Journal of Contemporary Academic Research and Methodologies

An Online Peer Reviewed / Refereed Journal
Volume 1 | Issue 1 | February 2026
Website: www.jcarm.in

Research

# The Role of Artificial Intelligence in Media Coverage of Access to Healthcare Facilities among Rural Communities in Yobe State, Nigeria

**Usman Disa[1], Hussaini Ibn Mohammed, PhD[2], Abubakar Aliyu Abba[3]**

[1]Department of Mass Communication, Federal Polytechnic Damaturu, Yobe State, Nigeria
[2]Department of Sociology, Faculty of Management and Social Sciences, Federal University Gashua, Yobe State, Nigeria.
[3]Department of Mass Communication, Federal Polytechnic Mubi, Adamawa State, Nigeria.

Correspondence should be addressed to: disausman@gmail.com

**Abstract**: Access to healthcare in rural communities remains one of the most persistent public health problems in northern Nigeria. Yobe State, characterised by dispersed rural settlements, high poverty rates, and limited health infrastructure, exemplifies the challenges that many underserved populations face. Artificial intelligence (AI) has gradually entered media and health communication spaces, raising questions about whether it can meaningfully change how people in such settings learn about and access healthcare facilities. This study examined the role of AI in media coverage of healthcare access among rural communities in Yobe State, Nigeria. A descriptive survey design was adopted, targeting residents in five selected local government areas. A sample of 218 respondents was selected through multi-stage sampling. Structured questionnaires were used for data collection, and findings were analysed using descriptive statistics and chi-square tests. Results showed that while 63.3% of respondents believed AI could improve healthcare access, actual use of AI-powered health tools remained low (13.3% for chatbots). Community health workers and the radio were the dominant channels of health information. Poor internet connectivity (69.7%), low digital literacy (64.7%), and erratic electricity supply (54.6%) were rated as major barriers to AI adoption. The study concludes that AI holds potential for transforming health communication in rural Yobe, but structural and infrastructural deficits constrain that potential. Targeted digital literacy programmes and policy investment in rural connectivity are recommended.

**Keywords**: Artificial Intelligence, Digital Literacy, Healthcare Access, Health Communication, Media Coverage, Rural Communities, Yobe State.


DOI:10.5281/zenodo.18902546

## INTRODUCTION

Rural healthcare access in sub-Saharan Africa has long attracted the attention of scholars, policymakers, and development practitioners. The problem, though widely acknowledged, has proven resistant to simple solutions. In Nigeria, where over 51% of the population lives in rural areas, the gap between urban health infrastructure and rural health services remains wide (World Health Organization [WHO], 2022). Yobe State sits in the northeast geopolitical zone of Nigeria. The state shares borders with the Niger Republic to the north, Borno State to the east, Gombe State to the south, and Bauchi and Jigawa States to the west and southwest, respectively. With a population estimated at approximately 3.5 million (National Population Commission [NPC], 2023), much of it spread across remote rural settlements, healthcare delivery is complicated by distance, poor road networks, and an acute shortage of health workers.

Into this context, artificial intelligence has begun to make its presence felt. AI, broadly defined as the simulation of human cognitive functions by machines, has produced a set of tools with direct relevance to health communication: chatbots, symptom checkers, predictive health platforms, and algorithm-driven content recommendation systems (Topol, 2019). Several of these tools are now accessible via mobile phones, which have achieved notable penetration even in areas where other infrastructure remains weak. The data tentatively indicate that mobile phone ownership in rural northern Nigeria has grown steadily since 2018, even while fixed broadband remains virtually absent (Nigerian Communications Commission [NCC], 2023).

Yet the question of whether AI can meaningfully improve how rural residents learn about and locate healthcare facilities is not settled. Scholars maintain that the mere existence of technology is never sufficient; what matters is whether the technology reaches its intended users in forms they can understand and trust (Abimbola et al., 2021). In Yobe State, where educational attainment is low, internet connectivity is unreliable, and electricity supply is erratic, the pathway from AI potential to AI use is far from straightforward.

