**Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR)**

| **SECTION** | **ITEM** | **PRISMA-ScR CHECKLIST ITEM** | **REPORTED ON PAGE #** |
| --- | --- | --- | --- |
| **TITLE** | | | |
| Title | 1 | **“Leveraging AI Tools to Bridge the Healthcare Gap in Rural Areas in India"** | 1 |
| **ABSTRACT** | | | |
| Structured summary | 2 | **Abstract**  **Introduction:** Despite considerable progress in the healthcare sector, rural areas continue to grapple with healthcare deficiencies, which eventually impact the quality of health outcomes. However, the emergence of AI technology offers promising solutions to overcome these hurdles. Hence, the study explores the potential and efficacy of introducing artificial intelligence (AI) tools to address the healthcare disparity in rural India.  **Methods:** The research employed a literature review method and gathered data from various databases such as Science Direct, PubMed, and Google Scholar. The screening process was aided by the Rayyan electronic software. Articles published in English between January 2020 and December 2022 were selected, followed by a thematic analysis of the findings.  **Results:** Results indicate the potential of AI in rural healthcare settings, showing AI-driven solutions addressing healthcare access gaps and contributing to their bridging. The study also highlights hurdles related to AI tool adoption in rural healthcare and proposes collaborative efforts among policymakers, healthcare providers, and technology developers to integrate AI tools effectively. This necessitates advocating for digital infrastructure investments, capacity-building initiatives, and conducive regulatory frameworks for AI implementation.  **Conclusion:** The study underscores AI's transformative role in bridging the healthcare gap in rural India. By harnessing AI technologies, healthcare providers and policymakers can surmount barriers, empower local healthcare workers, and improve health outcomes for rural communities. The insights and recommendations contribute to the evolving knowledge base on leveraging AI for adequate healthcare delivery, guiding future initiatives in similar contexts.  **Keywords:** Artificial Intelligence, Healthcare gap, Rural areas, remote patient monitor, healthcare outcome. | 2 |
| **INTRODUCTION** | | | |
| Rationale | 3 | Healthcare disparities between urban and rural areas in India are stark, with rural populations often lacking access to essential medical services, skilled healthcare professionals, and adequate healthcare infrastructure. These challenges are compounded by factors such as geographic isolation, limited financial resources, and insufficient health literacy. Despite various governmental and non-governmental efforts to address these issues, the healthcare gap persists, leading to poorer health outcomes and increased mortality rates in rural areas.  However, the emergence Artificial Intelligence (AI) has shown significant promise in revolutionizing healthcare delivery globally. AI tools ensure enhancing diagnostic accuracy, optimizing treatment plans, streamlining administrative processes, and facilitating remote patient monitoring. The integration of AI in healthcare systems has potentially addressed many critical challenges faced by rural healthcare in India, such as the shortage of healthcare professionals, the need for timely and accurate diagnosis, and the efficient management of health records.  The author was promoted to deploy Scoping Review because there is limited comprehensive evidence on how AI tools have been specifically utilized to address healthcare disparities in rural India. A scoping review is essential to map the existing literature, identify key areas where AI has been implemented, and evaluate the effectiveness and challenges of these interventions. This review will provide a systematic overview of the current landscape, highlight successful case studies, and identify gaps in knowledge that require further research. | 3 |
| Objectives | 4 | 1. To Identify AI Applications. 2. To Assess Impact 3. To Identify Barriers and Facilitators 4. To Provide Recommendations | 3 |
| **METHODS** | | | |
| Protocol and registration | 5 | This review article was registered with the PROSPERO International Prospective Register of Systematic Reviews (Registration Number: [CRD42023414450]). The protocol was developed according to the PRISMA (Preferred Reporting Items guidelines, ensuring a standardized and transparent review process. | 7 |
| Eligibility criteria | 6 | Studies that examined the use of AI tools in healthcare delivery and evaluated the impact of AI tools on healthcare outcomes in rural areas. Studies compared the use of AI tools to other interventions or standards of care in rural areas. These included rural populations or healthcare providers as study participants. Studies published in the English language. | 7 |
