Journal of Theoretical Accounting Research
ISSN: 1556-5106
Volume 22 Issue 1 Year 2026 Page 92-106

Rural Healthcare and AI: Transformative Potential or Technological Optimism Under Financial Strain?

Jolly Masih[1] **Suresh Chandra Sharma2***

[1]Associate Professor, BML Munjal University, Gurugram. Email- Jolly.masih@bmu.edu.in, Orchid Id : 0000-0002-8420-1517
[2*]Assistant Professor, CCS National Institute of Agriculture Marketing, Jaipur. Email- assistant.professor1@ccsniam.ac.in, Orchid Id : 0009-0004-5818-3134

Abstract
This study interrogates the emerging role of artificial intelligence (AI) as a potential equaliser in rural India's deeply entrenched healthcare inequalities—contexts where limited medical infrastructure, delayed diagnoses and inadequate preventive care have long constrained public health outcomes. At its centre lies a fundamental question: *can AI meaningfully bridge gaps that traditional healthcare systems have struggled to close?* To explore this, the research examines not only the technical promise of AI-enabled tools but also the human realities that shape their acceptance—awareness, trust, financial capacity and lived experience.
Employing a mixed-methods design, the study draws on survey responses from 20 healthcare professionals and 500 rural residents, complemented by public social media data. Machine-learning models—linear regression, logistic regression and Random Forest—were deployed to identify predictors of AI adoption, while Natural Language Processing (NLP) sentiment analysis and chi-square tests illuminated patterns in public attitudes and behavioural intent.
The findings reveal a nuanced landscape: 41.7% of respondents expressed positive sentiment, 47.9% remained neutral and 10.4% voiced concerns. Neutrality was driven largely by limited exposure to AI, whereas negative perceptions reflected anxieties around data privacy, infrastructural fragility and affordability. Strikingly, younger and more educated individuals demonstrated greater familiarity with AI, while lower-income households, despite restricted access, showed a pragmatic willingness to rely on low-cost AI-driven services. Trust emerged as a powerful predictor of advocacy for AI use ($\chi^2 = 64.79$, $p < 0.001$), underscoring the psychological and social dimensions of technological adoption.
Collectively, the study highlights an urgent need for targeted AI literacy initiatives, stronger digital and financial infrastructure and equitable governance frameworks. As India stands on the cusp of an AI-assisted healthcare transformation, the question is no longer *whether* AI can support rural health systems, but *how thoughtfully, responsibly and*

Keywords: Artificial intelligence, Rural healthcare, Machine learning models, Trust and adoption, Financial barriers

1. Introduction

Artificial Intelligence (AI) is redefining the global healthcare sector through advanced computational systems such as machine learning, deep learning, and natural language processing (Srivastava et al., 2020; Lu et al., 2022). These technologies enable the analysis of large, complex datasets to support clinical decision-making, early interventions, and improved healthcare delivery. AI systems enhance diagnostic accuracy, automate routine medical tasks, and streamline workflows, emerging as powerful enablers in reducing systemic healthcare gaps—particularly within underserved rural communities (Guo & Li, 2018; Denvir, 2019).

In rural India, where healthcare infrastructure remains limited, medical specialists are scarce, and financial vulnerability is widespread, AI holds considerable potential to deliver transformative and cost-efficient solutions (Hart et al., 2002; Mars, 2013). Rural households often face high out-of-pocket expenditures, limited access to formal credit, and inconsistent health-insurance coverage. In this context, AI-driven tools can automate diagnostic procedures, support disease prediction, and strengthen preventive-care systems, thereby reducing both medical and financial burdens. AI-enabled chatbots, mobile health (mHealth) platforms, and intelligent decision-support systems have demonstrated effectiveness in broadening access to timely healthcare information and services (Amato et al., 2017; Ashwini et al., 2022; Kuziemsky et al., 2019). Further, AI-supported telemedicine systems offer remote consultations and specialist access, addressing longstanding geographical and financial barriers (Kurpad et al., 2024; Turner-Lee, 2019).

Recent global market analyses reflect the accelerating adoption of AI in healthcare. The AI-in-healthcare sector, valued at USD 18.7 billion in 2023, is projected to reach USD 317.1 billion by 2032 (Grand View Research, 2024; Knowledge Sourcing Intelligence, 2023). The Asia-Pacific market is expected to rise from USD 4.6 billion in 2023 to USD 50.9 billion by 2030. India's AI healthcare market, valued at USD 758.8 million in 2023, is estimated to reach USD 8.7 billion by 2030, propelled by persistent rural challenges such as treatment delays, long travel distances, and limited financial access. Studies have shown that AI-enhanced decision-making and improved service efficiency can significantly strengthen healthcare quality in resource-constrained regions (Kumar & Joshi, 2022; Shinners et al., 2023).

Emerging AI solutions—such as telemedicine, mobile diagnostics, chatbots, and AI-powered drones—have contributed to reducing treatment delays, enhancing early detection, and minimising financial losses associated with late diagnosis (Das et al., 2023; Wang et al., 2021). mHealth applications facilitate medication adherence, predictive analytics anticipate disease outbreaks, and wearable devices enable continuous monitoring, reducing unnecessary clinical visits and associated travel costs (Yang et al., 2023; Zhang et al., 2021). Moreover, AI integrated with rural fintech systems offers new possibilities for micro-insurance enrolment, automated claims verification, and digital lending for essential healthcare expenditures (Masih et al., 2025.; Vinod et al., 2021; Malik et al., 2025).

Despite these advancements, the deployment of AI in rural healthcare faces persistent challenges, including data-privacy concerns, digital illiteracy, unreliable connectivity, and limited financial capacity among rural households and local institutions (Mars, 2013; Shinners et al., 2023). Addressing these constraints requires robust ethical governance frameworks and inclusive financial models to ensure equitable access and sustainable implementation.

This study seeks to examine how AI can effectively bridge healthcare and financial-access gaps in rural India by identifying AI-driven interventions that enhance availability, early diagnosis, preventive care, and affordability. By simultaneously exploring socio-technical and rural-finance dimensions, the study aims to guide policymakers and healthcare stakeholders towards sustainable, inclusive, and financially viable models of AI adoption (Wang et al., 2021; Turner-Lee, 2019).

2. Literature Review

The integration of Artificial Intelligence (AI) into the healthcare system is reshaping traditional models of service delivery, with profound implications for rural healthcare ecosystems and rural financial resilience. Advancements in AI technologies—such as machine learning (ML), natural language processing (NLP), deep learning (DL), and robotic process automation (RPA)—are increasingly being utilised to enhance access, efficiency, and quality of care, particularly in underserved regions (Kumar & Joshi, 2022; Das et al., 2023). These tools offer promising solutions to the persistent challenges faced by rural populations, including inadequate infrastructure, shortages of medical professionals, geographical isolation, and high out-of-pocket expenditures (Guo & Li, 2018; Hart et al., 2002). From a financial perspective, AI-enabled platforms can reduce treatment delays, lower travel-related costs, support teleconsultation financing, streamline micro-insurance claim processing, and improve cost transparency for rural households (Knowledge Sourcing Intelligence, 2023). Understanding consumer satisfaction levels and preferences is therefore essential not only for healthcare delivery but also for insurers and rural financial institutions seeking to design affordable and accessible insurance mechanisms. Incorporating such insights enables stakeholders in both healthcare and insurance sectors to make data-driven decisions, fostering a more equitable, financially inclusive, and responsive healthcare system that better serves the diverse socio-economic needs of rural consumers (Masih et al., 2025).