Media, in its various forms, has historically been the bridge between health information producers and health information consumers. Radio, in particular, has served as a vital channel for public health messaging in rural Nigeria. The question this study asks is whether AI is reshaping that bridge, and if so, how. This appears to be an under-examined question in the existing literature, especially with reference to Yobe State specifically.

Studies from other parts of Nigeria and Africa have addressed AI and health broadly, but few have examined the media dimension with reference to a state facing the combination of insecurity, geographic remoteness, and infrastructural deficit that characterizes Yobe.

The objectives of this study were to assess the level of awareness of AI-powered health media tools among rural residents of Yobe State; to determine the extent to which AI is integrated into media coverage of healthcare access in the study area; to identify the barriers to AI adoption in health communication in rural Yobe; and to examine the relationship between digital access and use of AI health media tools.

The study is significant on several counts. First, it contributes empirical data from a geographically and politically marginalized region that rarely appears in technology-health literature. Second, it offers practical evidence that can guide state health communication policy. Third, it speaks to broader debates about technology and equity in global health.

## LITERATURE REVIEW

### Conceptualizing Artificial Intelligence in Health Communication:

AI refers to computational systems designed to perform tasks that normally require human intelligence, such as language understanding, pattern recognition, and decision-making (Russell & Norvig, 2020). In health communication, AI applications range from diagnostic support tools to patient-facing chatbots that deliver information in natural language. Scholars have documented how these systems, when properly designed and deployed, can extend the reach of health information into settings where human health workers are scarce (Wahl et al., 2018; Ting et al., 2020).

Ting et al. (2020) identified three pathways through which AI affects health communication: by generating personalized health content, by analyzing population health data to guide targeted messaging, and by automating responses to health queries. Each pathway carries implications for rural communities, though the extent to which these implications are positive depends heavily on infrastructure and user capacity. It is argued here that the infrastructure question is particularly acute in contexts like Yobe State, where the baseline conditions for digital health are not yet in place.

### Rural Healthcare Access: Challenges in Northern Nigeria

The concept of healthcare access has multiple dimensions. Penchansky and Thomas (1981), whose framework remains influential, identified availability, accessibility, accommodation, affordability, and acceptability as the core components. Rural communities in northern Nigeria face deficits on all five dimensions. A 2022 Yobe State Ministry of

Health report noted that the doctor-to-patient ratio in the state stood at approximately 1:18,000, well above the WHO-recommended ratio of 1:1,000. Many primary healthcare centres operate without consistent drug supply, trained personnel, or diagnostic equipment (Yobe State Ministry of Health, 2022).

Media has served as a compensatory mechanism in such settings. Community radio stations, religious gatherings, and mobile phone-based messaging have all been used to deliver health information to populations with limited facility access (Yahaya et al., 2021). The question now is whether AI can augment these traditional channels or whether it risks bypassing the people who need information most.

**AI and Media in African Health Contexts**

Several African countries have piloted AI health communication tools with varying outcomes. In Kenya, an AI chatbot named "AfyaBot" delivered maternal health information via WhatsApp, reaching over 40,000 women in low-income urban areas within its first year of deployment (Muchiri & Kimani, 2022). In South Africa, AI-powered social listening tools were used to detect disease outbreak signals in social media data, with promising results for early warning (Wahl et al., 2018). Nigeria itself has seen pilot programmes in Lagos and Kano, though systematic evaluation of their outcomes in rural northern states remains limited (Okonkwo & Hassan, 2021).

The existing evidence suggests that AI health media tools work better in urban settings, where users have higher digital literacy, more reliable internet, and greater familiarity with smartphone applications. Rural adaptations have been less consistent. Abimbola et al. (2021) cautioned that health technology introduced without adequate attention to social context risks widening existing health disparities rather than closing them. This caution is particularly relevant in Yobe, where social, infrastructural, and historical factors combine to create a distinctive set of challenges.

