A Mixed-Methods Comparative Analysis of Curriculum Readiness and Workforce Adaptability in Low- and Middle-Income Countries

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Abstract

The rapid proliferation of artificial intelligence (AI) in public health practice has outpaced the development of formal training competencies in educational curricula, particularly within low- and middle-income countries (LMICs). Despite increasing adoption of AI-driven epidemiological modeling, predictive analytics, and health communication tools, a persistent knowledge gap exists in structured, competency-based AI training for public health students and professionals (Semi et al., 2026). This study employed a mixed-methods comparative design to assess curriculum readiness and workforce adaptability for AI integration across 47 public health institutions in six LMICs (India, Nigeria, Kenya, Bangladesh, Nepal, and Ethiopia). Quantitative surveys administered to 849 public health faculty members and 1,204 final-year students revealed that only 12.3% of institutions offered formal AI competency training, while 89.4% of respondents identified curriculum reform as an urgent priority. The AI literacy assessment demonstrated that students scored significantly lower on applied AI problem-solving tasks (mean 41.2%, SD 18.7) compared to foundational public health competencies (mean 76.8%, SD 12.4), $t(1203) = 28.4$, $p < 0.001$. A five-pillar framework encompassing technical foundations, ethical and regulatory literacy, experiential learning, governance and policy, and equity and access is proposed as a replicable model. The findings underscore the critical need for systematic integration of AI competencies into public health curricula, with particular attention to faculty development, infrastructural constraints, and ethical safeguards in resource-limited settings. Practical implications include structured faculty training pathways, open-access AI literacy tools, and policy recommendations for institutional curriculum reform.

Keywords: Artificial Intelligence Literacy, Public Health Education, Curriculum Readiness, Workforce Adaptability, Low- and Middle-Income Countries

1. Introduction

1.1 Background

Artificial intelligence is fundamentally reshaping public health practice, transforming functions ranging from disease surveillance and epidemiological modeling to health communication and policy analysis (Sallam, 2025). Large language models such as ChatGPT, Claude, and Gemini have been employed in real-time outbreak detection, risk stratification, and the development of data-driven policy briefs, offering unprecedented capabilities for data-informed decision-making (Sallam, 2025). AI-driven algorithms have markedly improved nowcasting techniques, enabling precise identification of transmission clusters and assessment of intervention effectiveness at population scales.

The World Health Organization has recognized the transformative potential of AI in advancing global health objectives, releasing comprehensive guidelines on ethics and governance of AI in healthcare in 2021 and regulatory considerations for AI in health in 2023 (Sood, Mishra, & Surya, 2024). These guidelines emphasize the need for capacity building and workforce preparedness to ensure equitable and responsible AI adoption, particularly in low- and middle-income settings where resource constraints present unique challenges.

However, despite these developments, formal training in AI literacy—defined as the ability to understand, critically evaluate, and responsibly apply AI technologies—has not been systematically integrated into public health education (Sallam, 2025). Students and practicing professionals often acquire AI skills through informal or ad hoc methods, leaving them unprepared for the data-driven decision-making landscape that increasingly characterizes modern public health practice.

1.2 Problem Statement

The widening gap between AI technological advancement and educational preparedness represents a critical challenge for global public health. While AI applications demonstrate potential for improving health outcomes through enhanced diagnostic accuracy—with studies reporting deep learning models achieving up to 98.16% accuracy for infectious disease detection—the workforce tasked with implementing these technologies often lacks foundational competencies in AI principles, ethics, and practical applications (Sallam, 2025).

This educational deficit is particularly pronounced in low- and middle-income countries, where structural barriers such as limited digital infrastructure, trained personnel shortages, financial constraints, and fragmented data governance systems further complicate AI integration (Sood et al., 2024). Faculty hesitancy remains a significant barrier to AI adoption in higher education, with surveys indicating that a substantial proportion of educators lack confidence or formal knowledge about AI technologies, creating a persistent cycle of educational inertia (Sallam, 2025). The United Nations International Children's Emergency Fund's Magic Box initiative and similar AI-driven programs in sub-Saharan Africa and India demonstrate successful applications, yet educational institutions in LMICs continue to lag in preparing graduates for this evolving landscape (Sallam, 2025; Sood et al., 2024).

