology is highlighted as having a potential to revolutionize healthcare in medical deserts?
   A) Blockchain.
   B) Artificial Intelligence.
   C) Quantum Computing.
   D) Virtual Reality.

Answer: B) Artificial Intelligence - True.

3. What role do Large Language Models (LLMs) play in healthcare according to the manuscript?
   A) They are mainly used for financial forecasting in health-care settings.
   B) They assist in patient record analysis and medical literature.
   C) They are used for enhancing physical therapies and surgeries.
   D) They have no significant role in current healthcare technologies.

Answer: B) They assist in patient record analysis and medical literature. - True.

4. What is a primary challenge in the deployment of AI technologies in medical deserts as discussed in the manuscript?
   A) Overabundance of data.
   B) Lack of skilled AI professionals.
   C) High costs of AI implementation.
   D) Resistance to technological change from local populations.

Answer: C) High costs of AI implementation - True.

Author contributions

S.Z. and P.K. performed literature search, data analysis and wrote the first draft of the manuscript, while L.R. and B.R. coordinated research work and conducted critical revision of the article. All co-authors approved the final version of the manuscript.

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Tables and figures

Table 1 Inclusion and exclusions criteria for the literature review.

Inclusion criteria	Exclusion criteria
Focus on medical deserts: studies providing insights into the characteristics and challenges of medical deserts	**Full text inaccessible**: papers for which the full text was not accessible
AI-based solutions: research involving AI or related techniques (e.g. machine learning, deep learning) that demonstrate an impact on improving medical services	**Irrelevant studies**: studies not directly related to healthcare or medical deserts, or not focused on AI in healthcare, particularly in remote areas
Application in medical fields: studies applicable to any medical field or facility directly providing patient services	**Lack of relevance**: studies lacking relevance to the improvement of healthcare services through AI and related technologies
Cost-effectiveness analysis: works including an evaluation of the cost-effectiveness of AI technologies in healthcare settings, regardless of the methodological approach	**Minimum inclusion criteria not met**: publications lacking a minimum of two inclusion criteria to enhance relevance by establishing connections between distinct approaches

Figure 1 PRISMA flow diagram

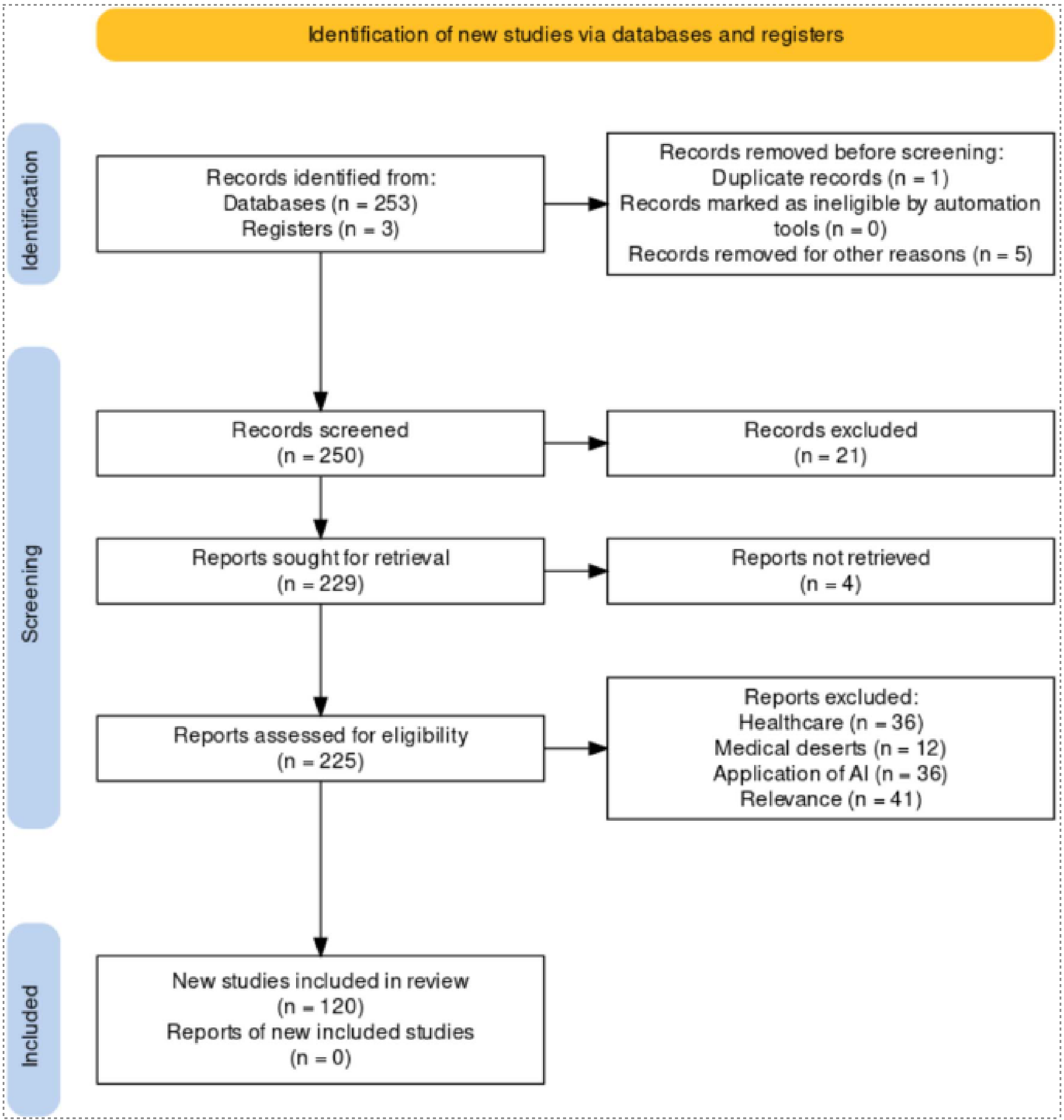

Figure 2 Conceptual framework for addressing healthcare challenges in rural areas