2.1 AI in Rural Healthcare Delivery

AI offers multi-layered benefits in rural healthcare, extending from diagnostics and treatment support to health education and continuous patient monitoring. The literature identifies several core applications, many of which also hold potential to reduce out-of-pocket expenses and logistical burdens for rural communities.

a) AI-Supported Diagnosis and Treatment

AI-driven diagnostic systems can interpret medical images such as X-rays, CT scans, and MRIs, supporting healthcare providers in making accurate and timely diagnoses (Guo & Li, 2018). These tools effectively detect various conditions, ranging from chronic diseases to mental health disorders. Diagnostic accuracy demonstrated by AI systems has been shown to exceed that of human clinicians in certain contexts. AI-enabled treatment planning may also be tailored to clinical histories and biomedical data, enabling precision care in resource-constrained settings while reducing avoidable medical costs through early detection.

b) Remote Monitoring and Telemedicine

AI-enhanced telemedicine platforms and remote-care devices have emerged as vital tools in rural healthcare delivery (Das et al., 2023; Kurpad et al., 2024). These systems enable clinicians to monitor patient conditions in real time, reducing the need for costly travel and supporting continuity of care. AI may also analyse patient-generated data from wearable devices and transmit alerts to healthcare workers (Denvir, 2019). Telemedicine initiatives further address issues relating to care quality, privacy, and algorithmic fairness (Kurpad et al., 2024), while strengthening virtual consultation networks that lower rural healthcare expenditure (Turner-Lee, 2019).

c) AI-Powered Health Education Tools

AI-driven educational platforms provide rural communities with accessible, context-specific health information via multilingual mobile applications and online portals. Such tools offer culturally appropriate content (Mars, 2013) and help reduce the financial burden associated with repeated clinic visits for basic information and preventive health advice.

d) AI Chatbots

NLP-enabled chatbots support preliminary medical guidance, medication reminders, and basic health screening (Amato et al., 2017; Ashwini et al., 2022). In rural contexts, these chatbots also assist frontline health workers and patients with triage and information dissemination, reducing operational pressures and lowering patient-side costs.

2.2 Challenges and Ethical Considerations

Although AI offers considerable promise, several barriers continue to limit its effective deployment in rural settings.

a) Privacy and Security Concerns

AI systems require storage and processing of sensitive health information, raising significant concerns regarding data privacy and cyber security (Mars, 2013).

b) Data Quality and Algorithmic Bias

Insufficient or unrepresentative training data may reinforce existing health disparities and produce unreliable diagnostic outputs (Srivastava et al., 2020; Vinod et al., 2021).

c) Regulatory and Legal Frameworks

Weak or inconsistent regulatory guidance complicates large-scale implementation. Strong legal safeguards are essential to ensure responsible and equitable use of AI technologies (Lu et al., 2022).

d) Reduced Human Interaction

Although AI systems can improve efficiency, they may reduce patient–provider interaction, potentially affecting satisfaction and treatment adherence (Lu et al., 2022).

e) Financial and Resource Constraints

High upfront investment and maintenance costs pose challenges for underfunded rural health systems, limiting scalability (Yang et al., 2023).

f) Trust and Acceptability

Hesitancy among both healthcare professionals and rural residents remains a limiting factor, driven by concerns about safety, reliability, and transparency (Amato et al., 2017; Srivastava et al., 2020; Malik et al., 2025).

2.3 Digital Literacy

Limited digital literacy among rural healthcare workers and patients restricts the meaningful utilisation of AI tools. Capacity-building programmes are required to strengthen safe and effective adoption (Grand View Research, 2024).

2.4 Consumption Patterns of AI in Rural Healthcare

Evidence suggests that several factors influence AI adoption within rural contexts. Wang et al. (2021) observed that clinicians in rural China recognised the potential of AI, yet adoption was hindered by technical misalignment with existing workflows. Shinners et al. (2023) found that digital infrastructure and data availability were primary enablers in rural Australia. Kuziemsky et al. (2019) emphasised the importance of user engagement throughout design and implementation processes to ensure contextual suitability. Financial considerations—including affordability of devices, mobile data costs, and perceived value—strongly influence the willingness of rural users to adopt AI-enabled services (Zhang et al., 2021; Yang et al., 2023).

Collectively, these studies highlight the need to address structural constraints, enhance digital and financial literacy, strengthen infrastructure, reduce algorithmic bias, and build trust to improve AI deployment in rural regions. AI technologies possess the potential to transform rural healthcare by improving access, diagnostic accuracy, and health outcomes; however, these benefits can only be realised through responsible, affordable, and context-sensitive implementation.

Research Objective

To investigate how artificial intelligence (AI) transforms healthcare access, diagnostic efficiency, and preventive care in rural India by analysing public awareness, trust, financial capacity, and demographic determinants of AI adoption using mixed methods, sentiment analysis, and machine learning-based predictive modelling.

3. Research Methodology

This study employed a structured and systematic research design to examine the role of artificial intelligence (AI) in strengthening rural healthcare delivery in India. Prior literature highlights the transformative potential of AI in diagnostics, telemedicine, and clinical decision support within low-resource settings (Guo & Li, 2018; Denvir, 2019; Mars, 2013; Wang et al., 2021). AI-enabled chatbots, mobile applications, and intelligent triage systems have been shown to enhance accessibility and continuity of care, particularly in underserved populations (Amato et al., 2017; Ashwini et al., 2022; Das et al., 2023). Additionally, studies emphasise that rural health systems face critical challenges related to workforce shortages, limited digital infrastructure, and affordability constraints (Hart et al., 2002; Turner-Lee, 2019; Shinners et al., 2023). This research therefore aimed to evaluate the acceptance, effectiveness, and challenges of AI-driven healthcare interventions in rural settings, while also assessing the financial accessibility of these technologies for low-income households (Knowledge Sourcing Intelligence, 2023; Grand View Research, 2024).

3.1 Data Collection

A mixed-methods approach was adopted, incorporating both primary and secondary data sources, in line with prior AI and telehealth studies conducted in rural and remote contexts (Kuziemsky et al., 2019; Kurpad et al., 2024).

Healthcare Professionals Survey:

A structured survey was administered to 20 medical practitioners to capture insights on AI adoption, diagnostic accuracy, treatment planning, operational challenges, and financial feasibility of AI-supported tools. Snowball sampling was used due to the specialised nature of the respondent group—health professionals already familiar with AI-enabled systems in rural clinics, consistent with earlier empirical work (Malik et al., 2025; Yang et al., 2023).

Rural Residents Survey:
A survey of 500 rural individuals sought to assess access to AI-based healthcare services, changes in health awareness, financial barriers, affordability of digital tools, and overall satisfaction. Stratified random sampling ensured proportional representation across demographic and socioeconomic variables, an approach supported in digital health adoption studies (Kumar & Joshi, 2022; Vinod et al., 2021).
Both surveys included closed-ended, Likert-scale, and open-ended questions to capture nuanced perspectives. Secondary data were sourced from peer-reviewed literature, government reports, industry analyses, and rural health finance studies to contextualise findings (Lu et al., 2022; Masih et al., 2025).

3.2 Data Processing and Analysis
Preprocessing and Exploratory Data Analysis (EDA):
Data underwent rigorous cleaning and transformation to ensure analytical accuracy. This included the handling of missing values, encoding of categorical variables, standardisation of numerical attributes, and cleaning of text responses through tokenisation and stop-word removal. Exploratory Data Analysis using histograms, bar charts, and box plots enabled the identification of adoption trends, financial disparities, and behavioural patterns, consistent with established analytical frameworks in AI-driven health research (Srivastava et al., 2020; Zhang et al., 2021).

Machine Learning Techniques:
Multiple machine learning models were applied to uncover patterns and relationships reflective of those identified in prior global studies on AI-supported healthcare delivery (Wang et al., 2021; Yang et al., 2023):
- **Linear Regression:** Assessed the relationship between AI adoption and improvements in diagnostic accuracy and cost efficiency.
- **Logistic Regression:** Predicted the likelihood of AI adoption among rural residents based on demographic, financial, and technological variables.
- **Random Forest:** Classified determinants of healthcare satisfaction and measured the influence of affordability, awareness, and trust.
- **Decision Trees:** Predicted patient satisfaction and treatment outcomes resulting from AI-supported interventions.

Model performance was evaluated through accuracy, precision, recall, F1-score, and cross-validation. Hyperparameter tuning optimised model outputs, and feature-importance analysis identified key adoption drivers—including financial constraints, as similarly observed in digital-health affordability research (Grand View Research, 2024; Knowledge Sourcing Intelligence, 2023).