Despite recognition of AI's importance for global health, no validated framework exists for systematically integrating AI competencies into public health curricula in LMICs. Existing curriculum models are predominantly developed for high-resource settings and fail to address the infrastructural, cultural, and economic realities that characterize educational institutions in LMICs. This study addresses this gap by conducting a mixed-methods comparative analysis of curriculum readiness and workforce adaptability across six LMICs.

1.3 Objectives of the Study

General objective:
To develop and validate a replicable framework for integrating AI competencies into public health education programs in low- and middle-income countries.

Specific objectives:

1. To assess current levels of AI literacy and curriculum readiness among faculty members and students in public health programs across selected LMICs.
2. To identify key barriers and facilitators for AI competency integration in public health curricula, including infrastructural, pedagogical, and institutional factors.
3. To propose and validate a contextualized five-pillar framework for AI literacy integration that addresses the unique constraints and opportunities in LMIC settings.
4. To evaluate the effectiveness of a pilot AI literacy intervention on student competency development and workforce adaptability indicators.

1.4 Research Questions

1. What is the current state of AI literacy training in public health programs across selected LMICs, and what proportion of institutions offer formal competency-based AI education?
2. What are the primary institutional, pedagogical, and infrastructural barriers that impede AI competency integration in LMIC public health curricula?
3. How does a structured five-pillar AI literacy framework compare to existing ad hoc approaches in terms of student competency outcomes and workforce preparedness indicators?
4. What contextual factors (faculty readiness, institutional support, resource availability) most significantly predict successful AI competency integration in LMIC public health education?

1.5 Significance of the Study

This research contributes to multiple stakeholders invested in strengthening global public health education and workforce development:

For practitioners and administrators: The validated AI literacy framework provides actionable guidance for curriculum reform, including specific competency domains, learning objectives, and implementation strategies tailored to LMIC contexts. The study identifies measurable indicators for monitoring progress and recommends open-access tools and resources that reduce cost barriers.

For policymakers: Findings inform national and institutional policy development by identifying critical resource needs, faculty development requirements, and infrastructure investments necessary for AI competency integration. The study's emphasis on ethical AI literacy and equity considerations provides evidence for regulatory frameworks.

For academic literature: This research extends existing conceptual models by empirically testing the applicability of AI literacy frameworks in LMIC educational settings, addressing the gap between theoretical recommendations and implementation realities documented in prior scoping reviews (Semi et al., 2026).

For future researchers: The mixed-methods approach and validated instruments provide methodological templates for replication across additional countries and contexts, facilitating comparative global health education research.

1.6 Scope and Limitations

This study was conducted across 47 public health institutions in six countries (India, Nigeria, Kenya, Bangladesh, Nepal, and Ethiopia) between January 2025 and March 2026, representing diverse geographic regions and development contexts. The research focused on undergraduate and graduate public health programs, excluding continuing professional education and informal training pathways. Data collection utilized online surveys, semi-structured interviews, and a pilot intervention study. Key limitations include: reliance on self-reported competency measures; potential sampling bias in the pilot intervention; variability in institutional research ethics approval processes across countries; and the inherent challenges of generalizing findings across LMICs with diverse educational systems and infrastructural contexts.

2. Literature Review

2.1 Conceptual Review

Artificial Intelligence Literacy in Public Health
AI literacy in public health encompasses the knowledge, skills, and attitudes required to understand, critically evaluate, and responsibly apply AI technologies in health research, policy, and practice (Sallam, 2025). This extends beyond technical proficiency to include ethical reasoning, data governance awareness, bias detection, and the ability to communicate AI-driven insights to diverse stakeholders. Semi et al. (2026) identified core competency domains including data science fundamentals, machine learning principles, natural language processing applications, algorithmic fairness, and implementation science.

Curriculum Readiness
Curriculum readiness refers to the capacity of educational institutions to design, deliver, and sustain competency-based AI education. This encompasses faculty preparation, institutional infrastructure, pedagogical resources, and assessment systems. In LMIC contexts, curriculum readiness is constrained by limited faculty expertise, inadequate computing resources, restricted internet access, and the absence of contextualized learning materials (Sood et al., 2024).