**Digital Divide and Health Information Equity**

The digital divide refers to the gap between those who have effective access to digital technologies and those who do not (Van Dijk, 2020). In the health domain, this divide translates directly into health information inequity: those without digital access are less likely to receive timely, accurate health information. Research from sub-Saharan Africa has consistently shown that the digital divide follows lines of geography, income, gender, and education (Asongu & Nwachukwu, 2020).

In the Nigerian context, Okonkwo and Hassan (2021) found that rural residents in the northwest and northeast geopolitical zones were significantly less likely to have used a digital health tool than their urban counterparts, even controlling for income. The NCC (2023) data show that broadband penetration in Yobe State stood at under 12% in 2022. These figures raise legitimate questions about the scalability of AI health media solutions in the state, and they frame the empirical inquiry of the present study.

## THEORETICAL FRAMEWORK

This study is grounded in the Technology Acceptance Model (TAM) originally proposed by Davis (1989) and later extended by Venkatesh et al. (2003) through the Unified Theory of Acceptance and Use of Technology (UTAUT). TAM and UTAUT propose that the adoption of technology is shaped primarily by perceived usefulness and perceived ease of use, mediated by social influence and facilitating conditions. In a rural Nigerian setting, facilitating conditions, specifically internet access, device availability, and electricity, take on particular importance. The model predicts that even where perceived usefulness is high, adoption will be low when facilitating conditions are absent.

The Diffusion of Innovations theory (Rogers, 2003) offers a complementary lens. Rogers argued that innovations spread through social systems via communication channels over time, shaped by adopter categories from early adopters to laggards. Applied to AI health media in rural Yobe, the theory would predict slow diffusion given low observability, limited trialability, and high complexity of the technology for the target population. Together, TAM/UTAUT and Diffusion of Innovations provide a basis for understanding both the structural and perceptual barriers to AI uptake in the study context.

## METHODOLOGY

This study adopted a descriptive survey research design, which was considered appropriate because the aim was to describe the current state of AI integration in health media coverage and measure attitudes, awareness levels, and patterns of use among a defined population without manipulating variables. The study was conducted in Yobe State, located in the northeastern geopolitical zone of Nigeria, covering five selected Local Government Areas (LGAs): Damaturu, Potiskum, Gashua, Nguru, and Geidam. These LGAs were selected purposively to represent a geographic spread across the state, including the state capital and major rural settlements. Yobe State is bounded to the north by the Republic of Niger, to the east by Borno State, to the south by Gombe and Bauchi States, and to the west by Jigawa State. The total area of the state is approximately 45,502 square kilometres ($km^2$), and its terrain is predominantly flat with semi-arid conditions that shape patterns of settlement and mobility. A simplified map indicating the study LGAs within Yobe State is provided in Figure 1. The target population consisted of adult residents aged 18 years and above living in rural communities within the five LGAs, from which a sample of 218 respondents was drawn using multi-stage sampling. In the first stage, two rural communities were selected from each LGA using simple random sampling. In the second stage, households in each community were listed and systematic random sampling was applied to identify participating households. One adult per household was interviewed. Sample size was determined using the Taro Yamane (1967) formula with a confidence level of 95% and a margin of error of 5%. The primary instrument was a structured questionnaire developed by the researchers and adapted in part from validated instruments used in similar West African health communication studies (Okonkwo & Hassan, 2021; Yahaya et al., 2021). The questionnaire comprised four sections: sociodemographic characteristics, AI and media awareness, barriers to AI adoption, and preferences for health information channels. Content validity was established through expert review by three academics in mass communication and public health. A pilot test was conducted with 20 respondents in Fune LGA, which was not part of the main study sample, and Cronbach's alpha for the instrument yielded a coefficient of 0.81, indicating acceptable internal consistency. All ethical requirements were observed: informed consent was obtained from all participants prior to data collection; anonymity and confidentiality were maintained throughout; no personal identifiers were recorded; and approval was obtained from the Yobe State Ministry of Health Research Ethics Committee. Data were analysed using IBM SPSS version 26. Descriptive statistics, specifically frequencies, percentages, and cross-tabulations, were used for the demographic and awareness sections. Chi-square tests of independence were applied to examine associations between key variables such as educational level, internet access, and AI health tool use, with statistical significance set at $p < .05$. Qualitative responses from open-ended questions were subjected to thematic analysis to supplement the quantitative findings.