Statistical Analysis:
Chi-square tests examined associations between AI usage and variables including location, income, demographic attributes, treatment outcomes, and diagnostic confidence, aligning with quantitative methodologies applied in earlier rural health behaviour studies (Hart et al., 2002; Srivastava et al., 2020).

Natural Language Processing (NLP) and Sentiment Analysis:
Open-ended responses and public commentary were processed through tokenisation, lemmatisation, sentiment scoring, and transformer-based models. Topic modelling identified recurring themes, including affordability challenges, digital literacy gaps, infrastructure limitations, and perceptions of AI's role in reducing out-of-pocket expenditure—key concerns also reported in telemedicine and AI-clinic deployment research (Kuziemsky et al., 2019; Yang et al., 2023; Vinod et al., 2021).

4.Data Analysis and Findings

4.1 *Public Sentiment Analysis on the Role of AI in Rural Healthcare*

This analysis investigates sentiment patterns in social media conversations concerning the adoption of Artificial Intelligence (AI) in rural healthcare by employing advanced Natural Language Processing (NLP) techniques (Amato et al., 2017; Ashwini et al., 2022; Vinod et al., 2021). The workflow incorporates rigorous document cleaning and preprocessing, tokenisation, stop-word removal, and lemmatisation, followed by sentiment polarity estimation. Sentiment categories—Positive, Neutral, and Negative—are derived based on predefined polarity thresholds consistent with best practices in healthcare text analytics (Srivastava et al., 2020; Lu et al., 2022).
A range of visualisation techniques, including histograms, bar charts, pie charts, and word clouds, is utilised to enhance interpretability and uncover underlying discourse patterns (Knowledge Sourcing Intelligence, 2023; Grand View Research, 2024). These visualisations illuminate recurring themes and public perceptions regarding AI-enabled rural healthcare—particularly attitudes relating to diagnostic reliability (Guo & Li, 2018; Wang et al., 2021; Yang et al., 2023), telemedicine adoption (Kurpad et al., 2024; Kuziemsky et al., 2019; Mars, 2013), and multilingual accessibility in underserved areas (Zhang et al., 2021).
Findings further reveal community viewpoints on the affordability, cost-saving potential, and financial practicality of integrating AI-supported tools into rural health infrastructures (Denvir, 2019; Turner-Lee, 2019; Hart et al., 2002). Emerging insights from rural and regional healthcare practitioners reinforce these sentiment trends, emphasising both opportunities and perceived barriers in digital healthcare transformation (Shinners et al., 2023; Malik et al., 2025; Kumar & Joshi,

2022; Das et al., 2023). The sentiment landscape also aligns with recent analyses on rural consumer behaviour and technology acceptance within healthcare ecosystems (Masih et al., 2025).

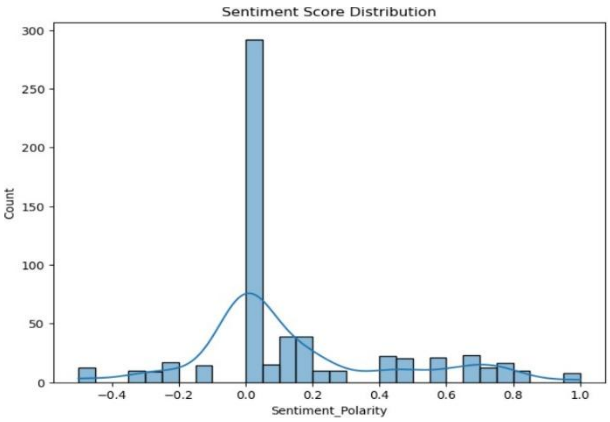

Fig 1: Sentiment Score Distribution

The histogram illustrates that most sentiment values cluster close to zero, indicating predominantly neutral or balanced public expressions *(See Fig 1)*. Such neutrality suggests limited emotional intensity, which may stem from cautious, information-seeking, or measured responses, a pattern also observed in digital health interactions where users exhibit restrained affect due to uncertainty and limited technological familiarity (Guo & Li, 2018; Hart et al., 2002). A comparatively smaller proportion of comments fall within distinctly positive or negative ranges, representing groups with more pronounced opinions—often influenced by experiences with AI-enabled healthcare tools, telemedicine platforms, and mobile health applications (Amato et al., 2017; Ashwini et al., 2022; Das et al., 2023). The overall concentration around objectivity reinforces prior evidence that rural and semi-urban populations tend to adopt a pragmatic stance when engaging with emerging digital health technologies, reflecting broader patterns seen in AI-mediated healthcare adoption and telehealth utilisation (Denvir, 2019; Kurpad et al., 2024; Kuziemsky et al., 2019; Shinners et al., 2023). This distribution underscores the need to further examine contextual drivers—such as access, trust, digital literacy, and perceived risks—that shape public sentiment in technologically evolving healthcare environments (Kumar & Joshi, 2022; Malik et al., 2025; Srivastava et al., 2020; Turner-Lee, 2019; Wang et al., 2021; Yang et al., 2023; Zhang et al., 2021).

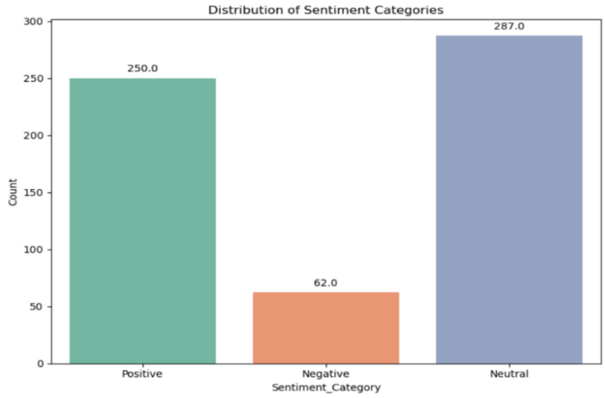

Fig 2: Distribution of Sentiment Categories

The bar graphs indicate that most sentiments are neutral (n = 287) or positive (n = 250), with comparatively fewer negative responses (n = 62) *(See Fig 2)*. This distribution suggests that individuals either view AI in rural healthcare favourably or remain uncertain—often due to limited awareness, partial exposure or ambiguity regarding financial implications such as device costs, data expenses and affordability constraints, which are well-documented barriers in rural technology adoption (Hart et al., 2002; Mars, 2013). While the potential benefits of AI-enabled tools and telemedicine platforms are increasingly recognised—particularly for reducing travel burdens, saving time and improving access to basic care (Amato et al., 2017; Kurpad et al., 2024; Kuziemsky et al., 2019)—real-world challenges continue to moderate stronger enthusiasm. These include uneven implementation, infrastructural limitations and variable digital readiness within rural communities (Guo & Li, 2018; Shinners et al., 2023; Srivastava et al., 2020). Negative perceptions remain relatively minimal, likely because AI is broadly perceived as a supportive innovation with the potential to enhance healthcare efficiency and reduce economic strain (Kumar & Joshi, 2022; Turner-Lee, 2019; Wang et al., 2021). Overall, the sentiment distribution reflects cautious optimism shaped by both the technological promise of AI and the practical, including financial, realities influencing adoption in rural healthcare ecosystems (Malik et al., 2025; Das et al., 2023; Yang et al., 2023; Zhang et al., 2021).