Workforce Adaptability
Workforce adaptability describes the ability of public health professionals to respond effectively to technological change, acquiring and applying new competencies as practice evolves. This includes continuous learning orientation, interdisciplinary collaboration skills, and the capacity to translate AI innovations into improved population health outcomes (Belfort, Mohan, & Hollier, 2025).

2.2 Theoretical Framework

The Technology Acceptance Model (TAM)
This study draws on the Technology Acceptance Model, which posits that perceived usefulness and perceived ease of use are primary determinants of technology adoption. In educational

contexts, faculty acceptance of AI integration depends on their assessment of AI's relevance to learning outcomes (usefulness) and their confidence in effectively teaching AI competencies (ease of use). The model guides the investigation of factors influencing curriculum adoption.

Diffusion of Innovations Theory

Rogers' Diffusion of Innovations Theory provides a lens for understanding how AI competency integration spreads through educational institutions. The theory identifies innovation characteristics—relative advantage, compatibility, complexity, trialability, and observability—that predict adoption rates. This framework informs the analysis of institutional variation in AI curriculum implementation and the identification of early adopters and laggards.

The Five-Pillar AI Literacy Framework

Sallam (2025) proposed a comprehensive framework for embedding AI literacy into public health curricula based on five interconnected pillars:

1. **Technical Foundations:** Basic principles of machine learning, data science, and natural language processing, equipping students with understanding of AI functionality and public health applications.
2. **Ethical and Regulatory Literacy:** Critical evaluation of algorithmic bias, data misuse, privacy concerns, and governance frameworks, helping students navigate legal and social implications.
3. **Experiential Learning:** Hands-on projects such as disease forecasting, policy simulation, and data analysis, ideally through interdisciplinary collaboration with computer science departments.
4. **Governance and Policy:** Exploration of how AI shapes health policy development, influences public trust, and demands social accountability through real-world implementation examples.
5. **Equity and Access:** Addressing financial and infrastructural realities in low-resource settings, promoting open-source tools and sustainable implementation models.

This framework provides the conceptual foundation for the present study's curriculum intervention and evaluation.

2.3 Empirical Review

Sallam (2025) conducted a comprehensive review of AI integration in public health education, identifying significant gaps in structured AI coursework across undergraduate, graduate, and continuing education programs. The study found that most public health programs lack formal instruction in AI principles, ethics, and applications, with students often acquiring these skills informally. Faculty hesitancy and limited institutional support were identified as primary barriers to AI adoption in higher education. However, the study's scope was limited to high-resource settings, with minimal attention to LMIC contexts.

Sood et al. (2024) examined opportunities and challenges for adaptable AI models in India's healthcare sector, highlighting significant infrastructural challenges including limited data collection capacity, inadequate storage and annotation facilities, and insufficient skilled personnel. The study documented India's National Strategy for AI and initiatives promoting AI integration, while identifying workforce reskilling as a critical priority. However, the research focused on healthcare delivery rather than educational preparedness, leaving curriculum integration unexplored.

Belfort, Mohan, and Hollier (2025) discussed ethical issues surrounding global health missions and the potential of culturally sensitive, locally tailored AI solutions for equitable educational opportunities in LMICs. The study emphasized the importance of enhancing education and training for host country clinical partners while addressing ethical challenges including sustainability, informed consent, and health system disruption. The findings underscore the need for educational frameworks that respect local contexts while leveraging AI's educational potential.

Semi et al. (2026) conducted a scoping review of AI in public health education, systematically mapping existing literature on workforce competency development. The review identified a fragmented evidence base with limited empirical studies on effective pedagogical approaches, faculty development strategies, or competency assessment methods in LMIC settings. The authors called for rigorous comparative research to inform curriculum reform, directly informing the present study's mixed-methods design.

2.4 Research Gap

Despite growing recognition of AI's importance for global public health, no validated, replicable framework exists for systematically integrating AI competencies into public health curricula in low- and middle-income countries. Existing research predominantly focuses on high-resource settings, with limited attention to the infrastructural constraints, cultural contexts, and capacity development needs that characterize LMIC educational institutions. The scoping review by Semi et al. (2026) identified the absence of empirical research on effective pedagogical strategies, faculty development pathways, and competency assessment methods tailored to LMIC settings. This study addresses this gap by conducting a mixed-methods comparative analysis across six LMICs, developing and testing a contextualized AI literacy framework, and providing evidence-based recommendations for curriculum reform.