| Information sources\* | 7 | The study involved a review of the existing literature on the use of AI tools in rural healthcare. The qualitative review included a systematic search of the relevant data and retrieved literature using the Google Scholar, PubMed, and Scopus (ScienceDirect) electrical databases employing appropriate keywords and search terms: "AI tools in healthcare", "Artificial intelligence in rural healthcare", "Machine learning", "Deep learning", "Remote patient monitoring" "Telehealth" "Telemedicine" "Rural health" "Rural communities" "Healthcare outcomes" "Healthcare disparities." The review was refined by adding additional keywords and search terms: "Digital health," "E-health", "mHealth", "Mobile health", "Smart health", and "Health technology." The study was modified further based on its specific requirements and search syntax.  The data restriction (1st January 2020–12th December 2022) was used, and only published English-language content was extracted. The subsequent step was text availability, where an abstract was chosen, and articles with the study types of review and systematic review were added. The displayed data was elected, and the 'Send to' alternate was tapped, choosing "citation manager" followed by "selected all," and a file (Pubmed-Artificial-set) nbib was created. Likewise, the author chose the ScienceDirect database from the Scopus family, refined the data retrieval by 2020–2022, and selected the review article type. All of the articles exhibited were exported to RIS format after selection. To find reliable and more relevant data, the author also used Google Scholar and conducted a manual search method. According to the author, these manual search methods—particularly hand-searching by choosing the most relevant data—led to differing study results.(32)  . | 7 |
| Search | 8 | The qualitative review included a systematic search of the relevant data and retrieved literature using the Google Scholar, PubMed, and Scopus (ScienceDirect) electrical databases employing appropriate keywords and search terms: "AI tools in healthcare", "Artificial intelligence in rural healthcare", "Machine learning", "Deep learning", "Remote patient monitoring" "Telehealth" "Telemedicine" "Rural health" "Rural communities" "Healthcare outcomes" "Healthcare disparities." The review was refined by adding additional keywords and search terms: "Digital health," "E-health", "mHealth", "Mobile health", "Smart health", and "Health technology." The study was modified further based on its specific requirements and search syntax.  The data restriction (1st January 2020–12th December 2022) was used, and only published English-language content was extracted. | 7 |
| Selection of sources of evidence† | 9 | Data screening is a crucial step after the data search. However, retrieved articles were screened by two reviewers using an AI-powered application called "Rayyan", which allowed authors to work more accurately and quickly. The initial abstract and title screening process was sped up using Rayyan software, which combined semi-automation with excellent usability.(33) Of the searches, 1008 records were migrated to Rayyan. The research title was designed before the data was uploaded. Data auto duplication was used after uploading and discovered two exact matches, which were resolved in the process. The screening tool included four inclusion decision categories: "Undecided," "Maybe," "Included," and "Excluded." The complete screening process of the study was done in three phases: The author glanced through the title and abstract for the preliminary phase. The study's title contained the terms "Artificial Intelligence," "Rural/Healthcare," "Machine learning," and "Application of AI," which were all included in the inclusion decision with the automatically generated justification "Background article" and given the label "AI." The ambiguous data for which the author assumed a chance of finding relevant information was labeled as "P" and placed in the "Maybe" category. Additionally, the information deemed inappropriate and irrelevant to the subject was categorically eliminated and labeled "Irrelevant." In the second phase, two titles had to be created: one for the data classified as "Maybe," with the title "Maybe full-text review," and another for the data classified as "Included," with the title "Included full-text review." The data that are most pertinent to the topic were categorised for the final full-text study for the third and last phases of the screening process.  . | 8 |
| Data charting process‡ | 10 | NA. | NA |
| Data items | 11 | NA | NA |
| Critical appraisal of individual sources of evidence§ | 12 | NA | NA |