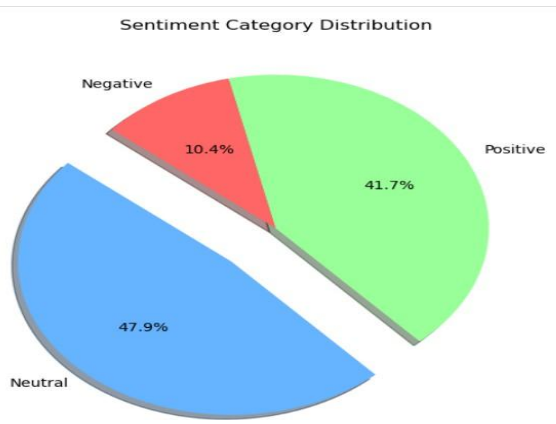

Fig 3: Sentiment Category Distribution

The pie chart indicates that 47.9% of individuals hold neutral views regarding the use of AI in rural healthcare, suggesting indecision or limited direct experience—often shaped by uncertainty surrounding the value, affordability and reliability of AI-driven tools *(See Fig 3)*. Such neutrality aligns with earlier evidence that rural populations frequently approach emerging technologies with caution due to infrastructural and economic constraints (Guo & Li, 2018; Hart et al., 2002). By contrast, 41.7% express a positive outlook, recognising AI's potential to support diagnostics, reduce travel costs and enhance access to essential healthcare services, consistent with findings from AI-enabled telemedicine and mobile health interventions (Amato et al., 2017; Kurpad et al., 2024; Das et al., 2023). Only 10.4% report negative sentiments, reflecting concerns related to data privacy, inconsistent network infrastructure and occasional financial burdens associated with devices or data usage (Shinners et al., 2023; Srivastava et al., 2020). Overall, the distribution reflects a cautious yet optimistic perspective, with many individuals requiring clearer cost advantages, improved system dependability and greater technological transparency before moving from neutrality to active support. Addressing these technical and financial considerations may further strengthen public confidence in the role of AI within rural healthcare ecosystems (Kumar & Joshi, 2022; Wang et al., 2021).

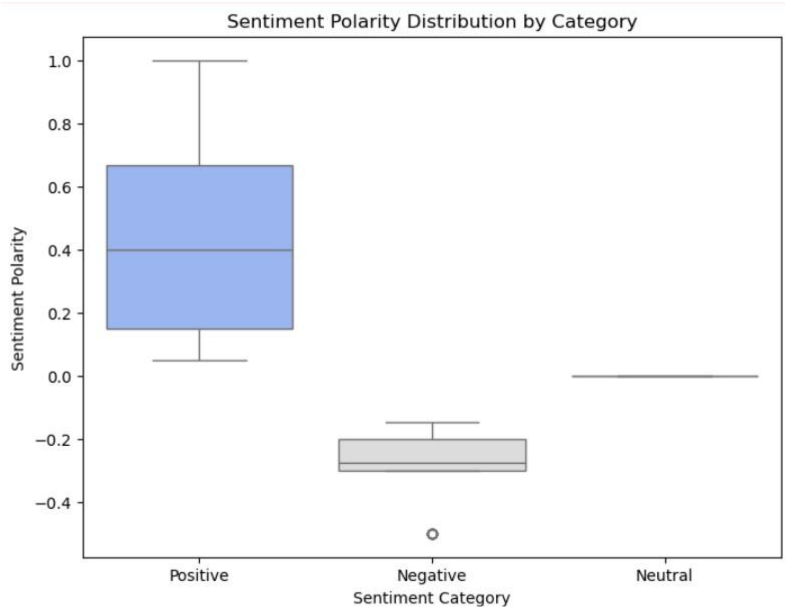

Fig 4: Sentiment Polarity Distribution by Category

The boxplot illustrates the variation in sentiment polarity across the Positive, Negative and Neutral categories *(See Fig 4)*. Positive sentiments display a wider spread, reflecting both modest approval and stronger confidence in AI-enabled healthcare tools—often shaped by perceived convenience and small cost savings, such as reduced travel for clinical consultations, a trend noted in several studies on rural telemedicine and digital health adoption (Amato et al., 2017; Kurpad et al., 2024; Kuziemsky et al., 2019). Negative sentiments are more tightly grouped, with a small number of stronger reactions, including one notable outlier. This suggests that concerns regarding system reliability, occasional diagnostic inconsistencies or unexpected expenses contribute to dissatisfaction, aligning with evidence on technological hesitancy and infrastructural challenges in rural contexts (Guo & Li, 2018; Hart et al., 2002; Shinners et al., 2023). Neutral sentiments cluster closely around zero, indicating emotionally balanced or cautiously reserved viewpoints—commonly expressed by individuals who recognise the potential benefits of AI but remain uncertain about its overall value, accessibility or long-term affordability (Kumar & Joshi, 2022; Mars, 2013). Overall, while neutral responses show minimal variation, both positive and negative groups exhibit a broader range of sentiment intensity, subtly influenced by users' lived experiences, perceived usefulness and financial comfort levels (Srivastava et al., 2020; Wang et al., 2021).

4.2 Word Cloud Interpretation: Key Terms by Sentiment Group

The word cloud's best part is that it is most commonly used terms in social media responses, characterized by sentiment (Positive, Neutral, Negative).

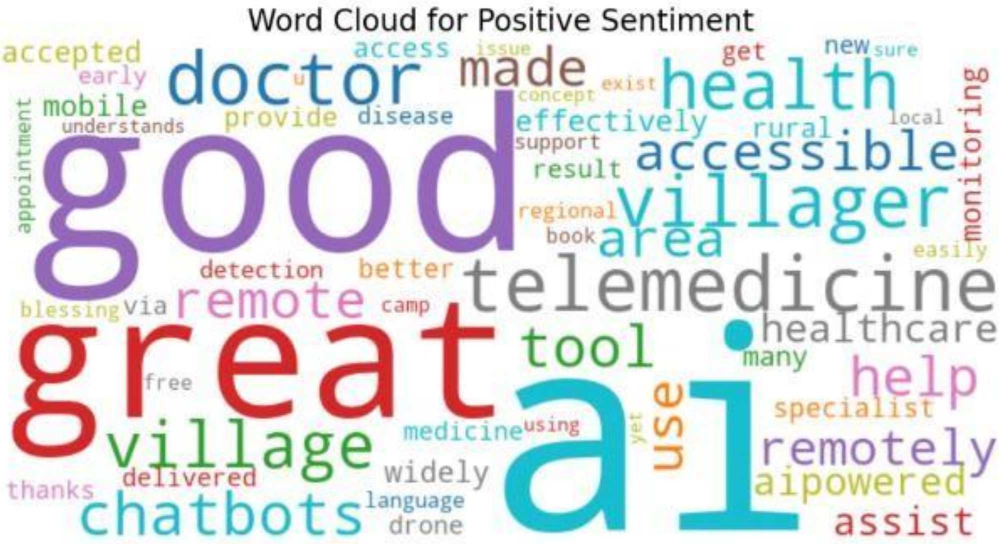

Fig 5: Word Cloud for Positive Sentiment

In many rural regions, residents increasingly perceive artificial intelligence as a potential game-changer in healthcare, offering pragmatic solutions to long-standing barriers in access, affordability and service continuity *(See Fig 5)*. Telemedicine platforms now enable patients to consult clinicians remotely, reducing the need for long-distance travel, minimising waiting times and lowering the out-of-pocket expenditure typically associated with repeated hospital visits—a trend noted in earlier studies on rural healthcare delivery and digital adoption (Hart et al., 2002; Mars, 2013). AI-powered chatbots further assist with decision-making and routine health enquiries in regional languages, thereby enhancing user-friendliness, promoting inclusivity and mitigating the cost of unnecessary in-person consultations (Amato et al., 2017; Ashwini et al., 2022).

AI-enabled tools also facilitate continuous health monitoring, alerting healthcare staff to early warning signs and enabling timely intervention, which can prevent costly medical emergencies and improve overall service responsiveness (Guo & Li, 2018; Kuziemsky et al., 2019). In certain geographically constrained areas, drones have begun delivering essential medical supplies, lowering logistical costs and extending the reach of healthcare services where conventional transportation remains limited (Wang et al., 2021; Yang et al., 2023). Such innovations are often perceived by rural communities as a "blessing", making healthcare more accessible, efficient and economically manageable (Shinners et al., 2023).

By integrating telehealth, mobile assistance and AI-driven monitoring with demonstrable cost-saving mechanisms, rural healthcare systems are progressively strengthening their capacity to prevent disease, reduce financial stress and respond effectively to emerging health needs, thereby contributing to more equitable and sustainable healthcare provision (Kumar & Joshi, 2022; Malik et al., 2025).