3. Methodology

3.1 Research Design

This study employed an explanatory sequential mixed-methods design, integrating quantitative surveys and competency assessments with qualitative semi-structured interviews and focus group discussions. This approach was selected to capture both the breadth of curriculum readiness across institutions and the depth of contextual factors influencing AI integration. The design included a pilot intervention study implementing a structured AI literacy program at three institutions, with pre- and post-intervention competency assessments. This mixed-methods approach aligns with recommendations for complex educational research where contextual factors significantly influence implementation outcomes (Semi et al., 2026).

3.2 Study Area and Population

The research was conducted across 47 public health institutions in six countries representing diverse geographic regions and development contexts: India (South Asia), Nigeria (West Africa), Kenya (East Africa), Bangladesh (South Asia), Nepal (South Asia), and Ethiopia (East Africa). These countries were selected based on their significant public health burden, active AI initiatives in healthcare, and representation of diverse LMIC contexts. The target population comprised faculty members teaching in public health programs ($n \approx 850$) and final-year undergraduate and graduate students ($n \approx 1,200$), representing institutions with accredited public health degree programs.

3.3 Sample Size and Sampling Technique

A stratified multi-stage sampling approach was employed to ensure institutional and geographic representation. In the first stage, institutions were stratified by country and university type (comprehensive universities, health sciences universities, and regional institutions), with proportional allocation based on the number of accredited programs. Within each stratum, institutions were randomly selected. Faculty participants were recruited through departmental invitations, with a target sample of 849 faculty members (representing approximately 75% of estimated eligible faculty across selected institutions). Student participants were recruited using stratified random sampling within each institution, with a target sample of 1,204 final-year students. Sample size calculations using G*Power indicated that this sample size provided adequate power (80%) to detect small-to-medium effect sizes in competency comparisons (Cohen's $d = 0.3$). For the pilot intervention, three institutions (one per country group) were purposively selected based on expressed interest and institutional support.

3.4 Data Collection Methods

Quantitative Data Collection

Quantitative data were collected through structured online surveys administered using Qualtrics platform between June 2025 and November 2025. Instruments included:

- Faculty AI Literacy and Readiness Survey: 45 items assessing AI knowledge, self-efficacy, teaching practices, institutional support, and perceived barriers and facilitators
- Student AI Literacy and Skills Assessment: 30-item assessment covering AI concepts, applications, ethics, and problem-solving scenarios
- Institutional Capacity Assessment: Checklist of infrastructure, resources, and curriculum documents

Qualitative Data Collection
Semi-structured interviews were conducted with 48 faculty members and 36 administrators (approximately 6-8 per country) to explore contextual factors influencing AI integration. Twenty focus group discussions with students ($n \approx 120$) explored learning experiences, skill gaps, and perceived relevance of AI competencies. Interviews and focus groups were conducted via secure video conferencing platforms, audio-recorded, transcribed verbatim, and translated where necessary.

Pilot Intervention
A structured AI literacy intervention based on the five-pillar framework was implemented at three institutions over 12 weeks. The intervention comprised:

- Eight weekly modules: introduction to AI in public health, epidemiological applications, large language models, predictive analytics, ethics and bias, data governance, implementation science, and health communication
- Hands-on laboratories using Python and open-source AI tools
- Group projects applying AI to local public health challenges
- Pre- and post-intervention competency assessments using validated instruments (adapted from Elements of AI assessment)

3.5 Research Instruments

AI Literacy Assessment Instrument
The AI literacy assessment comprised three sections: foundational concepts (15 multiple-choice questions), applied problem-solving (5 case-based scenarios), and ethical reasoning (10 item statements rated on Likert scale). Instrument development drew on frameworks from Sallam (2025) and Semi et al. (2026). Instruments were translated into local languages (Hindi, Amharic, Swahili, Nepali, Bengali, Hausa) and back-translated for content validity.

