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Awareness, adoption, and predictors of artificial intelligence use among public health researchers in Bo District, Sierra Leone: a cross-sectional study

Daniel Kamara[1]

kamaradaniel328@gmail.com

Njala University College of Medical Sciences

Research Article

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Abstract

Background

Artificial intelligence (AI) is increasingly applied in global health research, yet empirical evidence on its uptake in low-resource settings is scarce. This study assessed awareness, adoption, and predictors of AI use among public health researchers in Bo District, Sierra Leone.

Methods

A cross-sectional survey was conducted with 200 public health researchers and research-related personnel across university, hospital, government, and non-governmental organisation (NGO) settings, selected by proportional stratified random sampling. Data were analysed with descriptive statistics, chi-square tests of independence, and binary logistic regression at a 5% significance level.

Results

Awareness of AI was high (149/200; 74.5%), but use of AI tools was low (71/200; 35.5%), and only 26.5% (53/200) had received any formal AI training. AI use was descriptively higher among trained respondents (43.4% versus 32.7%), but the association between training and adoption was not statistically significant ($\chi^2 = 1.964$, df = 1, $p = 0.161$). The association between AI use and perceived improvement in research quality was likewise non-significant ($\chi^2 = 0.821$, df = 2, $p = 0.663$). In binary logistic regression, none of the examined predictors AI tool use, AI training, institution type, or years of experience significantly predicted perceived improvement (all $p > 0.05$).

Conclusions

Despite high awareness, AI adoption among public health researchers in Bo District is at an early stage and is not explained by training or institution type alone. The awareness–adoption gap points to structural and infrastructural determinants that individual-level factors do not capture, underscoring the need for structured capacity-building embedded within supportive institutional environments.

Background

Artificial intelligence (AI) the simulation of human cognitive functions such as learning, reasoning, and pattern recognition by computer systems has emerged as a transformative resource in public health research. Techniques including machine learning, deep learning, natural language processing, and predictive analytics have been applied to epidemiological analysis, disease surveillance, health-systems evaluation, and evidence synthesis, often with greater speed and accuracy than conventional methods (Davenport & Kalakota, 2019; Topol, 2018). In high-income settings, these applications have improved

analytical efficiency and strengthened evidence-based decision-making (Chomutare et al., 2022; Jiang et al., 2017).

In low- and middle-income countries (LMICs), particularly across sub-Saharan Africa, adoption has been slower and uneven. Inadequate digital infrastructure, limited access to high-quality data, shortages of technical expertise, and weak governance frameworks have constrained effective use, so that many institutions continue to rely on manual or basic statistical approaches (Organization, 2021; Reis et al., 2021). Understanding whether, and under what conditions, researchers in such settings take up AI is therefore a prerequisite for responsible investment in digital research capacity.

In Sierra Leone, public health research is central to addressing malaria, maternal and child mortality, and recurrent infectious-disease threats, and routine data are captured through platforms such as the District Health Information Software 2 (DHIS2). Despite the growing availability of digital health data, the application of AI tools in research remains minimal, and little is documented at the district level. Bo District home to Njala University, Bo Government Hospital, the District Health Management Team, and several NGOs serves as a major research hub outside Freetown, making it an appropriate setting to examine adoption where both urban and rural, and academic and service, contexts coexist.

This study is framed by the Technology Acceptance Model (TAM), which holds that perceived usefulness and perceived ease of use shape attitudes, behavioural intention, and ultimately actual system use, with external variables acting indirectly through these beliefs (Davis, 1989; Holden & Karsh, 2009). TAM offers a parsimonious lens for distinguishing awareness from use and for interpreting the role of training and institutional context in a low-resource research environment. Accordingly, the study assessed three questions: (i) the levels of AI awareness, training, and tool use among public health researchers in Bo District; (ii) whether AI training is associated with AI adoption; and (iii) whether AI use, training, institution type, and experience predict perceived improvement in research quality. Findings on the barriers to adoption and on institutional readiness from the same study are reported in a companion paper (Kamara, under review).