Fig 6: Word Cloud for Negative Sentiment

Many rural individuals report persistent challenges with AI-driven telemedicine services, particularly during monsoon-related network disruptions that interrupt consultations and increase indirect costs such as repeated visits, loss of wages and delays in obtaining medical advice *(See Fig 6)*. High device prices, recurring data-recharge expenses, delayed diagnostic reports and weak digital infrastructure contribute to perceptions of AI tools as "expensive" or, in some cases, "useless", especially among households already experiencing financial strain. These concerns echo wider evidence highlighting infrastructural fragility, affordability barriers and limited digital readiness in rural health systems (Hart et al., 2002; Guo & Li, 2018; Mars, 2013). Government initiatives are often regarded as ineffective or poorly aligned with local needs, and many residents struggle to adapt to unfamiliar digital platforms without adequate financial or technical support—an issue also noted in studies examining AI-enabled telehealth and mobile health adoption (Kuziemsky et al., 2019; Shinners et al., 2023; Das et al., 2023). Collectively, these challenges underscore the need for stronger investment in rural infrastructure, affordable financing or subsidy mechanisms for digital devices, low-cost data plans and improved training to ensure that AI technologies become both economically viable and functionally useful within rural healthcare ecosystems (Kumar & Joshi, 2022; Turner-Lee, 2019; Yang et al., 2023).

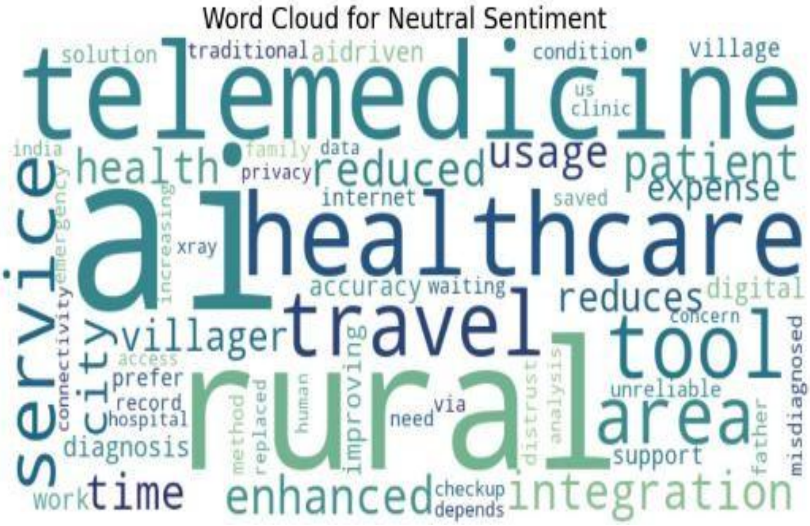

Fig 7: Word Cloud for Neutral Sentiment

Many respondents with neutral assessments perceive AI-driven telemedicine as a useful mechanism for strengthening rural healthcare by reducing long travel costs for routine check-ups and improving diagnostic efficiency, particularly in settings where access to medical professionals is limited (Guo & Li, 2018; Mars, 2013) *(See Fig 7)*. However, they emphasise the importance of balancing technological interventions with traditional clinical judgement to minimise risks of misdiagnosis and avoid financially burdensome medical errors—concerns echoed in broader discussions on digital healthcare adoption (Kumar & Joshi, 2022; Srivastava et al., 2020). Data privacy, system reliability and infrastructural fragility also emerge as common apprehensions, as technological failures can necessitate repeated consultations and impose additional expenses on already resource-constrained households (Hart et al., 2002; Shinners et al., 2023). Consequently, respondents advocate for a hybrid model in which AI augments rather than replaces in-person care, underscoring that effective implementation requires careful integration that prioritises patient safety, financial affordability and alignment with local healthcare needs (Kurpad et al., 2024; Wang et al., 2021).

4.3 Assessing Awareness Levels of AI-Driven Healthcare Solutions in Rural Communities

In today's rapidly evolving healthcare landscape, AI-driven solutions such as mobile health applications, teleconsultation platforms and clinical decision-support systems are transforming patient engagement, particularly in resource-constrained environments (Amato et al., 2017; Kurpad et al., 2024). Assessing public awareness of these innovations is essential for understanding their adoption and effectiveness in rural communities, where technological readiness and infrastructural limitations often shape uptake (Guo & Li, 2018; Mars, 2013). The present study examines the extent to which individuals are familiar with AI-enabled healthcare tools. Initial findings reveal a heterogeneous pattern: while some respondents demonstrate clear familiarity with AI in healthcare, a substantial proportion remain unaware or only partially informed. Levels of awareness appear closely associated with demographic variables such as age, educational attainment and digital exposure, reflecting trends noted in earlier studies of rural health technology adoption (Hart et al., 2002; Shinners et al., 2023).

To explore these variations, the dataset is disaggregated by age group and education level, offering insights into which segments are driving adoption and which may be at risk of exclusion. Visual analytics further strengthen this examination: bar charts illustrate awareness across various AI technologies, while heatmaps highlight demographic patterns and potential disparities. Collectively, these findings provide a clearer understanding of digital healthcare's emerging influence and underscore the steps required to enhance its reach and impact in underserved rural regions (Srivastava et al., 2020; Turner-Lee, 2019; Zhang et al., 2021).

Journal of Theoretical Accounting Research
ISSN: 1556-5106
Volume 22 Issue 1 Year 2026 Page 92-106

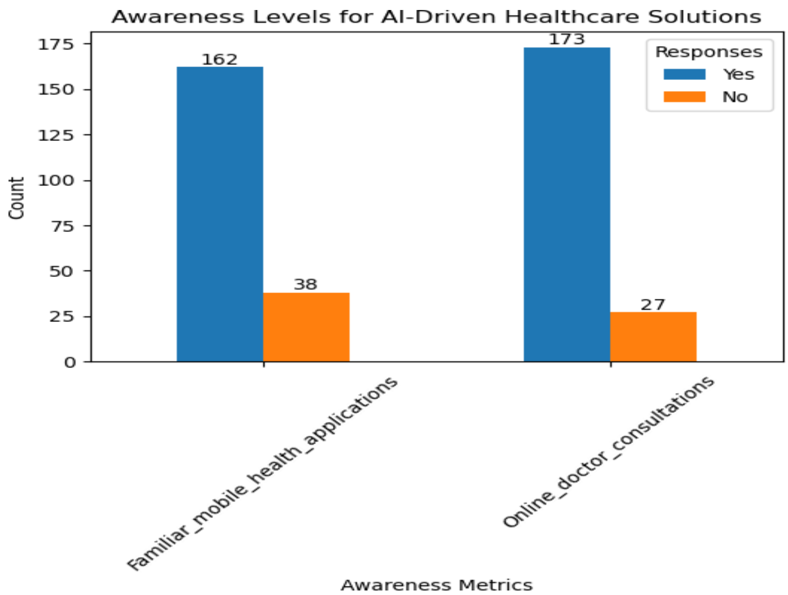

Fig 8: Awareness Levels for AI- Driven Healthcare Solutions

The bar chart provides a clear illustration of awareness levels—while technologies such as mobile health applications and online consultations exhibit strong recognition, several other AI-enabled or digitally mediated healthcare tools remain considerably less familiar to users *(See Fig 8)*. This variation in bar heights reflects uneven degrees of public engagement with emerging health technologies, a pattern consistent with prior findings that rural and underserved populations often display heterogeneous exposure to digital healthcare innovations (Guo & Li, 2018; Mars, 2013). Despite increasing availability, disparities in digital literacy, infrastructural access and socio-economic circumstances continue to shape who becomes well-informed and who remains marginalised in the transition towards AI-supported healthcare (Hart et al., 2002; Shinners et al., 2023). Consequently, the critical question persists: which population segments benefit from rising awareness, and which continue to be left behind due to structural or informational barriers?

