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Exploring the Potential and Future Outlook of AI in Improving Healthcare in Rural Communities in the United States of America

Utulu, Emmanuel Chukwugozim[1]

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Abstract:

➢ ***Background:***

Rural healthcare service delivery in the United States remains a major issue due to a lack of adequate infrastructure, qualified healthcare practitioners, and facilities. These deficiencies have reduced healthcare access and worsened rural-urban health disparities. Artificial intelligence have been shown to contribute to healthcare service delivery and its advancement globally, but its impact in service delivery for rural populations in the United State have been largely underexplored. This paper addresses this gap by investigating the impact of artificial intelligence in improving healthcare service delivery, accessibility to healthcare services, and health outcomes of individuals living in rural regions in the United States.

➢ ***Methods:***

To retrieve relevant literature, JSTOR, Web of Science, Scopus, and PubMed/MEDLINE databases were searched for relevant articles based on a predetermined inclusion and exclusion criteria. The CASP appraisal tool was used to assess the quality of the included papers. Thematic analysis was employed to analyze the data extracted from these articles.

➢ ***Findings:***

The database search yielded an initial 57 articles. Following exclusion of duplicate articles and those which does not fit into the search criteria, 8 articles were determined to meet the inclusion criteria, and subsequently included and subjected to further analysis. After the included papers were critically analyzed and explored, four key themes were identified. These themes includes: (i) Patient engagement and adherence to care services (ii) Diagnostic accuracy and timeliness, (iii) Infrastructure limitations, and (iv) Closing the digital divide.

➢ ***Conclusion:***

This extensive investigation shows that AI has the potential to improve rural US healthcare access, diagnostic precision, health outcomes, and patient participation. However, infrastructure gaps, algorithmic biases, and digital inequality currently restrict its transformative potential. Equitable data inclusion, ethical AI design, and rural infrastructural improvements are needed to overcome these systemic barriers to sustainable healthcare.

Keywords: *Artificial Intelligence, Rural Communities, Healthcare Service Delivery, Healthcare Improvement, Future Outlook, United State of America.*

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I. INTRODUCTION

Rural communities' healthcare requirements are often neglected due to a lack of money, medical facilities, and healthcare specialists (Pahune, 2024). The rapid breakthroughs in artificial intelligence (AI) have sparked interest in using AI to the healthcare problems faced by rural communities. AI-based healthcare solutions have the potential to improve the quality, efficacy, and accessibility of healthcare services in rural areas (Pahune, 2024). As a result, the healthcare industry is looking to implement cutting-edge AI technologies in rural areas. Artificial intelligence is a fast-growing field of computer science that uses computers to mimic human learning, memory, analysis, and even creativity, all of which normally need human intelligence (Hamet & Trembla, 2017). Artificial intelligence is a rapidly developing computer technology that has begun to be widely used in the medical field to reduce medical errors in rural regions and to increase the professionalism and efficiency of clinical practice (Guo & Li, 2018). The rapid development of electronic medical records, personal health records, and health information technology has led to the creation of a massive amount of multimedia information in the form of documents, forms, photos, and audio.

Accordingly, it is expected that patients will gain from the application of artificial intelligence technology (Ming *et al.*, 2018). AI-assisted clinical trials are capable of processing massive volumes of data and producing very accurate results (Shaheen, 2021). Medical AI companies create systems that support patients at every step. In order to help patients improve their quality of life, clinical intelligence also evaluates their medical data (Greenberg *et al.*, 2020). Numerous problems plague healthcare systems worldwide, such as limited access, exorbitant expenses, waste, and an ageing population. Healthcare systems are strained by pandemics like the coronavirus (COVID-19), which leads to inadequate or inaccurate diagnostic testing, a shortage of protective gear, overworked doctors, and a breakdown in information sharing.

➢ *Problem Statement*

Rural US healthcare remains a major issue due to a lack of adequate infrastructure, qualified doctors, and facilities (Bassey *et al.*, 2024). These deficiencies have reduced healthcare access and worsened rural-urban health disparities (Reilly, 2021). Rural areas often have physician shortages, limited access to specialty medical services, poor health facilities, and high chronic sickness rates, with geographic remoteness also making healthcare delivery inefficient and timely care difficult (Bassey *et al.*, 2024).

Recent AI holds the potential to solve systemic issues and improve healthcare in poor areas with promising advancement such as telehealth and machine learning diagnostics (Greenberg *et al.*, 2020; Pahune, 2024). However, even with these promising advances, rural healthcare systems have limited AI use. Poor digital infrastructure, insufficient technological competency among healthcare practitioners and patients, fiscal constraints, and ethical challenges related to data privacy, security, and equality are major impediments (Chaturvedi *et al.*, 2025). Thus, AI's long-term potential to improve rural healthcare delivery is unexplored among rural population in the US. This gap emphasizes the need to study the effective integration of AI into rural healthcare systems to deliver equitable, sustainable, and high-quality healthcare to disadvantaged US communities.

➢ *Research Aim and Objectives*

The study aims to explore the potential and future outlook of AI in enhancing healthcare delivery, accessibility, and outcomes in rural communities in the United States of America.

- *The specific objectives are:*

✓ To examine the current challenges facing healthcare delivery in rural communities in the USA.
✓ To analyze the existing and potential applications of AI technologies in rural healthcare, including diagnostics, telemedicine, patient monitoring, and administrative efficiency.
✓ To evaluate the role of AI in reducing healthcare disparities and improving access to quality medical services in underserved rural populations.
✓ To assess the opportunities and limitations of integrating AI into rural healthcare systems.

➢ *Research Question*

What is the role and future outlook of artificial intelligence in enhancing healthcare access and outcomes in rural communities across the United States?