Methods

Study design and setting

A cross-sectional survey was conducted in Bo District, Southern Province, Sierra Leone. The district was selected purposively as a principal public health research hub outside the capital, hosting academic, hospital, government, and non-governmental research actors across urban and rural settings. The cross-sectional design was appropriate for establishing prevalence, patterns, and associations in a context where AI application is still emerging; it does not support strong causal inference.

Population and eligibility

The target population comprised individuals engaged in public health research in Bo District, including academic researchers and students at Njala University, health-facility research officers and data managers, monitoring and evaluation officers, disease-surveillance staff, and programme managers in governmental and non-governmental organisations (estimated at approximately 1,000 individuals). Eligible participants were adults aged 18 years and above who had worked or studied in the district for at least six months and were directly involved in public health research, data management, analysis, or evidence-based decision-making. Clinical or administrative staff without research responsibilities, and those unwilling to provide informed consent, were excluded.

Sample size and sampling

The sample size was estimated using Yamane's formula for finite populations, $n = N / [1 + N(e^2)]$, with $N = 1{,}000$ and a margin of error $e = 0.05$ at the 95% confidence level, giving $n \approx 286$; adjustment for an anticipated 10% non-response yielded ≈ 318 (Yamane, 1973). Owing to time, budgetary, and logistical constraints, the achieved analytic sample was set at 200 respondents, which retained adequate power to detect moderate associations when combined with stratified sampling. Respondents were selected by proportional stratified random sampling to represent the principal stakeholder groups (academic, hospital, government, and NGO).

Instrument and data collection

Data were collected over a two-week period using a structured questionnaire comprising closed-ended and Likert-scale items on AI awareness, training, tool use, perceived impact on research quality and efficiency, and barriers to adoption. Content validity was established through expert review by specialists in public health and research methodology, and items were grounded in the established technology-adoption literature. The instrument was pilot-tested outside the study area to refine wording and clarity, and internal consistency was assessed prior to full administration. Questionnaires were self-administered, with assistance provided where necessary. The questionnaire was developed specifically for this study and has not been published previously; the full English-language instrument is provided as Additional file 1.

Statistical analysis

Data were coded, cleaned, and analysed in SPSS and JASP. Descriptive statistics (frequencies and percentages) summarised respondent characteristics, awareness, training, and utilisation. Chi-square tests of independence assessed associations between categorical variables, and binary logistic regression examined the influence of AI tool use, AI training, institution type, and years of research experience on perceived improvement in research quality. All tests were two-sided and conducted at a 95% confidence level, with statistical significance set at $p < 0.05$.

Ethical considerations

Ethical approval was obtained from the Njala University Research Review Board on 14 October 2025, prior to data collection. All procedures involving human participants were performed in accordance with the Declaration of Helsinki and applicable national research-ethics guidelines of Sierra Leone. Participation was voluntary, written informed consent was obtained from all respondents, and confidentiality and anonymity were maintained throughout.

Results

Awareness, training, and utilisation of AI

Among the 200 respondents, awareness of AI was high: 149 (74.5%) reported being aware of AI and 51 (25.5%) were not. Formal AI training was uncommon: only 53 respondents (26.5%) had received any AI-related training, whereas 147 (73.5%) had not. Utilisation lagged well behind awareness 71 respondents (35.5%) reported using AI tools in their research, while 129 (64.5%) did not (Table 1). The gap between near-universal awareness and limited use indicates that adoption of AI in public health research in the district remains at an early stage.

Table 1
Awareness, training, and utilisation of AI among public health researchers (N = 200)

Indicator	Category	n	%
Aware of AI	Yes	149	74.5
	No	51	25.5
Received AI training	Yes	53	26.5
	No	147	73.5
Used AI tools	Yes	71	35.5
	No	129	64.5
Note: Percentages are of the total sample (N = 200).			