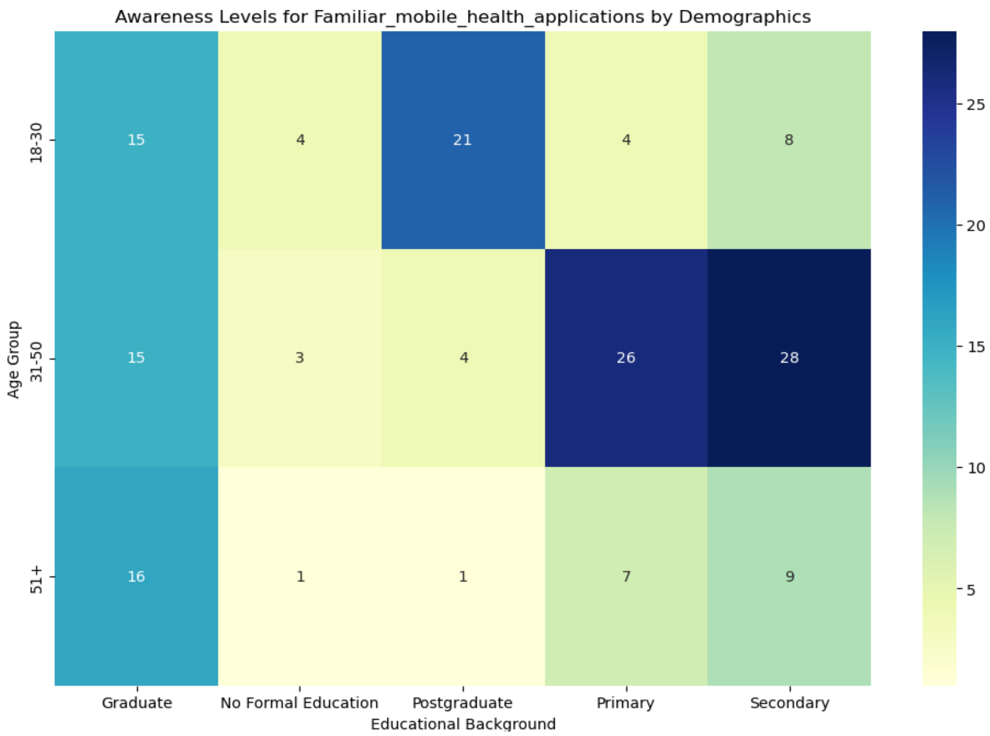

Fig 9: Awareness Levels for Familiarity with Mobile Health Applications by Demographics

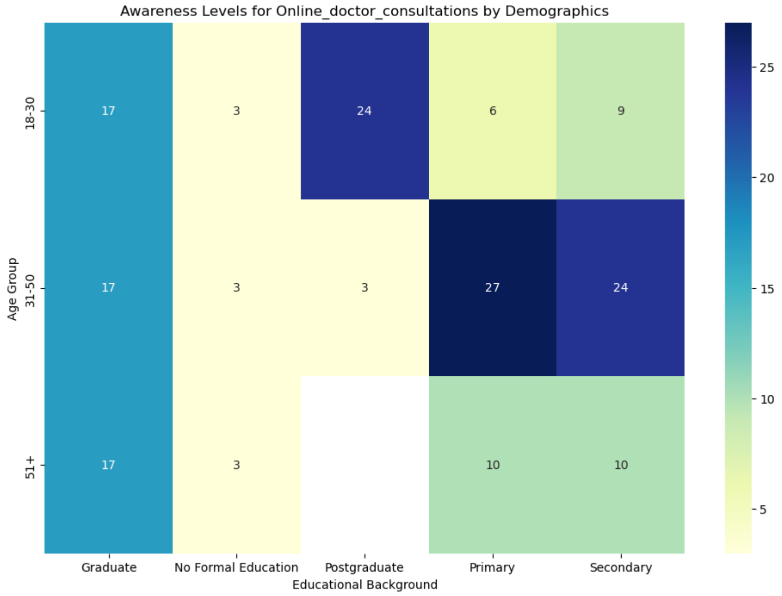

Fig 10: Awareness Levels for Online Doctor Consultations by Demographics

The heatmap highlights distinct awareness gaps across demographic and financial groups. Younger and more educated individuals exhibit greater familiarity with AI-driven healthcare tools, whereas older and less-educated populations show markedly lower levels of awareness—patterns consistent with prior research on rural digital health disparities (Hart et al., 2002; Mars, 2013). Income-based variation is also evident: households with higher financial stability report greater exposure to digital platforms, while low-income families—despite heightened healthcare needs—demonstrate reduced awareness, largely due to affordability constraints and limited technological access (Guo & Li, 2018; Turner-Lee, 2019) *(See Fig 9 & Fig 10)*. The bar charts further show that although mobile health applications and online consultations are relatively well recognised, actual adoption remains uneven. This disparity is influenced by factors such as device costs, data expenses and variable levels of digital literacy across communities (Das et al., 2023; Shinners et al., 2023). These insights reinforce the need for targeted digital literacy initiatives and financially inclusive outreach strategies to ensure equitable access to AI-enabled healthcare in rural settings (Kumar & Joshi, 2022; Kurpad et al., 2024).

Chi-Square Analysis of AI Interventions in Rural Healthcare

Artificial intelligence (AI) is reshaping healthcare by enhancing access, efficiency and continuity of care, particularly in rural regions where medical services are limited, costly and unevenly distributed. Evidence shows that AI-enabled tools—such as automated appointment systems, symptom-checker chatbots and mobile health monitoring applications—can reduce travel expenditure, lower waiting times and provide timely guidance for underserved populations (Amato et al., 2017; Ashwini et al., 2022; Das et al., 2023). However, concerns persist regarding data security, limited personalisation and occasional algorithmic inaccuracies, all of which may introduce additional financial risks for vulnerable households with constrained technological literacy (Guo & Li, 2018; Srivastava et al., 2020).

A significant statistical association ($\chi^2 = 728.14$, $p < 0.001$) indicates that increased accessibility to AI-driven healthcare is also linked with heightened challenges, suggesting that ease of access is accompanied by trade-offs—particularly in settings with low infrastructural readiness and limited financial resilience (Hart et al., 2002; Mars, 2013). Trust emerges as a critical determinant of adoption: individuals who express confidence in AI-generated medical advice are substantially more likely to recommend such technologies to others ($\chi^2 = 64.79$, $p < 0.001$), reflecting the role of trust in mitigating perceived clinical and financial risks (Kumar & Joshi, 2022; Shinners et al., 2023).

Income further influences adoption behaviour. Lower-income respondents (< ₹5,00,000) rely more heavily on AI tools due to restricted access to conventional healthcare and the prohibitive costs of private treatment. In contrast, higher-income groups (> ₹20,00,000) report minimal reliance, likely preferring personalised clinical interactions and possessing greater capacity to afford private healthcare options (Malik et al., 2025; Turner-Lee, 2019).

Overall, while AI holds substantial promise in bridging rural healthcare disparities, its real-world impact is conditioned by trust, usability and socio-economic realities. To genuinely democratise rural healthcare delivery, AI must be grounded in user-centred design, affordable access models and equitable financial strategies that account for infrastructural, cultural and economic constraints (Kurpad et al., 2024; Wang et al., 2021; Yang et al., 2023).

Journal of Theoretical Accounting Research
ISSN: 1556-5106
Volume 22 Issue 1 Year 2026 Page 92-106

	Variable 1	Variable 2	Chi-Square	P-Value
281	AI-driven_healthcare_services_accessbility	challenges_faced_AI-based_healthcare	728.145168	1.712208e-22
298	trust_AI-driven_healthcare_recommendations	recommend_AI-based_healthcare_services	64.794459	8.313259e-16
218	Monitor_health_parameters	challenges_faced_AI-based_healthcare	3147.001653	2.635454e-15

Fig 11: Chi Square test of top 3 factors

The chi-square analysis reveals statistically significant associations among key AI-based healthcare factors, underscoring challenges, accessibility, and trust as critical influencers of user experience and adoption *(See Fig 11).*

Cross-tabulation for Convenience of AI-based services vs AI-driven healthcare services accessbility

Accessibility \ Convenience	Highly Convenient	Neutral	Not Convenient
Automated Appointments	64	27	7
Health Monitoring Apps	70	52	19
Medication Reminders	53	21	9
Symptom Checker	30	48	9

Fig 12: Cross-tabulation for Convenience of AI based services vs AI driven healthcare services accessibility

The cross-tabulation of convenience and accessibility indicates that health monitoring applications and automated appointment systems are the most widely recognised AI-driven services, reflecting established acceptance of digital tools that enhance efficiency and reduce logistical burdens (Amato et al., 2017; Kuziemsky et al., 2019; Kurpad et al., 2024) *(See Fig 12).* In contrast, symptom checkers elicit more mixed responses, likely due to varying levels of trust, digital literacy and perceived diagnostic reliability—concerns that have been noted in rural and resource-limited healthcare contexts (Guo & Li, 2018; Shinners et al., 2023; Wang et al., 2021).