➢ *Significance of the Study*

This research contributes to the literature on AI and rural healthcare in the US; an area of study which is understudied compared to metropolitan healthcare access. This study is also significant as it provides information on how AI can enhance the delivery of healthcare services for rural population in the US, ensuring equal access to healthcare services, just like their counterparts in urban areas of the country. The findings of this study also has the potential to help policymakers create more effective health policies and reforms by revealing the challenges and opportunities of AI adoption in rural health systems. It can help healthcare professionals and management find AI-driven solutions to improve efficiency, diagnosis, and service delivery in resource-constrained environments. AI's ability to close gaps, increase healthcare equality, and improve rural health outcomes has social ramifications, which was explored in this paper, followed by the provision of implications and recommendations to improve AI usage in healthcare service provision for rural population in the US.

➢ *Scope of the Study*

This study examines how AI improves rural US healthcare delivery. It also investigates rural healthcare systems' challenges, including limited access to doctors, poor infrastructure, and health disparities, and how AI-driven solutions can help address this challenge. The scope of this study is limited only to studies conducted in the US to ensure a contextually relevant finding. The studies included were selected using an inclusion and exclusion criteria as guide which is detailed in the methodology section.

II. METHODOLOGY

A systematic literature review is employed for this research. This involves searching and analyzing existing articles to address a particular research question (Bramer, 2018).

➢ *Search Strategy*

A comprehensive search of academic databases, including the JSTOR, Web of Science, Scopus, and PubMed/MEDLINE was done to retrieve relevant literature. The search terms (see Table 1) were combined using Boolean operators of 'AND,' and 'OR' to create a search string which was used to search the identified databases.

Table 1 Search Terms

Concept	Search Terms / Keywords
Artificial Intelligence	“artificial intelligence” OR “AI” OR “machine learning” OR “deep learning” OR “neural network” OR “intelligent systems” OR “algorithmic decision-making” OR “automation in healthcare”
Healthcare	“healthcare” OR “health services” OR “clinical care” OR “medical diagnosis” OR “treatment” OR “digital health” OR “telemedicine” OR “e-health” OR “primary care” OR “patient engagement”
Rural Communities (U.S.)	“rural health” OR “rural communities” OR “rural America” OR “underserved areas” OR “remote populations” OR “frontier health” OR “health disparities” OR “rural hospitals” OR “rural healthcare access”
Outcomes / Benefits	“health outcomes” OR “healthcare access” OR “patient satisfaction” OR “adherence to care” OR “diagnostic accuracy” OR “health equity” OR “digital divide”
Geographical Filter	“United States” OR “U.S.” OR “America” OR “USA”

Table 2 Search String

<table>
<tr><th>Databases</th><th>Search String</th></tr>
<tr><td>JSTOR</td><td rowspan="4">("artificial intelligence" OR "AI" OR "machine learning" OR "deep learning" OR "neural network")
AND
("healthcare" OR "digital health" OR "telemedicine" OR "primary care")
AND
("rural health" OR "rural communities" OR "underserved areas" OR "remote populations")
AND
("United States" OR "USA" OR "America")
AND
("health outcomes" OR "access to care" OR "diagnostic accuracy" OR "patient engagement" OR "digital divide")</td></tr>
<tr><td>Web of Science</td></tr>
<tr><td>Scopus</td></tr>
<tr><td>PubMed/MEDLINE</td></tr>
</table>

- *Inclusion and Exclusion Criteria*

The inclusion and exclusion criteria ensured that the selected studies provided relevant, high-quality evidence for this systematic review (Charrois, 2015). Papers that investigated the use of AI to improve rural US healthcare delivery were included. Geographic location, healthcare environment, demographics, and methodological relevance were factors that determine eligibility.

Exclusion criteria were used to eliminate studies that does not align with the inclusion criteria and also had characteristics that could compromise the validity, reliability, or applicability of the results (Patino & Ferreira, 2018). These included studies from outside the US, studies conducted on urban healthcare system, and rural healthcare AI adoption studies without practical proof. Table 3 shows this review's inclusion and exclusion criteria.

Table 3 Inclusion and Exclusion Criteria

Criteria	Inclusion	Exclusion
Study Population	Studies focusing on the rural US population	Studies conducted outside of the US or involving populations not relevant to the study question.
Research Design	Studies with quantitative and qualitative research design.	Studies without a clear research design.
Language	Studies published in the English language.	Studies in languages other than English.
Publication Year	Studies published within the last ten years (from 2015 to 2025) were included.	Studies published before 2015 will be ignored.
Study Location	Studies conducted in a rural or medically underprivileged community in the United States	Studies conducted in locations outside of the US.

- *Study Selection*

The identification phase of study selection was done to identify relevant articles by conducting a thorough search of different databases. The study selection process was done in strict adherence to the PRISMA (Preferred Reporting Items for Systematic Reviews guidelines (Page *et al.*, 2021). All retrieved articles were imported into a reference management software (Zotero) to remove duplicates. A two-stage screening process was employed:

- Title and Abstract Screening: Two independent reviewers screened the titles and abstracts of all articles against the inclusion/exclusion criteria.
- Full-Text Review: The full text of all potentially eligible articles were retrieved and independently assessed by two reviewers. Any disagreements were resolved through discussion and by consulting a third reviewer.

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➢ *Data Extraction*

According to Taylor *et al.* (2021) data extraction is the step in a systematic review that takes place between locating relevant research and examining the data. The aims of data extraction are to acquire information on the included studies' demographic and study characteristics. A standardized data extraction table was created to illustrate the characteristics of the included studies.

➢ *Study Quality Assessment*

After screening (article selection) is complete, the systematic review process's Quality Assessment phase began. Thus procedure aids in evaluating the trustworthiness, applicability, and quality of research, critical appraisal of scientific studies is vital for enabling practitioners and researchers to base their decisions on reliable evidence. The methodological quality and risk of bias of the included studies was assessed using an appropriate critical appraisal tool. The choice of tool was the Critical Appraisal Skills Program developed CASP checklists for every study design. This quality assessment tool was used to contextualize the findings rather than to exclude studies.