Institutional distribution of awareness

Awareness was broadly distributed across institution types. Of the 149 respondents aware of AI, the largest share was affiliated with universities (32.2%), followed by hospitals (30.9%), government institutions (20.8%), and NGOs (16.1%). Among the 51 respondents who were unaware, hospitals accounted for the largest share (35.3%), followed by universities (29.4%), government (19.6%), and NGOs (15.7%), broadly mirroring the overall institutional composition of the sample (Table 2).

Table 2
Awareness of AI by institution type (N = 200)

Awareness	Government	Hospital	NGO	University	Total
Aware (n = 149)	31 (20.8)	46 (30.9)	24 (16.1)	48 (32.2)	149 (100)
Not aware (n = 51)	10 (19.6)	18 (35.3)	8 (15.7)	15 (29.4)	51 (100)
Total	41 (20.5)	64 (32.0)	32 (16.0)	63 (31.5)	200 (100)
Note: Values are n (row %). Percentages are within awareness category.					

Association between AI training and AI adoption

Among respondents who had not received AI training, 48 of 147 (32.7%) used AI tools; among those who had received training, 23 of 53 (43.4%) did so. Although descriptively trained respondents were more likely to use AI tools, the difference was not statistically significant (Table 3).

A chi-square test of independence found no significant association between AI training and AI tool use ($\chi^2 = 1.964$, df = 1, p = 0.161; Fisher's exact p = 0.182). The test assumption was met, with all expected cell counts exceeding five (minimum expected count = 18.81). Thus, receipt of training did not, on its own, distinguish users from non-users in this sample.

Table 3
AI training by AI tool use, with test of association (N = 200)

AI training	Did not use AI	Used AI	Total
Not received	99 (67.3)	48 (32.7)	147 (100)
Received	30 (56.6)	23 (43.4)	53 (100)
Total	129 (64.5)	71 (35.5)	200 (100)
Note: Values are n (row %). Pearson $\chi^2 = 1.964$, df = 1, p = 0.161; Fisher's exact p = 0.182.			

AI use and perceived research quality

Perceptions of whether AI improved research quality were mixed in both user groups. Among the 129 non-users, 55 reported that AI improved research quality, 43 were unsure, and 31 reported no improvement; among the 71 users, 35 reported improvements, 21 were unsure, and 15 reported none (Table 4). Descriptively, a somewhat higher proportion of users perceived a positive effect, but a substantial share of both groups remained uncertain.

A chi-square test of independence found no statistically significant association between AI tool use and perceived improvement in research quality ($\chi^2 = 0.821$, df = 2, p = 0.663), with all expected counts exceeding five (minimum expected count = 16.33). The null hypothesis of no relationship between AI adoption and perceived research quality was therefore not rejected.

Table 4
AI tool use by perceived improvement in research quality (N = 200)

AI tool use	No	Not sure	Yes	Total
Did not use AI	31	43	55	129
Used AI	15	21	35	71
Total	46	64	90	200
Note: Cells are counts. Pearson $\chi^2 = 0.821$, df = 2, p = 0.663.				

Predictors of perceived improvement

A binary logistic regression examined AI tool use, AI training, institution type, and years of research experience as predictors of perceived improvement. None of the predictors reached significance at the 5% level: AI tool use (B = − 0.312, p = 0.304), AI training (B = 0.253, p = 0.439), institution type (B = 0.015, p = 0.908), and years of experience (B = − 0.195, p = 0.178) (Table 5). Individual characteristics thus did not independently account for perceived improvement, consistent with a role for contextual and infrastructural factors beyond the modelled variables.

Table 5
Binary logistic regression predicting perceived improvement (N = 200)

Predictor	B	p	Interpretation
AI tools used	−0.312	0.304	Not significant
AI training received	0.253	0.439	Not significant
Institution type	0.015	0.908	No effect
Years of experience	−0.195	0.178	Weak, non-significant trend
Note: B = unstandardised logistic regression coefficient. No predictor was significant at p < 0.05.			