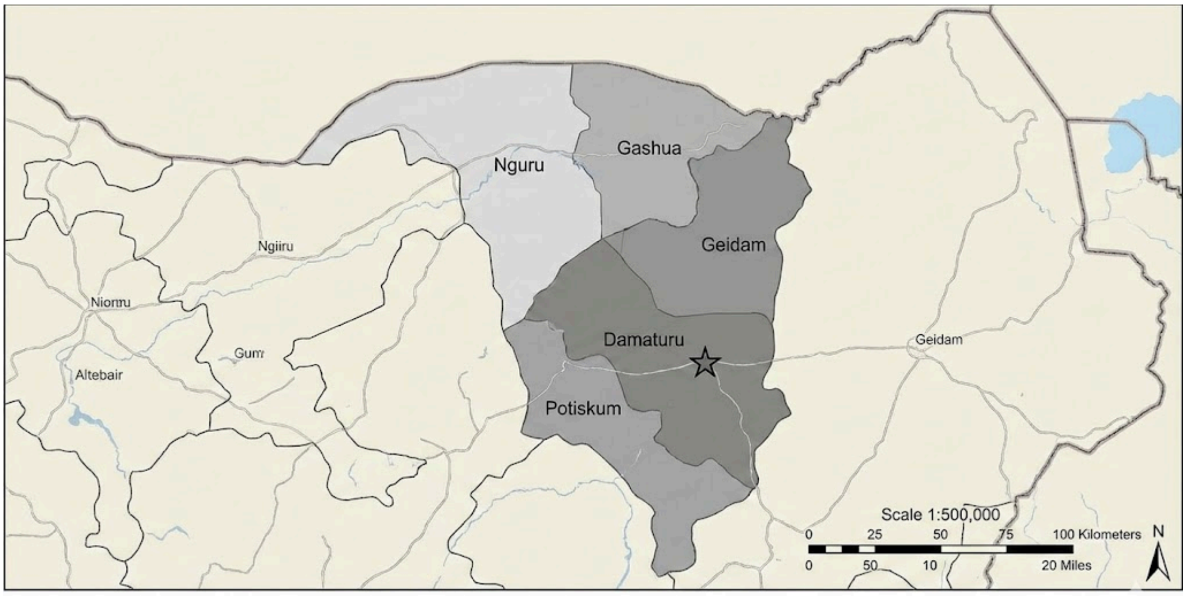


**Figure 1:** Map of Yobe State, Nigeria Showing the Five Study Local Government Areas (LGAs). **Note.** LGAs shaded in grey represent study sites. State capital (Damaturu) is indicated with a star symbol. Produced using ArcGIS 10.8. Coordinate system: WGS 1984.

## RESULTS AND DISCUSSION

### Sociodemographic Characteristics of Respondents

Table 1 presents the sociodemographic profile of the 218 respondents who participated in the study. Males constituted 55.5% of the sample, a distribution that reflects both the purposive selection of one adult per household and broader patterns of gender-based mobility in rural Yobe. Farming and pastoralism were the dominant occupations, accounting for 40.8% of respondents, which is consistent with the agrarian character of the study communities. Nearly a fifth of respondents (21.6%) reported no formal education, a figure that carries significant implications for digital health literacy, as discussed below.