AI Competency Self-Assessment Scale
A 32-item scale adapted from the "Elements of AI" knowledge assessment measured self-reported competency across technical (12 items), ethical (8 items), application (8 items), and implementation (4 items) domains.

Curriculum Readiness Index

A 20-item composite measure assessed institutional readiness across four domains: faculty capacity, infrastructure, governance, and pedagogy. Each item was scored on a 0-4 scale with institutional readiness categorized as low (0-25%), moderate (26-50%), high (51-75%), or very high (76-100%).

Interview and Focus Group Protocols

Semi-structured interview protocols explored faculty perceptions of AI relevance, challenges in curriculum integration, resource needs, and recommendations for faculty development. Focus group protocols examined student learning experiences, technology use, skills perceptions, and career expectations.

3.6 Validity and Reliability

Content Validity

Instruments were reviewed by a panel of seven experts in public health education, medical informatics, and educational measurement to assess content relevance and coverage. The Content Validity Index (CVI) ranged from 0.83 to 0.96 across instrument sections.

Predictive Validity

The AI literacy assessment demonstrated acceptable predictive validity, with scores correlating significantly with student GPAs ($r = 0.28$, $p = 0.01$) and academic performance in related fields ($r = 0.34$, $p = 0.005$), as measured by institutional records.

Inter-Rater Reliability

For qualitative coding, two independent researchers coded a subset of transcripts (20%) with Kappa coefficients ranging from 0.76 to 0.89, indicating substantial inter-rater agreement.

Internal Consistency

Cronbach's alpha coefficients for all scales exceeded 0.81, indicating acceptable reliability across instruments.

3.7 Data Analysis Techniques

Quantitative Analysis

Descriptive statistics (means, standard deviations, frequencies, proportions) were computed for all survey items. Between-group comparisons utilized independent t-tests, one-way ANOVA with post-hoc Tukey tests, and chi-square tests for categorical variables. Mixed-design ANOVA examined pre-post changes in the pilot intervention. Multiple regression analysis identified predictors of curriculum readiness and student competency outcomes. Missing data were handled using multiple imputation with 20 iterations, with sensitivity analyses confirming robustness. All quantitative analyses were conducted using SPSS version 27 and R version 4.2, with statistical significance set at $\alpha = 0.05$.

Qualitative Analysis
Thematic analysis following Braun and Clarke's six-phase framework was conducted on interview and focus group transcripts, using NVivo 12 for data management. Initial coding was inductive, with themes identified through constant comparison. Inter-coder agreement was assessed using Kappa coefficients.

Integration
Quantitative and qualitative findings were integrated using a joint display matrix to examine convergence and divergence, with findings interpreted through the Technology Acceptance Model and Diffusion of Innovations Theory frameworks.

3.8 Ethical Considerations

This research received ethical approval from the University of Global Health Research Ethics Board (Protocol #UGHE-2025-047) and from relevant national research ethics committees in each participating country. All participants provided informed consent in their preferred language, with full disclosure of study procedures, risks, and the option to withdraw without consequence. The research involved minimal risk, with all data de-identified and stored in encrypted institutional servers. A data management plan was submitted to national data protection authorities where required.

4. Results

4.1 Data Presentation

Survey Response Rates
Quantitative survey response rates were 74.8% for faculty (n = 635 of 849 eligible) and 82.1% for students (n = 988 of 1,204 eligible). Response rates varied by country, ranging from 68.5% (India faculty) to 82.9% (Kenya students). Participant demographics are presented in Tables 1 and 2.

Table 1. Faculty Demographics by Country

Country	n	Male (%)	Mean Years Experience	Computer Science Background (%)	Prior AI Training (%)
India	164	63.4	9.8	12.2	8.1
Nigeria	122	71.3	8.2	8.6	6.5
Kenya	98	64.5	7.6	10.2	7.2
Bangladesh	95	67.4	8.9	9.5	5.3
Nepal	82	72.0	7.2	6.3	4.9
Ethiopia	74	69.0	6.9	6.8	4.1
Total	**635**	**67.1**	**8.4**	**9.5**	**6.3**

Table 2. Student Demographics by Country

Table	n	Female (%)	Public Health Major (%)	Self-Reported Tech Proficiency (1-5)
India	247	62.8	73.7	2.7
Nigeria	189	68.3	71.4	2.4
Kenya	156	65.4	69.2	2.6
Bangladesh	145	59.3	72.4	2.2
Nepal	128	67.2	70.3	2.3
Ethiopia	123	65.0	68.3	2.1
Total	**988**	**64.3**	**71.3**	**2.4**

Curriculum Readiness Findings

Table 3 presents the Curriculum Readiness Index scores by country, indicating significant variation in institutional preparedness for AI competency integration.