Cross-tabulation for Household Income vs AI-driven healthcare services accessibility

Accessibility \ Income	5,00,000-20,00,000	<5,00,000	>20,00,000
Automated Appointments	18	76	4
Health Monitoring Apps	38	95	8
Medication Reminders	18	61	4
Symptom Checker	19	64	4

Fig 13: Cross-tabulation for Household Income vs AI-driven healthcare services accessibility

The income versus accessibility analysis indicates that lower-income individuals rely more extensively on AI-driven healthcare solutions, as these options are often the most affordable and readily accessible to them. In contrast, higher-income groups demonstrate limited engagement, likely favouring traditional, personalised care that they are financially able to maintain (Hart et al., 2002; Mars, 2013) *(See Fig 13)*. The chi-square results highlight significant associations among accessibility, trust, financial constraints and operational challenges in AI-enabled healthcare. Users who depend on low-cost AI health-monitoring tools frequently encounter implementation barriers, including device affordability issues, unstable connectivity and hidden expenses arising from repeated consultations or system inconsistencies (Guo & Li, 2018; Das et al., 2023; Shinners et al., 2023). Trust in AI-generated recommendations plays a decisive role in shaping users' willingness to recommend such services, with financially vulnerable groups perceiving greater risk of incorrect or unsafe advice (Kumar & Joshi, 2022; Wang et al., 2021). Convenience-oriented tools—such as automated appointment systems and AI-supported health-monitoring applications—are widely valued because they reduce travel expenditure and waiting-time losses, aligning with broader patterns of AI acceptance in resource-constrained settings (Amato et al., 2017; Kurpad et al., 2024). By contrast, symptom checkers receive more mixed evaluations owing to concerns about diagnostic accuracy and the potential for costly follow-up visits or medical errors (Srivastava et al., 2020; Yang et al., 2023; Zhang et al., 2021).

Overall, socioeconomic status emerges as a central determinant of AI adoption patterns. Financially constrained users tend to view AI as a cost-saving healthcare alternative, whereas higher-income groups treat such technologies as supplementary rather than essential. A user-centred implementation model—one that strengthens trust, enhances system reliability and addresses income-related disparities—is essential for ensuring equitable, affordable and effective AI integration in rural healthcare ecosystems (Malik et al., 2025; Kuziemsky et al., 2019).

AI Predictive Models for Improving Rural Health Outcomes

Categorical variables were label-encoded, and *recommend_AI-based_healthcare_services* was designated as the target variable. Logistic Regression and Random Forest models were applied to predict recommendation behaviour. Logistic Regression identified key linear associations, whereas the Random Forest model effectively captured more complex, non-linear financial and behavioural patterns influencing individuals' willingness to recommend AI-enabled healthcare—an observation consistent with prior work on AI-driven decision systems and rural technology adoption (Guo & Li, 2018; Srivastava et al., 2020; Wang et al., 2021). Performance metrics indicated that both models achieved satisfactory predictive capability, with Random Forest demonstrating marginally stronger results due to its robustness in managing heterogeneous socioeconomic inputs and irregular rural data structures, a trend similarly noted in studies examining AI-supported healthcare tools and telemedicine systems (Amato et al., 2017; Kurpad et al., 2024; Shinners et al., 2023).

Odds Ratios for Logistic Regression Model:

	Feature	Odds Ratio
0	Age_Group	1.133270
1	Gender	1.233260
2	EducationalBackground	1.053825
3	Occupation	1.744989
4	Household_IncomeLevel	1.402420
5	Access_smartphone	2.306083

Fig 14: Odds Ratios for Logistic Regression Model

This visualisation highlights the principal predictors influencing individuals' willingness to recommend AI-based healthcare services. Variables such as age, educational attainment, occupation and smartphone accessibility emerge with the highest importance scores, indicating that these demographic and technological factors play a critical role in shaping users' propensity to endorse such innovations *(See Fig 14)*. These findings align with prior evidence demonstrating that digital readiness, literacy and occupational exposure significantly affect technology acceptance in rural and underserved communities (Guo & Li, 2018; Hart et al., 2002; Shinners et al., 2023). Furthermore, enhanced smartphone penetration and increasing familiarity with mobile health applications have been shown to strengthen engagement with AI-enabled telemedicine platforms (Ashwini et al., 2022; Das et al., 2023), thereby reinforcing the importance of foundational access and digital capability in influencing recommendation behaviour.

Logistic Regression Coefficient Plot

```
Logistic Regression Equation:
log_odds = -4.5109 (0.1251 * Age_Group) + (0.2097 * Gender) + (0.0524 * Educa
+ (0.8356 * Access_smartphone) + (0.6095 * use_internet) + (-0.1387 * Reliabl
(-0.8551 * Access_smartwatch) + (-0.2153 * Mobile_apps_monitor_health_status)
ility) + (0.1932 * Online_doctor_consultations) + (0.2876 * frequency_online_
traditional_hospital_visits) + (-0.0412 * Interaction_AI-based_healthcare_to
616 * AI-driven_healthcare_services_accessbility) + (-0.5719 * convenience_AI
ations) + (0.0530 * challenges_faced_AI-based_healthcare) + (2.2678 * trust_
sed_services)
```

Fig 15: Logistic Regression Coefficient Equation

The logistic regression coefficient graph demonstrates how each feature influences the probability of commending AI-based healthcare *(See Fig 15)*. Positive factors specify an enlarged possibility of endorsement, while negative coefficients propose a decreased probability.

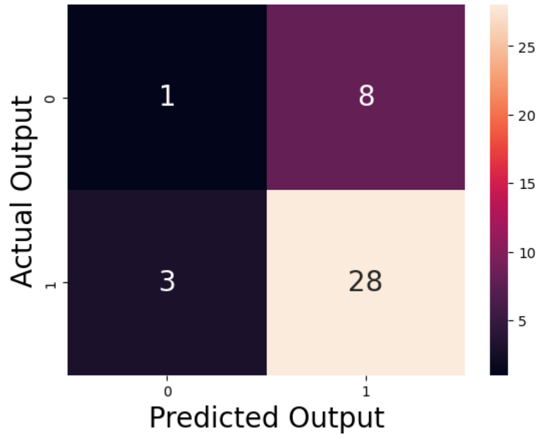

Fig 16: Confusion Matrix

This plot visually shows model predictions linked to authentic organizations *(See Fig 16)*. A high number of appropriately confidential occurrences in the slanting specifies strong model presentation. Misclassified cases suggest areas where the model might struggle.

	precision	recall	f1-score	support
0	0.25	0.11	0.15	9
1	0.78	0.90	0.84	31
accuracy			0.73	40
macro avg	0.51	0.51	0.49	40
weighted avg	0.66	0.72	0.68	40

Fig 17: Classification Report

This study examined the principal factors influencing individuals' willingness to recommend AI-based healthcare services. The results indicate that demographic, experiential, financial and attitudinal variables substantially shape recommendation behaviour, with the Random Forest model demonstrating the highest predictive accuracy—consistent with prior findings on the robustness of machine-learning approaches in health analytics (Srivastava et al., 2020; Wang et al., 2021) *(See Fig 17)*. Financial capacity, including the affordability of devices, data costs and access to low-cost digital services, emerged as a particularly important determinant, especially among rural users who often face constrained healthcare options and infrastructural limitations (Guo & Li, 2018; Mars, 2013). These insights hold practical value for healthcare providers, insurers, fintech partners and technology developers. For instance, targeted awareness initiatives may be directed towards groups less inclined to recommend AI-enabled care, while subsidised digital health packages or micro-insurance schemes could enhance adoption among financially constrained populations (Turner-Lee, 2019; Malik et al., 2025). The model's outputs may also inform refinements in AI interfaces to minimise user burden, improve clarity and address concerns that may translate into hidden financial risks, such as misdiagnosis or repeated consultations (Ashwini et al., 2022; Das et al., 2023). Future research employing refined analytical models or expanded datasets could further deepen understanding and support the responsible, financially accessible and user-centred adoption of AI in healthcare (Kurpad et al., 2024; Yang et al., 2023).