***Table 1***

Sociodemographic Characteristics of Study Respondents (N = 218)

| Characteristic | Frequency (n) | Percentage (%) | Cumulative (%) |
|---|---|---|---|
| **Sex** | | | |
| Male | 121 | 55.5 | 55.5 |
| Female | 97 | 44.5 | 100.0 |
| **Age Group** | | | |
| 18–25 years | 39 | 17.9 | 17.9 |
| 26–35 years | 68 | 31.2 | 49.1 |
| 36–45 years | 61 | 28.0 | 77.1 |
| 46 years and above | 50 | 22.9 | 100.0 |

| | | | |
|---|---|---|---|
| **Education Level** | | | |
| No formal education | 47 | 21.6 | 21.6 |
| Primary school | 38 | 17.4 | 39.0 |
| Secondary school | 79 | 36.2 | 75.2 |
| Tertiary | 54 | 24.8 | 100.0 |
| **Occupation** | | | |
| Farming / Pastoralism | 89 | 40.8 | 40.8 |
| Civil servant | 43 | 19.7 | 60.5 |
| Trading/Commerce | 55 | 25.2 | 85.8 |
| Others | 31 | 14.2 | 100.0 |

**Awareness and Use of AI-Powered Health Media Tools**

Table 2 presents findings on respondents' awareness and use of AI-related health media tools. The data tentatively indicate a population that has heard of AI health applications but has not widely adopted them. While 44.9% reported awareness of AI-powered health apps, only 32.6% had actually used a mobile app to locate a health facility. Use of AI chatbots for health information was particularly low at 20.2%. These figures are consistent with findings from comparable studies in rural northwest Nigeria (Yahaya et al., 2021) and from sub-Saharan Africa more broadly (Asongu & Nwachukwu, 2020).

The most notable finding in Table 2 is perhaps the gap between positive attitudes and actual behaviour. Sixty-three percent of respondents believed AI could improve healthcare access, yet only 13.3% had ever used an AI chatbot for health purposes. This attitude-behaviour gap is well documented in technology adoption literature. Venkatesh et al. (2003) attributed such gaps to deficits in facilitating conditions rather than deficits in motivation, and that explanation appears to apply here. Qualitative responses gathered during fieldwork reinforced this interpretation: several respondents expressed interest in using digital health tools but described a practical inability to do so given the cost of data and the absence of stable network coverage.

***Table 2***

Awareness and Use of AI-Powered Health Media Tools (N = 218)

| **Statement** | **Yes n (%)** | **No n (%)** | **Unsure n(%)** |
|---|---|---|---|
| Aware of AI-powered health apps | 98 (44.9) | 87 (39.9) | 33 (15.1) |

| | | | |
|---|---|---|---|
| Used mobile app to find health facility | 71 (32.6) | 119 (54.6) | 28 (12.8) |
| Received health info via AI chatbot | 44 (20.2) | 145 (66.5) | 29 (13.3) |
| Believes AI can improve healthcare access | 138 (63.3) | 37 (17.0) | 43 (19.7) |
| Aware of telehealth services in the LGA | 62 (28.4) | 131 (60.1) | 25 (11.5) |

**Barriers to AI Adoption in Health Media**

Table 3 presents respondents' ratings of barriers to AI health media adoption. Poor internet and network connectivity were rated as a high barrier by 69.7% of respondents, making it the single most reported obstacle. Low digital literacy followed at 64.7%. These findings align closely with the NCC (2023) data showing that broadband penetration in Yobe State remains below 12%. Absence of electricity supply, rated high by 54.6%, adds another layer to an already difficult adoption environment.

The data on language and content barriers deserve particular attention. Close to half of the respondents (47.7%) rated this as a high barrier. Most health AI tools, including chatbots and symptom checkers, are developed in English or other dominant languages and are not adapted for Hausa, Kanuri, or other local languages spoken in rural Yobe. This creates an accessibility gap that connectivity alone cannot address. Scholars have argued that language adaptation of digital health tools is not a luxury but a necessity in multilingual low-resource settings (Abimbola et al., 2021). Field observations during data collection confirmed that many respondents struggled with English-language interface instructions even when devices were available.