Discussion

This study documents a marked gap between awareness and use of AI among public health researchers in Bo District: roughly three in four respondents were aware of AI, but only about one in three had used AI tools, and barely a quarter had received any formal training. This awareness adoption gap is consistent with evidence that familiarity with an emerging technology does not translate directly into use in resource-constrained settings, and it aligns with the TAM proposition that awareness is a precondition for, but not a determinant of, actual use (Davis, 1989; Holden & Karsh, 2009).

Neither AI training nor AI use was significantly associated with the outcomes examined. Trained respondents were descriptively more likely to use AI tools (43.4% versus 32.7%), yet the association was not significant ($\chi^2 = 1.964$, df = 1, p = 0.161), and AI use was not significantly associated with perceived

improvement in research quality ($\chi^2 = 0.821$, df = 2, p = 0.663). In multivariable analysis, none of AI use, training, institution type, or experience predicted perceived improvement. Read through TAM, these results suggest that training may raise capability (perceived ease of use) without, in isolation, generating the perceived usefulness and enabling conditions required for sustained adoption (Chew & Achananuparp, 2022; Sani et al., 2026).

The pattern is better explained by structural rather than individual determinants. Where infrastructure is unreliable, tools are costly, and institutional policies are absent, capability alone is unlikely to convert into routine use an interpretation reinforced by the companion analysis of barriers and institutional readiness from the same study (Kamara, under review). This is congruent with broader accounts of the digital divide, in which infrastructural and organisational inequalities shape access to and benefit from emerging technologies (Chomutare et al., 2022; Organization, 2021).

The findings have practical implications. Sensitisation campaigns that raise awareness are necessary but insufficient; investment should prioritise structured, applied training coupled with reliable connectivity, affordable tool access, and institutional AI policies. Embedding AI and data-science competencies within public health curricula and continuing professional development at institutions such as Njala University would help convert high awareness into competent, ethical use.

Limitations

Several limitations warrant caution. The cross-sectional design precludes causal inference, and reliance on self-reported measures may introduce response and social-desirability bias. Outcomes reflect perceived rather than objectively measured research quality. The achieved sample (200 of a calculated 318) reduces precision for smaller subgroup effects, so non-significant associations should not be read as firm evidence of no effect. Finally, the single-district setting limits generalisability to other regions of Sierra Leone.

Conclusions

Awareness of AI among public health researchers in Bo District is high, but actual use of AI tools is limited and is not explained by training or institution type alone. The absence of significant individual-level predictors of perceived improvement points to structural and infrastructural determinants of adoption. Converting awareness into effective, responsible AI use will require coordinated investment in applied training, digital infrastructure, and institutional governance, supported by further longitudinal and multi-district research.

Abbreviations

AI
Artificial intelligence
DHIS2

District Health Information Software 2

LMIC

Low- and middle-income country

NGO

Non-governmental organisation

SPSS

Statistical Package for the Social Sciences

TAM

Technology Acceptance Model

WHO

World Health Organization.

Declarations

Ethics approval and consent to participate

This study was reviewed and approved by the Njala University Research Review Board on 14 October 2025, prior to data collection. All procedures involving human participants were performed in accordance with the ethical standards of the approving committee and with the 1964 Declaration of Helsinki and its later amendments, and with applicable national research-ethics guidelines of Sierra Leone. Written informed consent was obtained from all participants prior to enrolment; participation was voluntary, and the confidentiality and anonymity of respondents were maintained throughout.

Consent for publication

Not applicable.

Competing interests

The author declares that he has no competing interests.

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Author Contribution

DK conceived and designed the study, collected and analysed the data, interpreted the findings, and drafted and approved the final manuscript.

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Data Availability

The datasets generated and analysed during the current study are available from the corresponding author on reasonable request.

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