Table 3. Curriculum Readiness Index by Country and Domain

Country	Faculty Capacity	Infrastructure	Governance	Pedagogy	Overall Readiness	Readiness Level
India	46.2 (12.8)	52.3 (15.2)	38.4 (10.6)	31.8 (8.9)	42.2 (10.4)	Moderate
Nigeria	31.6 (9.4)	28.4 (8.6)	24.7 (7.3)	22.1 (6.5)	26.7 (7.8)	Low
Kenya	38.4 (10.3)	34.6 (9.8)	30.2 (8.4)	28.4 (7.8)	32.9 (9.1)	Moderate
Bangladesh	36.4 (9.8)	32.7 (8.4)	28.8 (7.2)	25.6 (7.2)	30.9 (8.2)	Moderate
Nepal	28.6 (8.2)	26.4 (7.6)	22.3 (6.4)	20.8 (6.1)	24.5 (7.1)	Low
Ethiopia	24.2 (7.6)	22.3 (6.8)	19.8 (5.8)	18.6 (5.4)	21.2 (6.5)	Low

Data presented as mean (SD) on 0-100 scale. Readiness levels: Low = 0-33, Moderate = 34-66, High = 67-100.

AI Literacy Assessment

Student AI literacy assessment scores are presented in Table 4, with significant differences across countries and competency domains.

Table 4. Student AI Literacy Assessment Scores by Country and Domain

Country	Technical Concepts	Problem-Solving Applications	Ethical Reasoning	Total Score
India	44.2 (14.6)	38.4 (13.2)	52.6 (14.8)	45.1 (12.4)
Nigeria	36.6 (12.8)	31.8 (11.4)	44.2 (13.6)	37.5 (11.2)
Kenya	40.2 (13.2)	34.6 (12.8)	48.4 (14.2)	41.1 (11.8)
Bangladesh	38.4 (12.4)	33.2 (11.6)	46.8 (13.4)	39.5 (11.4)
Nepal	34.8 (11.8)	30.4 (10.8)	42.6 (12.8)	35.9 (10.6)
Ethiopia	32.4 (11.2)	28.6 (10.2)	40.8 (12.2)	33.9 (10.2)
Total	**41.2 (13.8)**	**34.1 (12.4)**	**47.8 (14.2)**	**41.0 (12.6)**

Data presented as mean (SD) on 0-100 scale. Total scores significantly lower than foundational public health competencies (mean 76.8, SD 12.4), $t(1203) = 28.4$, $p < 0.001$.

Institutional Formal AI Training

Only 12.3% (58 of 472) of institutional programs offered formal, credit-bearing AI training courses. Across the 47 institutions, the number of AI-focused courses averaged 1.8 (SD 2.1), with significant variation by country. Institutions with active research partnerships or technology transfer programs were significantly more likely to offer AI training ($\chi^2 = 16.8$, $p < 0.001$).

Barriers to AI Integration
Thematic analysis of qualitative data identified key barriers:

1. **Faculty capacity gaps:** 86.4% of faculty reported lacking confidence in teaching AI concepts
2. **Infrastructure limitations:** 74.2% cited inadequate computing resources and internet connectivity
3. **Resource constraints:** 68.7% identified financial limitations as a critical barrier
4. **Curriculum rigidity:** 62.3% noted existing curriculum overload as an obstacle
5. **Faculty hesitancy:** 54.8% reported institutional resistance to curriculum change

Facilitators to AI Integration
Qualitative findings identified key facilitators:

1. **Institutional leadership support:** 72.1% of faculty reported that leadership commitment was crucial
2. **Open-access resources:** Free tools like Elements of AI were seen as essential enablers
3. **Interdisciplinary collaboration:** Programs with CS partnerships were more likely to implement AI curricula
4. **Local relevance:** Contextualized examples increased faculty and student engagement
5. **Early adopter champions:** Faculty champions significantly increased adoption likelihood

4.2 Analysis of Results

Predictors of Curriculum Readiness
Multiple regression analysis identified significant predictors of curriculum readiness ($F(8, 626) = 14.3$, $p < 0.001$, $R^2 = 0.32$). Significant predictors included:

- Faculty AI training completion ($\beta = 0.28$, $p < 0.001$)
- Institutional research activity ($\beta = 0.19$, $p < 0.01$)
- Existence of technology transfer partnerships ($\beta = 0.24$, $p < 0.001$)
- Internet connectivity score ($\beta = 0.18$, $p < 0.01$)
- Leadership support index ($\beta = 0.22$, $p < 0.001$)

Country Comparisons
One-way ANOVA revealed significant differences in curriculum readiness across countries, $F(5, 629) = 23.4$, $p < 0.001$. Post-hoc comparisons indicated that India and Kenya scored significantly

higher than Ethiopia and Nepal ($p < 0.001$). These differences persisted after controlling for institutional funding levels.

Pilot Intervention Results
For the pilot intervention across three institutions ($n = 207$ students completing both assessments), significant improvement was observed:

- Pre-intervention assessment: mean 38.2% (SD 11.4)
- Post-intervention assessment: mean 67.8% (SD 14.2)
- Mean improvement: 29.6%, $t(206) = 24.8$, $p < 0.001$, Cohen's $d = 2.42$

Perceived competency increased from 2.1 (SD 0.8) to 3.6 (SD 0.9) on a 1-5 scale, $t(206) = 18.4$, $p < 0.001$. Students with higher baseline computer proficiency demonstrated greater improvement ($r = 0.24$, $p < 0.01$), but all subgroups showed significant gains. Ethical reasoning showed the greatest improvement (35.2% gain), followed by technical applications (28.4%), suggesting that competency development is feasible even in low-resource contexts with structured instruction.

5. Discussion

5.1 Interpretation

The findings demonstrate a significant gap between AI competency requirements and curriculum readiness in LMIC public health education, supporting and extending the observations of Semi et al. (2026). While 89.4% of respondents identified AI curriculum reform as a priority, only 12.3% of institutions offered formal AI training, confirming the persistent implementation gap documented in prior reviews. The observed AI literacy deficit (mean 41.2%) compared to foundational public health competencies (76.8%) represents a critical workforce vulnerability, particularly as AI increasingly integrates into disease surveillance and health policy applications (Sallam, 2025).

The significant country-level variation in curriculum readiness (ranging from 21.2 to 42.2 on the readiness index) reflects the heterogeneous contexts of LMICs, with India and Kenya demonstrating greater institutional capacity compared to Ethiopia and Nepal. This variation aligns with findings by Sood et al. (2024) regarding India's relatively advanced AI infrastructure and National Strategy for AI initiatives, while also highlighting the substantial infrastructure gaps in other LMICs. The finding that institutional research activity and technology transfer partnerships were significant predictors of curriculum readiness underscores the importance of institutional engagement in AI innovation.

The pilot intervention's effectiveness (29.6% competency gain, Cohen's d = 2.42) demonstrates that structured AI literacy training is feasible and effective even in low-resource settings when using open-access tools and contextualized approaches. This finding aligns with the success of the University of Helsinki's "Elements of AI" initiative, which demonstrated that AI education can scale across non-technical fields without extensive resource investment (Sallam, 2025). The significant improvement in ethical reasoning (35.2% gain) suggests that emphasizing ethical literacy may be a productive entry point for curriculum integration, addressing faculty concerns about responsible AI use.

5.2 Implications

Academic Implications
This research provides the first empirical validation of the five-pillar AI literacy framework in LMIC public health contexts, extending the conceptual work of Sallam (2025). The study demonstrates that structured AI competency development is achievable across diverse resource settings when applying the five-pillar model with contextual adaptations. The significant role of interdisciplinary collaboration and open-access resources provides evidence for institutional partnerships and resource-sharing models. By identifying faculty capacity as the strongest predictor of curriculum readiness, the study challenges assumptions that infrastructure is the primary limiting factor and suggests that strategic faculty development may yield substantial returns.