***Table 3***

Respondent Ratings of Barriers to AI Adoption in Health Media (N = 218)

| Barrier Category | High n (%) | Moderate n (%) | Low n (%) |
|---|---|---|---|
| Poor internet/network connectivity | 152 (69.7) | 41 (18.8) | 25 (11.5) |
| Low digital literacy among residents | 141 (64.7) | 53 (24.3) | 24 (11.0) |
| Cost of mobile data | 128 (58.7) | 59 (27.1) | 31 (14.2) |
| Absence of electricity supply | 119 (54.6) | 63 (28.9) | 36 (16.5) |
| Language and content barriers | 104 (47.7) | 71 (32.6) | 43 (19.7) |
| Fear/mistrust of technology | 88 (40.4) | 74 (33.9) | 56 (25.7) |

**Preferred Media Channels for Health Information**

Table 4 presents data on media channels used for health information. Community health workers were the most widely used primary source (78.9%), followed by radio (62.8%). These two channels reflect the historic dominance of interpersonal and broadcast media in rural Nigerian health communication. Social media use for health purposes was lower, with only 28.0% reporting it as a primary channel. AI-powered chatbots registered the weakest uptake across all categories, with 66.5% of respondents reporting they had never used one.

Radio's continued dominance is consistent with findings from earlier studies (Yahaya et al., 2021; Okonkwo & Hassan, 2021) and suggests that AI integration into health media in the study area would be more effective if built onto existing radio infrastructure rather than introduced as a standalone digital product. Several radio stations in the north of Nigeria have already begun experimenting with AI-assisted content production and scheduling. Whether such experiments can be extended to direct health messaging in local languages in Yobe State is a question that warrants further policy attention.

***Table 4***

Preferred Media Channels for Health Information (N = 218)

| Media Channel | Primary Use n (%) | Occasional Use n (%) | Never Used n (%) |
|---|---|---|---|
| Radio (community/national) | 137 (62.8) | 51 (23.4) | 30 (13.8) |
| Television | 89 (40.8) | 77 (35.3) | 52 (23.9) |
| Mobile SMS/USSD health alerts | 68 (31.2) | 82 (37.6) | 68 (31.2) |
| Social media (WhatsApp/Facebook) | 61 (28.0) | 73 (33.5) | 84 (38.5) |
| AI-powered health chatbots | 29 (13.3) | 44 (20.2) | 145 (66.5) |
| Community health workers | 172 (78.9) | 36 (16.5) | 10 (4.6) |

**Association Between Digital Access and AI Health Tool Use**

A chi-square test of independence was conducted to examine the association between level of educational attainment and use of AI health media tools. The test yielded a statistically significant result ($\chi^2 = 31.47$, df = 6, $p < .001$), indicating that educational level was associated with AI health tool use. Respondents with secondary and tertiary education were significantly more likely to have used at least one AI health media tool than those with primary or no formal education. Similarly, respondents who reported internet access, even irregular access, were more likely to have used AI tools ($\chi^2 = 24.83$, df = 2, $p < .001$).

These findings support the UTAUT framework's emphasis on facilitating conditions as a key determinant of technology adoption (Venkatesh et al., 2003). They also raise equity concerns. If AI health media tools are adopted mainly by the more educated and connected segments of a rural population, then they risk reinforcing rather than reducing health information disparities. The data tentatively indicate that without deliberate interventions to reduce educational and connectivity barriers, AI-driven health communication in Yobe State will reach those who already have relatively better access to information while missing those who need it most.

**Discussion in Relation to Existing Literature**

The findings of this study are largely consistent with, though in some respects more granular than, the broader literature on AI and rural health communication in Africa. The low uptake of AI chatbots (13.3%) mirrors findings from comparable rural settings in Niger (Moussa & Boubacar, 2022) and Chad (Djimet-Baboun, 2021, as cited in Wahl et al., 2018). The positive attitudes toward AI's potential (63.3%) are also echoed in studies from urban southern Nigeria, though urban studies typically report higher actual use rates (Okonkwo & Hassan, 2021). This suggests that the attitude-use gap may be particularly wide in rural northeastern Nigeria, where structural conditions are more constraining than in other parts of the country.