➢ *Data Analysis*

The extracted data were grouped and analyzed thematically. Key themes related to the benefits, barriers, and future potential of AI will be identified and explored. The results were summarized in narrative text to provide a comprehensive overview of the current evidence. The thematic analysis of the synthesized data were conducted to directly address the research objectives. This involved identifying patterns, trends, and relationships within the literature. The analysis also focused on describing the landscape of current AI use, evaluating its effectiveness based on the reported outcomes, and constructing a forward-looking perspective on how AI could transform healthcare in rural America. The findings were discussed in the context of existing healthcare disparities and technology adoption framework.

III. RESULTS

➢ *Search Outcomes*

Following the search of the databases, 57 articles were retrieved. Using the Zotero reference management software, 14 duplicates were identified and removed. The remaining 43 articles were screened based on their titles and abstracts. 11 articles were excluded as their titles and abstracts were not in alignment with the objectives of this current study. The remaining 32 articles were screened against the predetermined inclusion and exclusion criteria. 24 articles were excluded as they did not meet the inclusion criteria of this study. The remaining 8 articles were adjudged to meet the inclusion criteria, and were included for further analysis. This procedure is further depicted using a PRISMA flowchart, presented in Figure 1.

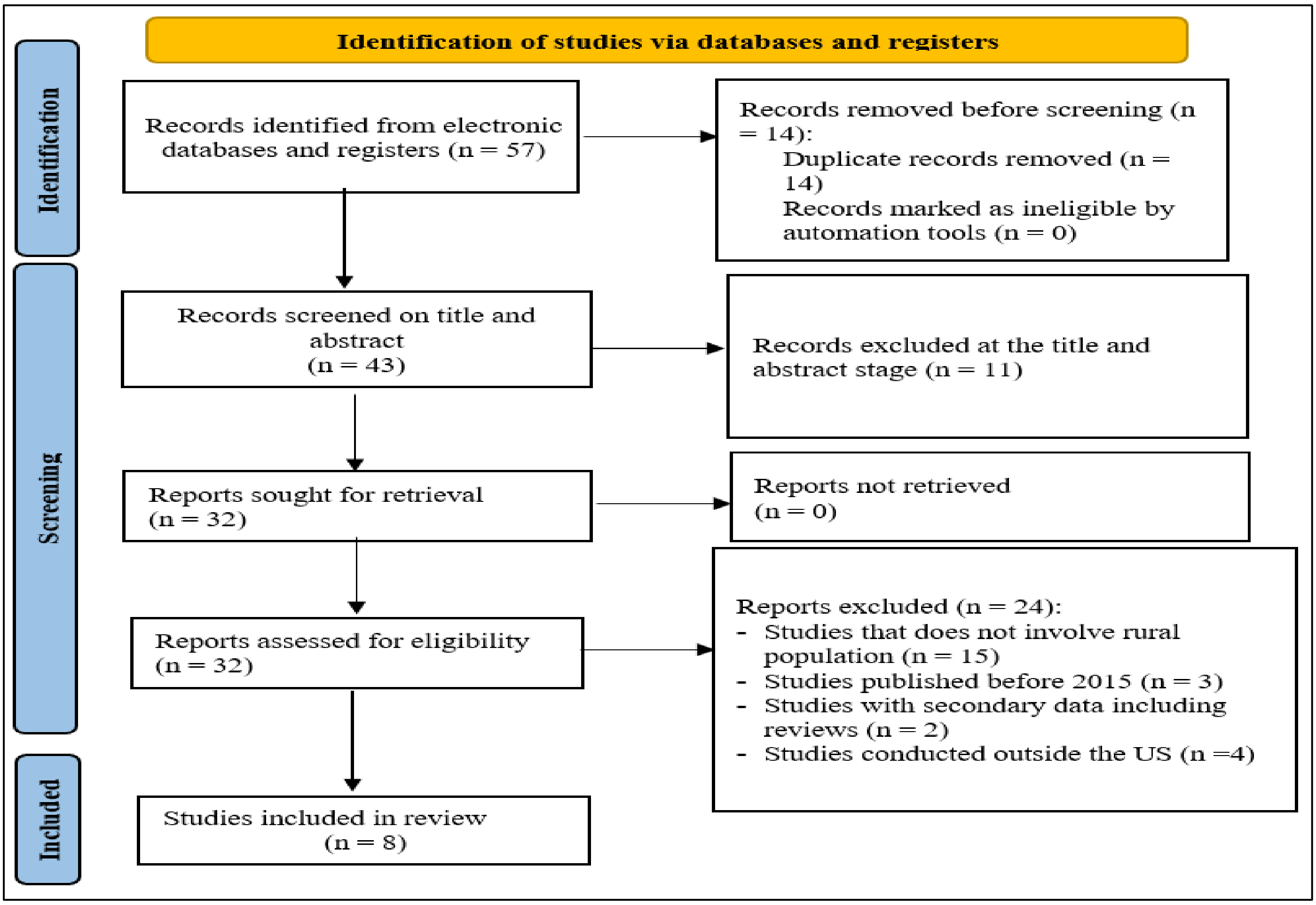

Fig 1 PRISMA Flowchart for the Article Selection Process (Page *et al.*, 2021).

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➢ *Characteristics of Included Articles*

All the included studies were conducted in the USA, with a focus on rural or medically underprivileged communities. The studies were conducted from 2015 to 2025 to ensure the extraction of contemporary and relevant information. Further characteristics of the included articles are presented using a Data Extraction Sheet in Table 4. The quality of the included articles were also appraised using the CASP tool, with outcomes presented in Table 5.