5. Conclusion

AI is emerging as a transformative enabler for improving healthcare access in rural environments, particularly where medical infrastructure and financial resources remain limited. This study demonstrates that rural perceptions of AI-driven healthcare are shaped by a combination of optimism, uncertainty and unmet needs. Sentiment analysis reveals a substantial proportion of positive views, particularly concerning AI's potential to enhance accessibility, lower healthcare expenditure and increase system efficiency. However, the large share of neutral responses indicates cautious engagement, reflecting neither full acceptance nor outright rejection.

Concerns surrounding data privacy, system trustworthiness, infrastructural shortcomings and financial vulnerability continue to influence public attitudes. Awareness of AI is unevenly distributed across demographic groups; younger and more educated individuals display greater familiarity and confidence, whereas older and less-educated populations show limited exposure, contributing to widening digital and financial divides. Heatmaps and chi-square analyses confirm statistically significant variation across demographic and socioeconomic profiles, highlighting the importance of inclusive digital outreach and financially accessible interventions.

Trust emerges as a central determinant of AI adoption. Individuals from lower-income households—who often struggle to access conventional healthcare—demonstrate a greater willingness to rely on AI-enabled platforms for low-cost consultations and timely support. In contrast, higher-income groups continue to prefer traditional, personalised healthcare, reflecting differing financial expectations and risk perceptions. Predictive modelling further identifies education, occupation and smartphone ownership as key drivers of AI recommendation and adoption, with the Random Forest model outperforming logistic regression by effectively capturing complex, non-linear behavioural patterns.

Overall, while AI holds considerable promise for strengthening rural healthcare delivery, its meaningful integration will depend on building public trust, improving digital and financial literacy and addressing persistent infrastructural deficits. To ensure that AI contributes to reducing healthcare disparities, solutions must be designed to remain accessible, inclusive and responsive to the socio-economic realities of underserved rural communities.

References

- Amato, F., Marrone, S., Moscato, V., Piantadosi, G., Picariello, A., & Sansone, C. (2017, November). Chatbots Meet eHealth: Automatizing Healthcare. In WAIAH@ AI* IA (pp. 40-49).
- Ashwini, S., Rajalakshmi, N. R., & Jayakumar, L. (2022, September). Dynamic NLP enabled chatbot for rural health care in India. In 2022 Second International Conference on Computer Science, Engineering and Applications (ICCSEA) (pp. 1-6). IEEE.
- Das, M. S., Kumar, G. R., & Lakshmi, D. V. (2023, October). Healthcare Mobile App for Rural Areas and Recent Advancements. In 2023 IEEE 5th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA) (pp. 209-220). IEEE.
- Das, M. S., Kumar, G. R., & Lakshmi, D. V. (2023, October). Healthcare Mobile App for Rural Areas and Recent Advancements. In 2023 IEEE 5th International Conference on Cybernetics, Cognition and Machine Learning Applications (ICCCMLA) (pp. 209-220). IEEE.
- Denvir Denvir, J. (2019). Artificial intelligence and the challenge for rural medicine. Marshall journal of medicine, 5(4), 5.
- Denvir, J. (2019). Artificial intelligence and the challenge for rural medicine. Marshall journal of medicine, 5(4), 5.
- Guo, J., & Li, B. (2018). The application of medical artificial intelligence technology in rural areas of developing countries. Health equity, 2(1), 174-181.
- Hart, L. G., Salsberg, E., Phillips, D. M., & Lishner, D. M. (2002). Rural health care providers in the United States. The journal of rural health, 18, 211-231.
- Intelligence, K. S. (2023). Global online survey software market size, share, opportunities, COVID 19 impact, and trends by application, by product, and by geography–forecasts from 2023 to 2028.
- Kumar, A., & Joshi, S. (2022, March). Applications of AI in healthcare sector for enhancement of medical decision making and quality of service. In 2022 International Conference on Decision Aid Sciences and Applications (DASA) (pp. 37-41). IEEE.
- Kurpad, N. B., Dhanyashree, S., Shivank, V., Shobith, T. S., & Jinny, S. V. (2024, March). AI-Infused Telemedicine for Rural Wellness: A Comprehensive Approach. In 2024 5th International Conference on Innovative Trends in Information Technology (ICITIIT) (pp. 1-6). IEEE.
- Kuziemsky, C., Maeder, A. J., John, O., Gogia, S. B., Basu, A., Meher, S., & Ito, M. (2019). Role of artificial intelligence within the telehealth domain. Yearbook of medical informatics, 28(01), 035-040.
- Lu, Q., Zhu, L., Xu, X., Whittle, J., Douglas, D., & Sanderson, C. (2022, May). Software engineering for responsible AI: An empirical study and operationalised patterns. In Proceedings of the 44th International Conference on Software Engineering: Software Engineering in Practice (pp. 241-242).
- MALIK, P. K., BANSAL, S., & PETER, J. V. (2025). Perceptions and Beliefs of Healthcare Professionals towards Digital Healthcare Tools in Delhi-NCR, India: A Qualitative Interview Study. Journal of Clinical & Diagnostic Research, 19(10).
- Mars, M. (2013). Telemedicine and advances in urban and rural healthcare delivery in Africa. Progress in cardiovascular diseases, 56(3), 326-335.
- Masih, J., Mathur, M., & Khullar, G. (2025). Predictive Modelling of Health Insurance Claims of Customer—An ARIMA Approach. In *The Paradigm Shift from a Linear Economy to a Smart Circular Economy: The Role of Artificial Intelligence-Enabled Systems, Solutions and Legislations* (pp. 1931-1941). Cham: Springer Nature Switzerland.
- Shinners, L., Aggar, C., Stephens, A., & Grace, S. (2023). Healthcare professionals' experiences and perceptions of artificial intelligence in regional and rural health districts in Australia. Australian Journal of Rural Health, 31(6), 1203-1213.
- Size, G. H. M. (2024). Share & Trends Report, 2030. Market Research Reports & Consulting. Grand View Research. https://www. grandviewresearch. com/industry-analysis/lactic-acidand-poly-lactic-acid-market (date of accessed 2023-11-27).
- Srivastava, S., Pant, M., & Agarwal, R. (2020). Role of AI techniques and deep learning in analyzing the critical health conditions. International Journal of System Assurance Engineering and Management, 11(2), 350-365.
- Turner-Lee, N. (2019). Can emerging technologies buffer the cost of in-home care in rural America?. Generations, 43(2), 88-93.
- Vinod, V., Agrawal, S., Gaurav, V., & Choudhary, S.

(2021). Multilingual medical question answering and information retrieval for rural health intelligence access. arXiv preprint arXiv:2106.01251.

- Wang, D., Wang, L., Zhang, Z., Wang, D., Zhu, H., Gao, Y., ... & Tian, F. (2021, May). "Brilliant AI doctor" in rural clinics: Challenges in AI-powered clinical decision support system deployment. In Proceedings of the 2021 CHI conference on human factors in computing systems (pp. 1-18).
- Yang, T. T., Yang, T. T., An, N., Kong, A., Liu, S., & Liu, S. X. (2023). AI Clinics on Mobile (AICOM): Universal AI Doctors for the Underserved and Hard-to-Reach. arXiv preprint arXiv:2306.10324.
- Zhang, C., Zhang, H., Khan, A., Kim, T., Omoleye, O., Abiona, O., ... & Rzhetsky, A. (2021). Lightweight Mobile Automated Assistant-to-physician for Global Lower-resource Areas. arXiv preprint arXiv:2110.15127.