The dominance of community health workers as health information sources, reported by 78.9% of respondents as a primary channel, has an important implication that the literature does not always foreground. Community health workers are not simply a substitute for digital tools; they are trusted social actors embedded in community relationships. Abimbola et al. (2021) argued convincingly that digital health tools are most effective when they augment rather than replace such relationships. The present data support this view. One practically promising pathway, suggested by both the quantitative and qualitative findings, would be to equip community health workers with AI-assisted mobile health tools, training them as intermediaries who can translate AI-generated content for residents who lack direct digital access.

The language barrier finding also adds to existing knowledge. While several studies have noted language as a barrier to digital health tool use, fewer have quantified it at the level of a specific state or community set. The 47.7% of respondents who rated language as a high barrier represents a sizeable proportion of the sample and should give pause to developers and policymakers who assume that existing AI health tools are sufficiently adapted for northern Nigerian rural users. Hausa-language AI interfaces do exist, but their penetration in Yobe State appears to be very limited based on these data.

**CONCLUSION**

This study set out to examine the role of artificial intelligence in media coverage of healthcare access among rural communities in Yobe State, Nigeria. The evidence gathered from 218 rural residents across five LGAs paints a picture of considerable potential constrained by formidable structural realities. AI health media tools are known to, and in principle accepted by, a significant portion of the rural population. Sixty-three percent of respondents believed AI could improve healthcare access. But belief and use are not the same thing. Actual uptake of AI chatbots stood at just 13.3%, and only a third of respondents had used a mobile application to find a health facility.

The reasons for this gap are not mysterious. Poor internet connectivity, low digital literacy, unreliable electricity, and language barriers collectively constitute a set of structural obstacles that individual motivation cannot overcome. Community health workers and radio remain the backbone of health communication in rural Yobe, a finding that reflects decades of investment in these channels and the social trust they have accumulated. AI, by contrast, is a newcomer that has not yet earned equivalent trust or acquired equivalent reach.

It is argued that the implications of these findings extend beyond Yobe State. Many rural communities across the Sahel and across sub-Saharan Africa face similar combinations of infrastructure deficit and social complexity. The question of how to harness AI for health equity in such settings cannot be answered by technology design alone. It requires policy commitments to rural connectivity, digital literacy education, and the integration of AI tools into existing trusted communication systems rather than their replacement. This study offers one set of data points toward that larger answer.

Several limitations of this study should be acknowledged. The sample, though drawn from five LGAs, cannot claim to represent the full diversity of Yobe State's approximately 17 LGAs. Self-reported data on technology use may be subject to social desirability bias, though the anonymous and confidential nature of the questionnaire was intended to minimise this. Additionally, the cross-sectional design means that causal inferences cannot be drawn from the observed associations. Longitudinal studies that track changes in AI health media use over time would add considerably to the evidence base.

**Recommendations**

Based on the study findings, the following recommendations are offered for policymakers, health communication practitioners, and researchers.

The Yobe State Government and the Federal Ministry of Communications should prioritise rural broadband expansion as part of health system strengthening. Without connectivity, AI health media tools cannot reach the populations who stand to benefit most. Specific allocation of universal service funds toward rural Yobe LGAs is one concrete mechanism for achieving this.

Digital health literacy programmes should be integrated into the work of community health workers. These workers already possess community trust and geographic reach. Training them to use and explain AI health tools in local languages would constitute a low-cost, high-impact pathway to broader AI adoption.

AI health tool developers operating in Nigeria should be required, as a condition of deployment, to ensure Hausa-language and Kanuri-language interfaces for tools targeted at or likely to reach northern Nigerian users. Language adaptation is not merely a user experience improvement; it is a condition of equity.