Table 4 Characteristics of Included Articles

Author (Year)	**Aim of Study**	**Country**	**Population**	**Sample Size**	**Methodology**	**Data Collection Method**	**Data Analysis Method**	**Key Findings**	**Themes**
Badal, Lee, & Esserman (2023)	To propose equity-focused design principles for AI in healthcare.	United States	Healthcare AI developers and policy systems	4,791	Quantitative empirical study	Survey	Conceptual framework analysis	AI should address disparities, include contextual adaptation, and promote shared decision-making.	Patient engagement; Diagnostic accuracy; Infrastructure limitations; Digital divide
Blease *et al.* (2020)	To predict expert perspectives on AI's impact on primary care by 2029.	United States	Health informatics experts	29 experts (Delphi panel)	Delphi consensus study	Expert panel survey	Qualitative thematic synthesis of consensus rounds	Experts predicted AI will enhance diagnosis accuracy and patient access, especially in underserved areas.	Patient engagement and adherence; Diagnostic accuracy
Campbell *et al.* (2021)	To analyze how AI-based therapies can be effectively integrated into healthcare delivery systems.	United States	Healthcare systems and AI developers	391	Implementation science framework	Survey	Thematic and process analysis	Adoption depends on context, user readiness, and infrastructure, especially in rural regions.	Patient engagement; Diagnostic accuracy
Green, Murphy, & Robinson (2024)	To explore how AI can address health disparities through data-	United States	Healthcare rural populations	2,118	Quantitative empirical study	Survey	Narrative synthesis	AI can uncover complex determinants of health disparities but depends on	Digital divide

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	driven insight.							equitable data representation.	
Howard & Borenstein (2018)	To examine how algorithmic bias affects AI and robotic systems, including medical AI.	United States	AI systems and healthcare applications	N/A	Conceptual / analytical study	Case illustrations from AI domains	Analytical and ethical critique	Bias in AI algorithms mirrors societal inequalities, risking unequal healthcare outcome.	Infrastructure limitations
Lin, Mahoney, & Sinsky (2019)	To explore how AI can improve patient–physician relationships and clinical efficiency.	United States	Primary care physicians and patients	5,510	Quantitative empirical study	Survey	Narrative and conceptual analysis	AI could reduce administrative burden and enhance personalization in healthcare, improving diagnostic and relational outcome.	Patient engagement; Diagnostic accuracy
Scheer *et al.* (2023)	To evaluate the effectiveness and engagement of an AI-driven digital therapy program among rural patients in the U.S.	United States	Rural adult patients with musculoskeletal pain	10,000+	Quantitative empirical study	Program data and user analytics	Descriptive and inferential statistics	High completion rate (73.8%) and equal clinical outcomes for rural participants; AI improved engagement and accessibility.	Patient engagement and adherence; Diagnostic accuracy
Veinot, Mitchell, & Ancker (2018)	To discuss how health informatics interventions can	United States	Health informatics users and developers	N/A	Perspective paper	Intervention evaluations	Thematic synthesis	Socioeconomic and digital gaps create unequal AI benefits;	Infrastructure limitations; Digital divide

	generate or worsen inequalities.							recommends safeguards for equity.	

Table 5 CASP Quality Appraisal

S/N	Authors (Year of publication)	Was there a clear statement of the aims of the research?	Is the methodology appropriate?	Was the research design appropriate to address the aims of the research?	Was the recruitment strategy appropriate to the aims of the research?	Was the data collected in a way that addressed the research issue?	Has the relationship between the researcher and participants been adequately considered?	Have ethical issues been taken into consideration?	Was the data analysis sufficiently rigorous?	Is there a clear statement of findings?	Is the research valuable?	Quality Score
1	Badal, Lee, & Esserman (2023)	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Yes	Yes	Yes	9
2	Blease *et al.* (2020)	Yes	Yes	Yes	Yes	Can't Tell	Can't Tell	Yes	Yes	Yes	Yes	8
3	Campbell *et al.* (2021)	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Yes	Yes	Yes	9
4	Green, Murphy, & Robinson (2024)	Yes	No	Yes	Yes	Yes	Can't Tell	Yes	Yes	Yes	Yes	8
5	Howard & Borenstein (2018)	Yes	Yes	No	No	Yes	Can't Tell	Yes	Yes	Yes	Yes	7
6	Lin, Mahoney, & Sinsky (2019)	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Yes	Yes	Yes	9
7	Scheer *et al.* (2023)	Yes	Yes	Yes	Yes	Yes	Can't Tell	Yes	Yes	Yes	Yes	9
8	Veinot, Mitchell, & Ancker (2018)	Yes	Yes	No	Yes	Yes	Can't Tell	Yes	Yes	Yes	Yes	8

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➢ *Key Themes Identified*

After the included papers were critically analyzed and explored, four key themes were identified. These themes were carefully identified, ensuring it addressed the main research question of this study, which is given as "What is the role and future outlook of artificial intelligence in enhancing healthcare access and outcomes in rural communities across the United States?" These themes include: (i) Patient engagement and adherence to care services (ii) Diagnostic accuracy and timeliness, (iii) Infrastructure limitations, and (iv) Closing the digital divide. These themes are further discussed critically in the next section.

➢ *Thematic Analysis*

- *Theme 1: Patient Engagement and Adherence to Care Services*

Five studies (Scheer *et al.*, 2023; Blease *et al.*, 2020; Lin, Mahoney & Sinsky, 2019; Campbell *et al.*, 2021; Badal, Lee & Esserman, 2023) contributed to this theme, demonstrating the potential of artificial intelligence in improving patient engagement and adherence in rural US healthcare settings. Scheer *et al*. (2023) conducted one of the only larger empirical investigations on an AI-driven digital therapy program for over 10,000 rural patients. A 73.8% completion rate and equivalent therapeutic results were seen, with rural persons engaging more with instructional content. This shows the potential of AI in equalizing regional access to therapeutic therapies and participation.

Blease *et al*. (2020) predicted expert opinions on AI's impact on primary care, supporting similar empirical results. The study's eminent health informaticians predicted that by 2029, artificial intelligence and machine learning will increase patient access to medical information and diagnosis accuracy, especially for rural populations, suggesting that AI can help individuals in rural regions prevent isolation and improve healthcare access. Lin, Mahoney, and Sinsky (2019) explored the relational and behavioural elements of AI use and found that AI can improve patient-physician interactions by reducing administrative hassles and increasing personalisation. Scheer *et al*. (2023) also agreed that well-structured AI technologies can improve patient and provider experiences by boosting human connection rather than replacing it. However, poor implementation can lead to depersonalized treatment, especially in among individuals with poor digital literacy.