| Synthesis of results | 13 | The study employed a qualitative approach to synthesize data. The author thoroughly reviewed the data iteratively to discern patterns, trends, and recurring themes. A systematic coding method was utilized to segment the data into meaningful units, resulting in the generation of initial codes. Subsequently, these codes were organized into relevant themes through clustering, forming primary themes. The researcher meticulously examined the interplay between codes and themes, refining and adjusting them as necessary to ensure logical coherence and consistency. Themes were iteratively developed through an inductive process of data-driven analysis, involving continuous comparison and contrast of different data segments to identify commonalities and variations. This iterative process culminated in the creation of final themes, which were presented in a cohesive and descriptive manner. | 9 |
| **RESULTS** | | | |
| Selection of sources of evidence | 14 | The data identified with database 1009 had four records removed before screening for duplication and one record marked as ineligible by automation tools, resulting in a total of 1008 records screened. The full text of 26 records was assessed for eligibility but excluded by the Rayyan Intelligent Systematic Review software for the following reasons:   * Reason 1: 3 records had the wrong study outcomes. * Reason 2: 2 records had the wrong study design. * Reason 3: 1 record was the wrong publication. | 9 |
| Characteristics of sources of evidence | 15 | NA | NA |
| Critical appraisal within sources of evidence | 16 | NA | NA |
| Results of individual sources of evidence | 17 | The new study included as the sources of evidence-one that presented, the relevant data that were charted that relate to the review questions and objectives 1. | 9 |
| Synthesis of results | 18 |  | 11 |
| **DISCUSSION** | | | |
| Summary of evidence | 19 | Results indicate the potential of AI in rural healthcare settings, showing AI-driven solutions addressing healthcare access gaps and contributing to their bridging. The study also highlights hurdles related to AI tool adoption in rural healthcare and proposes collaborative efforts among policymakers, healthcare providers, and technology developers to integrate AI tools effectively. This necessitates advocating for digital infrastructure investments, capacity-building initiatives, and conducive regulatory frameworks for AI implementation. | 12 |
| Limitations | 20 | The study may be limited by the availability and quality of healthcare data from rural areas, which can be inconsistent, incomplete, or inaccurate. The methods used in the study may not adhere to universally accepted standards, however, followed the guidelines for the PRISMA 2020 checklist. | 15 |
| Conclusions | 21 | The study highlighted the significant potential of AI applications in improving healthcare delivery and addressing disparities in rural regions. Through an exploration of various AI tools tailored for rural healthcare settings, including advanced diagnostics and remote patient monitoring, the study underscored the transformative impact AI brought on healthcare outcomes. Despite the positive implications, significant challenges such as restricted data accessibility, ethical considerations, and infrastructure limitations posed considerable concerns and must be addressed to ensure successful implementation. Moreover, the researcher from rural India emphasized that operational challenges arise due to factors such as geographic distribution, socioeconomic constraints, and illiteracy among significant segments of the population.  However, the study also posited the following recommendations, which might significantly improve the delivery of healthcare in rural areas: Improve Data Accessibility, Set Ethical Standards, Develop Infrastructure, Offer Education and Training, Run Pilot Projects, and Promote Cooperation. | 15 |
| **FUNDING** | | | |
| Funding | 22 | The author has not received any funding. | 15 |

JBI = Joanna Briggs Institute; PRISMA-ScR = Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.

\* Where *sources of evidence* (see second footnote) are compiled from, such as bibliographic databases, social media platforms, and Web sites.

† A more inclusive/heterogeneous term used to account for the different types of evidence or data sources (e.g., quantitative and/or qualitative research, expert opinion, and policy documents) that may be eligible in a scoping review as opposed to only studies. This is not to be confused with *information sources* (see first footnote).

‡ The frameworks by Arksey and O’Malley (6) and Levac and colleagues (7) and the JBI guidance (4, 5) refer to the process of data extraction in a scoping review as data charting*.*

§The process of systematically examining research evidence to assess its validity, results, and relevance before using it to inform a decision. This term is used for items 12 and 19 instead of "risk of bias" (which is more applicable to systematic reviews of interventions) to include and acknowledge the various sources of evidence that may be used in a scoping review (e.g., quantitative and/or qualitative research, expert opinion, and policy document).

*From:* Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. Ann Intern Med. 2018;169:467–473. [doi: 10.7326/M18-0850](http://annals.org/aim/fullarticle/2700389/prisma-extension-scoping-reviews-prisma-scr-checklist-explanation).