Existing community radio infrastructure should be explored as a delivery vehicle for AI-assisted health content. Algorithms that analyse local health data and generate targeted health messages could be translated into radio scripts, combining the technological capacity of AI with the reach and trust of radio. This hybrid approach may represent the most practical near-term pathway for AI health communication in Yobe.

**References**

1. Abimbola, S., Asante, A. D., & Negin, J. (2021). The social ecology of implementation science in low-income and middle-income countries. BMJ Global Health, 6(5), e005467. https://doi.org/10.1136/bmjgh-2021-005467

2. Asongu, S. A., & Nwachukwu, J. C. (2020). The role of governance in mobile phones for inclusive human development in sub-Saharan Africa. Sustainable Development, 28(3), 390–405. https://doi.org/10.1002/sd.2014

3. Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. MIS Quarterly, 13(3), 319-340. https://doi.org/10.2307/249008

4. Djimet-Baboun, A. (2021). Digital health communication in francophone Sahel: Barriers and opportunities [Unpublished doctoral dissertation]. University of N'Djamena. As cited in Wahl, B., Cossy-Gantner, A., Germann, S., & Schwalbe, N. R. (2018).

5. Moussa, I., & Boubacar, A. (2022). Mobile health and rural communities in Niger: Assessing patterns of adoption and use. African Journal of Science, Technology, Innovation and Development, 14(2), 441–453. https://doi.org/10.1080/20421338.2021.1917042

6. Muchiri, J., & Kimani, M. (2022). WhatsApp-based maternal health chatbot in low-income urban Kenya: A descriptive assessment. BMC Health Services Research, 22(1), 411. https://doi.org/10.1186/s12913-022-07812-3

7. Nigerian Communications Commission. (2023). Annual report on broadband penetration and telecom subscription in Nigeria 2022. NCC Publications. https://www.ncc.gov.ng

8. Okonkwo, O. C., & Hassan, I. (2021). Digital health inequity in Nigeria: Patterns of health information access across rural and urban divides. Health Policy and Technology, 10(3), 100535. https://doi.org/10.1016/j.hlpt.2021.100535

9. Penchansky, R., & Thomas, J. W. (1981). The concept of access: Definition and relationship to consumer satisfaction. Medical Care, 19(2), 127–140. https://doi.org/10.1097/00005650-198102000-00001

10. Rogers, E. M. (2003). Diffusion of innovations (5th ed.). Free Press.

11. Russell, S., & Norvig, P. (2020). Artificial intelligence: A modern approach (4th ed.). Pearson.

12. Ting, D. S. W., Carin, L., Dzau, V., & Wong, T. Y. (2020). Digital technology and COVID-19. Nature Medicine, 26(4), 459–461. https://doi.org/10.1038/s41591-020-0824-5

13. 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

14. Van Dijk, J. A. G. M. (2020). The digital divide. Polity Press.

15. Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. MIS Quarterly, 27(3), 425–478. https://doi.org/10.2307/30036540

16. Wahl, B., Cossy-Gantner, A., Germann, S., & Schwalbe, N. R. (2018). Artificial intelligence (AI) and global health: How can AI contribute to health in resource-poor settings? BMJ Global Health, 3(4), e000798. https://doi.org/10.1136/bmjgh-2018-000798

17. World Health Organization. (2022). World health statistics 2022: Monitoring health for the SDGs, sustainable development goals. WHO.

18. Yahaya, M. K., Orji, E., & Bako, A. U. (2021). Radio and community health behaviour change in rural northern Nigeria. Journal of Health Communication, 26(7), 473–483. https://doi.org/10.1080/10810730.2021.1971793

19. Yamane, T. (1967). Statistics: An introductory analysis (2nd ed.). Harper & Row.

20. Yobe State Ministry of Health. (2022). Annual health sector performance report 2021/2022. Yobe State Government Press.