AI therapies' adoption and scalability depend on their integration into consumers' lifestyles and care systems (Campbell *et al.*, 2021). Their study shows that engagement with AI in rural healthcare settings requires technical innovation, infrastructural integration, worker readiness, and community acceptability. Badal, Lee, and Esserman (2023) offer an evaluation of AI design approach that links patient contact to equity and contextual adaptation, requiring localized, clinically relevant, and collaborative AI solutions to address healthcare access and adherence inequities. Badal, Lee, and Esserman (2023) supports this by suggesting that adding biographical and socioeconomic health factors to AI drugs improves rural effectiveness and empowers underprivileged communities.

- *Theme 2: Diagnostic Accuracy and Timeliness*

Five of the included studies (Lin, Mahoney, and Sinsky, 2019; Blease, 2020; Campbell, 2021; Badal, Lee, and Esserman, 2023; Scheer, 2023) highlight the potential of AI on improving healthcare diagnosis and decision-making, especially for marginalized groups. According to Scheer *et al*. (2023), AI-driven digital care program were shown to improve pain, anxiety, and productivity among rural participants. This suggests that AI can speed diagnosis and therapy and overcome accessibility constraints, improving patient outcomes.

Blease *et al.* (2020) predicted that AI will greatly improve diagnosis accuracy by 2029, demonstrating the future and predictive potential of AI when it comes to diagnostic healthcare services. Similarly, Lin, Mahoney, and Sinsky (2019) suggested that AI systems can help healthcare professionals optimize diagnostic methods and reduce human error, highlighting the practical potential of AI. These predictive and theoretical evidences suggest that AI holds the present ability and future potential to reduce physician shortages and increase specialist accessibility in rural America, improving diagnostic precision and treatment efficacy.

On diagnostic accuracy, Campbell *et al*. (2021) argued that AI's diagnostic potential can only be realized through proper application and contextual adaptation. This is because infrastructure and scalability issues, especially in rural regions, limit AI advancement. In mitigating this, Badal, Lee, and Esserman (2023) suggested regionalizing diagnostic methods to reduce rural health inequalities, positing that AI can improve rural U.S. healthcare diagnosis accuracy and efficiency, but only with equitable integration, proper infrastructure, and validation.

- *Theme 3: Infrastructure Limitations*

This theme was supported by three of the included papers (Howard and Borenstein, 2018; Veinot, Mitchell, and Ancker, 2018; Badal, Lee, and Esserman, 2023). Evidence from Howard and Borenstein (2018) demonstrate that rural US healthcare infrastructure can hinder AI's potential for healthcare service delivery. They argue that although AI carries enormous potential to improve healthcare delivery, but digital bias, uneven access, and socio-technical differences can limit its use in rural places (Howard and Borenstein, 2018). Howard and Borenstein (2018) further claim that bias-trained datasets, which reflect societal inequality, can prejudice AI algorithms. According to Howard and Borenstein (2018), AI algorithms are commonly designed using urban-centric data which does not reflect the realities of rural population, and such biases can cause treatment or diagnostic discrepancies in rural healthcare systems. According to Howard and Borenstein (2018), AI accessibility can disadvantage low-digital-literate people, and without better infrastructure and ethics, AI can further limit the access to healthcare services for rural populations.

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Since socioeconomically advantaged people have better access to and competency with digital technology, Veinot, Mitchell, and Ancker (2018) argue that health informatics treatments, including AI applications, can worsen health inequalities in not ethically developed. In rural America, internet connectivity, device accessibility, and digital literacy are lower than in cities, worsening healthcare inequities (Veinot, Mitchell, and Ancker, 2018). However, their study questions the idea that technological innovation alone ensures fair outcomes, arguing that without inclusive design and assessment frameworks, AI can marginalize rural areas rather than improve healthcare access (Veinot, Mitchell, and Ancker, 2018).

To overcome these difficulties, Badal, Lee, and Esserman (2023) recommend locally adaptable, equity-focused, and contextually adapted AI systems for population-specific health factors. They urge for AI integration into healthcare systems to reduce disparities and increase efficiency. Their findings show that rural U.S. communities need technological capabilities and data infrastructures that reflect regional, cultural, and socioeconomic diversity to apply AI. Evidence from these included articles indicate that biased algorithms and unequal internet connection prevent rural healthcare AI from realizing its potential in rural areas in the US.

- *Theme 4: Closing the Digital Divide*

Based on Veinot, Mitchell, and Ancker (2018), Badal, Lee, and Esserman (2023), and Green, Murphy, and Robinson (2024), this theme emerged. If digital gaps are addressed, artificial intelligence can improve healthcare access and outcomes, especially in disadvantaged and rural regions, according to Badal, Lee, and Esserman (2023). Due to poor internet access, digital literacy, and healthcare inequality, Veinot, Mitchell, and Ancker (2018) argue that rural and low-income locations are less likely to benefit from AI-driven medical advances. They argue that AI developments can worsen healthcare inequalities in rural America without inclusive design and equitable distribution techniques, which are necessary to improve healthcare results in these places.

When used properly, AI can improve healthcare equity, according to Green, Murphy, and Robinson (2024). Their research shows that AI-driven data analytics can find genetic, environmental, and social health links that traditional methods miss. However, this capability is crucial as it can help rural areas receive more targeted and contextual healthcare services; however, equitable data representation and infrastructure readiness often temper their optimism (Green, Murphy, and Robinson, 2024). Veinot, Mitchell, and Ancker (2018) also shows concern that AI insights can favor urban or affluent demographics more than their rural counterparts without enough rural data or internet access policies. The two studies show a paradox, suggesting that AI can improve health equity through diversified data processing only by improving rural regions' digital infrastructure, connectivity, literacy, and accessibility (Veinot, Mitchell, and Ancker, 2018; Green, Murphy, and Robinson, 2024).