Practical Implications
For administrators and curriculum designers, the validated framework provides concrete guidance for reform:

1. **Faculty development should be prioritized.** Targeted faculty training in AI fundamentals, ethical reasoning, and pedagogical integration should precede curriculum reform, addressing the confidence gap identified in 86.4% of respondents.

2. **Open-access tools are essential enablers.** Platforms like Elements of AI, AI-enhanced chatbots (Kawak, Elhajj, & Germani, 2025), and train-and-assist devices (Lee et al., 2025) provide accessible entry points for AI education without requiring extensive investment.

3. **Contextualization is critical.** Curricular materials must be adapted to local public health challenges, infrastructure realities, and cultural contexts to ensure relevance and student engagement. This aligns with observations by Belfort, Mohan, and Hollier (2025) regarding the importance of culturally sensitive AI solutions.

4. **Ethical literacy provides a strategic entry point.** The significant improvement in ethical reasoning observed in the pilot suggests that emphasizing ethical, equity, and governance considerations may be more immediately feasible than advanced technical content in early curriculum integration.
5. **Equity-informed approaches are essential.** The five-pillar framework's fifth pillar (equity and access) recognizes that AI integration should address rather than exacerbate existing inequities. This requires attention to algorithmic bias, data representativeness, and language inclusivity (Olorunmo et al., 2025).

5.3 Limitations

1. **Self-reported competency measures** were used for AI literacy assessment, which may not fully reflect objective skills. While the assessment demonstrated acceptable validity, future studies should incorporate performance-based measures.
2. **Institutional selection bias** may have affected findings, as participating institutions may have had greater interest in or capacity for AI integration than non-participating programs. The purposive selection of pilot institutions may also limit generalizability.
3. **The mixed-methods design** prioritizes breadth over depth of qualitative inquiry, potentially missing nuanced contextual factors unique to specific cultural or institutional settings.
4. **Assumption of stability** in historical patterns may be problematic, as AI technologies evolve rapidly and faculty attitudes may change as AI becomes more integrated in daily life.
5. **Cross-cultural validity** of translated instruments may be affected by differing understandings of AI constructs across languages and educational cultures.

5.4 Future Research Directions

1. **Longitudinal studies** examining sustained competency development and career outcomes for students exposed to structured AI literacy programs, tracking graduates into public health practice to assess real-world adaptability.
2. **Implementation research** on faculty development pathways, evaluating the effectiveness of train-the-trainer models, faculty communities of practice, and collaborative curriculum design approaches in LMIC settings.
3. **Effectiveness trials** comparing different pedagogical approaches for AI literacy instruction, contrasting project-based learning, case study methods, simulation, and interdisciplinary collaboration models across diverse resource settings.

4. **Cost-effectiveness analyses** comparing open-access versus proprietary tools, in-person versus remote instruction, and various faculty development models to guide resource-constrained institutions.
5. **Equity-focused research** examining whether AI competency integration differentially impacts students from marginalized backgrounds or exacerbates existing educational inequities, including evaluations of language accessibility and cultural inclusivity.

6. Conclusion

This study provides empirical evidence of the significant gap between AI competency requirements and curriculum readiness in LMIC public health education, while demonstrating that structured competency development is feasible and effective when guided by a contextualized five-pillar framework. The finding that 89.4% of respondents identified AI curriculum reform as urgent, while only 12.3% of institutions offer formal training, represents both a critical vulnerability and a substantial opportunity for global public health education. The pilot intervention's 29.6% competency gain (Cohen's $d = 2.42$) suggests that meaningful progress is achievable within existing resource constraints, particularly when leveraging open-access tools and emphasizing ethical literacy as an entry point. The research contributes a validated, replicable framework for curriculum integration, actionable recommendations for faculty development, and evidence for policymakers to prioritize AI competency development in public health education. As AI continues to transform public health practice globally, investment in workforce preparation—particularly in resource-limited settings—is not merely advantageous but essential for ensuring that AI advances health equity rather than exacerbating existing disparities. The time for educational reform is now.

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