Based on these perspectives, Badal, Lee, and Esserman (2023) argue that ethical AI design should deliberately reduce inequalities while improving efficiency or diagnostic accuracy. Local adaptation, collaborative decision-making, and biographical and social determinants of health in AI models are pragmatic principles that is recommended by the study (Badal, Lee, and Esserman, 2023). The study also highlight the need for a context-sensitive AI solutions to bridge the digital divide gap and technological literacy between rural and urban areas since rural healthcare has community-specific issues including poor infrastructure and varying ailment frequencies (Badal, Lee, and Esserman, 2023).

In summary, these studies that informs this theme show that bridging the digital divide is both technical and ethical, and that AI can improve healthcare access and outcomes in rural U.S. communities only if developers and policymakers priorities equity, inclusivity, and infrastructural investment.

IV. DISCUSSION

- *Patient Engagement and Adherence to Care Services*

This review found growing consensus that artificial intelligence has the potential to improve rural healthcare patient engagement and adherence, but its implications are both promising and concerning. The findings from the review show that in rural areas, AI can improve therapy availability and continuity, but its success depends on social, infrastructural, and ethical circumstances. Topol (2019) supports this finding by confirming that AI technology can revolutionize patient engagement and care service adherence when integrated into supporting systems that build trust and connection. In further agreement, Scott *et al*. (2021) found that AI-driven care models holds the potential to empower and include patients' engagement and adherence to care services, but can equally conflict with empathy. This occurs when AI systems are poorly integrated without meeting the usability demands of its users, thereby alienate healthcare interactions, especially in rural locations where patient knowledge or trust in technology is low (Scott *et al.*, 2021).

AI's success in improving rural healthcare adherence depends on availability, literacy, and cultural relevance, according to the findings of this current review. This is supported by research which argues that digital innovations often fail in disadvantaged populations owing to local context and user preparedness (Greenhalgh *et al.*, 2019). Wei *et al.* (2025) further supported this claim by positing that AI-assisted telemedicine improved chronic disease treatment with continued support and training. This suggests that AI can improve remote patient healthcare participation through trust, usability, training, and inclusion.

- *Diagnostic Accuracy and Timeliness*

Findings from this study illustrate that AI can improve diagnostic accuracy and timeliness by effectively processing complicated data, uncovering subtle diagnostic indications, and helping clinicians discover early illness in areas with limited expert resources. This aligns with another study by Rajpurkar *et al*. (2022) who found that AI-driven diagnostic systems, especially in radiology and pathology, can improve diagnostic precision and speed clinical decision-making. This also supports Guo and Li (2018) assertion who found that AI can enhance remote health outcomes and care efficiency. However, Guo and Li (2018) recognizes that such advantages are context-dependent and requires investment in technology to work effectively in rural regions. This also agrees with Perez *et al*. (2023) who posits that algorithmic performance generally decreases when applied to populations or situations outside than training datasets, showing that AI may reproduce inequality.

However, the findings of this review did not entirely agree with existing studies as Obermeyer *et al*. (2019) showed that algorithmic bias in healthcare AI systems can underdiagnose high-risk patients in marginalized populations, calling for socioeconomic and biographically sensitive AI designs. Sendak *et al*. (2020) also propose that workflow integration, physician training, and equitable data representation are needed for AI to enhance rural diagnostic speed, suggesting that AI can close the diagnosis inadequacy in rural regions and promotes equal access to healthcare services; however, it must be fair, reliable, and contextually relevant.

➢ *Infrastructure Limitations*

This review found that AI future outlook in improving healthcare services in rural regions in the US can be hindered by lack of necessary infrastructure and resources. This finding supports growing studies showing how infrastructural inequities and algorithmic bias hinder healthcare AI use. This current finding agrees with Joseph (2022) who reported that biased training datasets from urban or high-resource populations underperform in low-resource or rural situations, prolonging diagnostic and treatment inequities. This means data and accessibility issues must be handled, ensuring its relevance to its target population before its benefits be transferred from urban to rural regions.

The findings also agrees with Alami *et al*. (2024) who found that AI technology's benefits in rural areas typically overlook the need for digital infrastructure, such as internet access and electronic health record interoperability, which are lacking in many rural US communities. Thus, these constraints hold the potential to further worsen the digital health gap and increase rural-urban healthcare quality discrepancies if not deployed in a fair way. Whitelaw *et al*. (2020) recommend transparent, fair, and contextually relevant AI regulation in healthcare to minimize this limitation. This suggest that if systemic and infrastructural issues are not addressed, AI deployment in rural healthcare can hinder healthcare access and equality.

➢ *Closing the Digital Divide*

This review found that the digital gap hinders equitable AI integration in healthcare, particularly in rural and underprivileged U.S. populations. This agrees with Campos-Castillo and Anthony (2021) who also found that rural Americans have a digital divide due to poor internet access, digital literacy, and socioeconomic inequities in digital health breakthroughs like AI-driven diagnostics and telemedicine. The FCC (2023) states that 17% of rural Americans lack high-speed broadband and knowledge for AI-enhanced healthcare which can further hinder its usage in healthcare sector that requires advanced technology and knowledge for diagnosis and remote treatment. Therefore, without technical infrastructure, community education, and collaborative AI design to bridge the digital divide, health literacy will drop and skepticism about digital medicines will rise, worsening rural healthcare inequities (Douthit *et al*., 2015). This is also supported by Sieck *et al*. (2021) who argue that equitable AI adoption requires justice, openness, and participatory governance, especially for excluded communities, to close the digital gap and improve AI use.

The U.S. Department of Health and Human Services' Rural Action Plan (HHS, 2022) shows that focused digital literacy training and infrastructure improvements can reduce the digital gap and improve rural AI integration to advance healthcare service delivery. These evidence shows that bridging the digital divide is a structural and ethical issue that requires coordinated public-private collaboration and inclusive design strategies to ensure that AI's transformative potential benefits all communities.

V. LIMITATIONS

Although this systematic review addresses its research question, there are some limitations that was encountered. Most of the studies included was predictive and conceptual, rather than empirical, limiting causal inferences about AI's impact on rural healthcare results.

The study designs and AI applications, including digital diagnostics and patient engagement technologies also varied, making direct comparisons and synthesis difficult.

Publication bias could have also influenced the results since positive research is more likely to be published than negative research on implementation or ethics.

This review focused solely on U.S. research, which can limit its generalizability and applicability to other rural healthcare systems with different structures and economies.

➢ *Implications of Findings*

The findings of this review directly affect healthcare policy, practice, and research. Drawing upon the findings of this review, to apply AI in healthcare for rural Americans, governments must invest in broadband development, digital literacy initiatives, and data fairness guidelines. Also, according to the findings of this review, in resource-constrained situations, healthcare practitioners and organizations should use AI as a tool to increase patient participation, diagnostic accuracy, and treatment continuity. This review also shows that regionally adaptable, transparent, and inclusive data sources that reflect rural populations in design and development are ethical requirements for AI systems in healthcare service delivery. There is also a need for future research to move from theoretical to community-based investigations of AI's long-term implications on rural health outcomes, health equity, and patient confidence. This is necessary to provide scientifically sound and socially appropriate AI-driven healthcare solutions.

VI. CONCLUSION

This extensive investigation shows that AI has the potential to improve rural US healthcare access, diagnostic precision, and patient participation. However, infrastructure gaps, algorithmic biases, and digital inequality currently restrict its transformative potential. Equitable data inclusion, ethical AI design, and rural infrastructural improvements are needed to overcome these systemic barriers to sustainable healthcare. The findings from this review affirms that AI can overcome the rural–urban healthcare gap provided it is guided by principles of fairness, inclusion, and contextual relevance. Future outlook in this context should focus on integrating AI into comprehensive health equity and community empowerment frameworks to ensure that technology benefits all social segments, especially historically marginalized and rural regions in the country.

REFERENCES

[1]. Alami, H., Lehoux, P., Papoutsi, C., Shaw, S. E., Fleet, R., & Fortin, J. P. (2024). Understanding the integration of artificial intelligence in healthcare organisations and systems through the NASSS framework: a qualitative study in a leading Canadian academic centre. *BMC health Services research*, 24(1), 701. https://doi.org/10.1186/s12913-024-11112-x

[2]. Badal, K., Lee, C. M., & Esserman, L. J. (2023). Guiding principles for the responsible development of artificial intelligence tools for healthcare. *Communications Medicine*, 3(1), 47. https://doi.org/10.1038/s43856-023-00279-9

[3]. Bassey, K. E., Juliet, A. R., and Stephen, A. O. (2024) AI-Enhanced lifecycle assessment of renewable energy systems. *Engineering Science & Technology Journal*, 5(7), 2082-2099.

[4]. Blease, C., Kharko, A., Locher, C., DesRoches, C. M., & Mandl, K. D. (2020). US primary care in 2029: A Delphi survey on the impact of machine learning. *PloS One*, 15(10), e0239947. https://doi.org/10.1371/journal.pone.0239947

[5]. Bramer, W.M., De Jonge, G.B., Rethlefsen, M.L., Mast, F. and Kleijnen, J. (2018) A systematic approach to searching: an efficient and complete method to develop literature searches. *Journal of the Medical Library Association: JMLA*, 106(4), p.531.

[6]. Campbell, J. P., Mathenge, C., Cherwek, H., Balaskas, K., Pasquale, L. R., Keane, P. A., Chiang, M. F., & American Academy of Ophthalmology Task Force on Artificial Intelligence (2021). Artificial Intelligence to Reduce Ocular Health Disparities: Moving From Concept to Implementation. *Translational Vision Science & Technology*, 10(3), 19. https://doi.org/10.1167/tvst.10.3.19

[7]. Campos-Castillo, C., & Anthony, D. (2021). Racial and ethnic differences in self-reported telehealth use during the COVID-19 pandemic: a secondary analysis of a US survey of internet users from late March. *Journal of the American Medical Informatics Association: JAMIA*, 28(1), 119–125. https://doi.org/10.1093/jamia/ocaa221

[8]. Charrois T. L. (2015). Systematic reviews: what do you need to know to get started? *The Canadian Journal of Hospital Pharmacy*, 68(2), 144–148.

[9]. Chaturvedi, U., Chauhan, S. B., & Singh, I. (2025). The impact of artificial intelligence on remote healthcare: enhancing patient engagement, connectivity, and overcoming challenges. *Intelligent Pharmacy*.

[10]. Douthit, N., Kiv, S., Dwolatzky, T., & Biswas, S. (2015). Exposing some important barriers to health care access in the rural USA. *Public Health*, 129(6), 611–620. https://doi.org/10.1016/j.puhe.2015.04.001

[11]. Federal Communications Commission (FCC). (2023). *2023 Broadband Deployment Report*.

[12]. Green, B. L., Murphy, A., & Robinson, E. (2024). Accelerating health disparities research with artificial intelligence. *Frontiers in Digital Health*, 6, 1330160. https://doi.org/10.3389/fdgth.2024.1330160

[13]. Greenberg, N., Docherty, M., Gnanapragasam, S., & Wessely, S. (2020). Managing mental health challenges faced by healthcare workers during covid-19 pandemic. *bmj*, *368*.

[14]. Guo, J., & Li, B. (2018). The Application of Medical Artificial Intelligence Technology in Rural Areas of Developing Countries. *Health Equity*, 2(1), 174–181. https://doi.org/10.1089/heq.2018.0037

[15]. Guo, J., & Li, B. (2018). The application of medical artificial intelligence technology in rural areas of developing countries. *Health equity*, 2(1), pp. 174-181.

[16]. Hamet, P., & Tremblay, J. (2017). Artificial intelligence in medicine. *Metabolism*, 69, S36-S40.

[17]. Howard, A., & Borenstein, J. (2018). The Ugly Truth About Ourselves and Our Robot Creations: The Problem of Bias and Social Inequity. *Science and Engineering Ethics*, 24(5), 1521–1536. https://doi.org/10.1007/s11948-017-9975-2

[18]. Joseph, J. (2025). Algorithmic bias in public health AI: a silent threat to equity in low-resource settings. *Frontiers in Public Health*, 13, 1643180. https://doi.org/10.3389/fpubh.2025.1643180

[19]. Lin, S. Y., Mahoney, M. R., & Sinsky, C. A. (2019). Ten Ways Artificial Intelligence Will Transform Primary Care. *Journal of General Internal Medicine*, 34(8), 1626–1630. https://doi.org/10.1007/s11606-019-05035-1

[20]. Ming, K., Qianfeng, H., and Lanjuan, L. (2018) AI assisted clinical diagnosis & treatment and development strategy. *Strategic Study of CAE*, 20, pp. 86-91.

[21]. Obermeyer, Z., Powers, B., Vogeli, C., & Mullainathan, S. (2019). Dissecting racial bias in an algorithm used to manage the health of populations. *Science (New York, N.Y.)*, 366(6464), 447–453. https://doi.org/10.1126/science.aax2342

[22]. Page, M. J., Moher, D., Bossuyt, P. M., Boutron, I., Hoffmann, T.C., Mulrow, C.D., Shamseer, L., Tetzlaff, J.M., Akl, E.A., Brennan, S.E., Chou, R.,

Glanville, J., Grimshaw, J.M., Hróbjartsson, A., Lalu, M.M., Li, T., Loder, E.W., Mayo-Wilson, E., McDonald, S. & McGuinness, L. A. (2021) PRISMA 2020 Explanation and elaboration: Updated Guidance and Exemplars for Reporting Systematic Reviews. *BMJ*, 372(160).

[23]. Pahune, S. A. (2024). A brief overview of how AI enables healthcare sector rural development. *Preprint retrieved from* https://doi.org/10.13140/RG,2(16675.63525)

[24]. Patino, C. M. & Ferreira, J. C. (2018) Inclusion and exclusion criteria in research studies: definitions and why they matter. *Jornal Brasileiro de Pneumologia*, 44, pp.84-84.

[25]. Perez, K., Wisniewski, D., Ari, A., Lee, K., Lieneck, C., & Ramamonjiarivelo, Z. (2025). Investigation into Application of AI and Telemedicine in Rural Communities: A Systematic Literature Review. *Healthcare (Basel, Switzerland)*, 13(3), 324. https://doi.org/10.3390/healthcare13030324

[26]. Rajpurkar, P., Chen, E., Banerjee, O., & Topol, E. J. (2022). AI in health and medicine. *Nature Medicine*, 28(1), 31–38. https://doi.org/10.1038/s41591-021-01614-0

[27]. Reilly, M. (2021). Health Disparities and Access to Healthcare in Rural vs. Urban Areas. *Theory in Action*, 14(2).

[28]. Scheer, J., Areias, A. C., Molinos, M., Janela, D., Moulder, R., Lains, J., Bento, V., Yanamadala, V., Dias Correia, F., & Costa, F. (2023). Engagement and Utilization of a Complete Remote Digital Care Program for Musculoskeletal Pain Management in Urban and Rural Areas Across the United States: Longitudinal Cohort Study. *JMIR mHealth and uHealth*, 11, e44316. https://doi.org/10.2196/44316

[29]. Scott, I. A., Carter, S. M., & Coiera, E. (2021). Exploring stakeholder attitudes towards AI in clinical practice. *BMJ Health & Care Informatics*, 28(1), e100450. https://doi.org/10.1136/bmjhci-2021-100450

[30]. Sendak, M. P., Ratliff, W., Sarro, D., Alderton, E., Futoma, J., Gao, M., Nichols, M., Revoir, M., Yashar, F., Miller, C., Kester, K., Sandhu, S., Corey, K., Brajer, N., Tan, C., Lin, A., Brown, T., Engelbosch, S., Anstrom, K., Elish, M. C., & O'Brien, C. (2020). Real-World Integration of a Sepsis Deep Learning Technology Into Routine Clinical Care: Implementation Study. *JMIR Medical Informatics*, 8(7), e15182. https://doi.org/10.2196/15182

[31]. Shaheen, M. Y. (2021) Applications of Artificial Intelligence (AI) in healthcare: A review. *ScienceOpen Preprints*.

[32]. Sieck, C. J., Sheon, A., Ancker, J. S., Castek, J., Callahan, B., & Siefer, A. (2021). Digital inclusion as a social determinant of health. *NPJ Digital Medicine*, 4(1), 52. https://doi.org/10.1038/s41746-021-00413-8

[33]. Taylor, K. S., Mahtani, K. R. and Aronson, J. K. (2021) Summarising good practice guidelines for data extraction for systematic reviews and meta-analysis. *BMJ Evidence-Based Medicine*, 26(3), 88-90.

[34]. Topol E. J. (2019). High-performance medicine: the convergence of human and artificial intelligence. *Nature Medicine*, 25(1), 44–56. https://doi.org/10.1038/s41591-018-0300-7

[35]. U.S. Department of Health and Human Services (HHS). (2022). *Rural Action Plan: Advancing Rural Health Equity*.

[36]. Veinot, T. C., Mitchell, H., & Ancker, J. S. (2018). Good intentions are not enough: how informatics interventions can worsen inequality. *Journal of the American Medical Informatics Association: JAMIA*, 25(8), 1080–1088. https://doi.org/10.1093/jamia/ocy052

[37]. Wei, Q., Pan, S., Liu, X., Hong, M., Nong, C., & Zhang, W. (2025). The integration of AI in nursing: addressing current applications, challenges, and future directions. *Frontiers in Medicine*, 12, 1545420. https://doi.org/10.3389/fmed.2025.1545420