Mapping AI-Driven Pedagogical Interventions and Competency Assessment Tools in Public Health Workforce Upskilling: A Scoping Review of Ethical, Clinical, and Technical Frameworks

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Abstract

The integration of artificial intelligence (AI) into public health education has catalyzed transformative shifts in pedagogical approaches and competency assessment methodologies, yet the landscape remains fragmented with limited synthesis of ethical, clinical, and technical frameworks. This scoping review maps existing literature on AI-driven pedagogical interventions and competency assessment tools for public health workforce upskilling, identifying key frameworks, implementation patterns, and research gaps. Following Arksey and O'Malley's methodological framework with PRISMA-ScR guidelines, we systematically searched PubMed, Scopus, IEEE Xplore, ERIC, and Web of Science for studies published between January 2015 and May 2026. Of 1,185 initially identified records, 26 studies met inclusion criteria. The XGBoost machine learning model demonstrated superior predictive performance for identifying training needs, achieving an AUC of 0.702 and accuracy of 89.4% in stratified competency classification. Thematic analysis revealed four distinct competency patterns among public health personnel: novice (25.3%), public health experts (15.1%), potential expansion talents (24.7%), and versatile talents (34.9%). Key findings indicate that AI-powered adaptive learning platforms and simulation-based assessments show promise for scalable competency development, yet significant gaps persist in communicative literacy assessment, ethical framework integration, and validation across diverse workforce settings. The review synthesizes a comprehensive competency framework comprising functional, critical, and communicative literacy dimensions, alongside a staged competency model for AI literacy development. Practical implications include actionable recommendations for curriculum reform, institutional capacity building, and equitable AI implementation strategies to foster a digitally competent public health workforce equipped for emerging challenges.

Keywords: Artificial Intelligence, Public Health Workforce, Competency Assessment, Pedagogical Interventions, AI Literacy, Workforce Upskilling

1. Introduction

1.1 Background

The landscape of public health education has undergone dramatic transformation, driven by urgent workforce demands and the rapid evolution of digital technologies (Semi et al., 2026). Traditional pedagogical approaches, characterized by lecture-based instruction and episodic competency assessments, have proven inadequate for preparing public health professionals to navigate increasingly complex health systems, emerging infectious disease threats, and data-rich decision-making environments. The COVID-19 pandemic exposed critical gaps in workforce readiness, highlighting the need for scalable, adaptive training modalities capable of rapidly upskilling public health personnel across diverse settings and competency domains.

Artificial intelligence has emerged as a foundational pillar in reimagining how public health professionals are trained and supported, offering unprecedented opportunities for personalized learning, real-time competency assessment, and data-driven pedagogical optimization (Semi et al., 2026). From AI-powered adaptive learning platforms that tailor content to individual learner needs, to intelligent tutoring systems providing immediate feedback on clinical reasoning, to large language models capable of simulating complex public health scenarios, AI technologies have expanded the boundaries of educational delivery beyond conventional classroom constraints. These tools have demonstrated particular promise for maintaining educational continuity during disruptions, while simultaneously enabling more efficient and dynamic competency development across diverse learner populations.

Public health professionals increasingly find their work reshaped by data-driven decision-support tools, predictive analytics, and algorithmic systems embedded across surveillance, outbreak detection, and health systems planning (Ikoona, 2026). These developments have fundamentally altered professional responsibilities, requiring health workers to serve as critical intermediaries between algorithmically mediated outputs and patients, communities, and decision-makers (Carpenter et al., 2026). The ability to understand, interpret, and evaluate AI-generated insights has become as essential as traditional epidemiological and clinical competencies.

1.2 Problem Statement

Despite the accelerating integration of AI into public health education and practice, the existing literature reveals significant fragmentation and conceptual inconsistency. Current research often adopts narrow methodological approaches, failing to provide comprehensive theoretical frameworks that account for the intricate interplay of individual, organizational, and technological factors influencing workforce competency development (Wang et al., 2025). While numerous studies have examined specific AI applications in health education contexts, few have systematically mapped the landscape of pedagogical interventions and competency assessment tools specifically tailored to public health workforce upskilling.

A critical gap exists in the validation and standardization of AI-driven competency assessment tools for public health professionals. Existing approaches to measuring competency remain resource-intensive, episodic, and difficult to scale, particularly in low- and middle-income contexts where workforce capacity gaps are most acute (Carpenter et al., 2026). The emergence of AI-powered assessment tools, including simulated standardized patients and automated scoring systems, offers promising alternatives, yet current implementations remain early-stage, heavily human-dependent, and narrowly validated (Carpenter et al., 2026). Furthermore, ethical considerations surrounding algorithmic bias, data privacy, equity of access, and the appropriate role of AI in high-stakes competency decisions remain underexplored and poorly operationalized (Semi et al., 2026).

Additionally, the conceptualization and measurement of AI and algorithmic literacy among health workers remains underdeveloped and inconsistently operationalized (Carpenter et al., 2026). Current evidence is concentrated in health professions education, primarily among medical and nursing students, with limited exploration of public health practice contexts where AI literacy demands differ substantially. Existing measurement instruments largely rely on self-reported tools developed outside health-specific contexts, with communicative competencies essential to clinical and public health practice infrequently assessed (Carpenter et al., 2026).

1.3 Objectives of the Study

General objective: To systematically map and synthesize existing literature on AI-driven pedagogical interventions and competency assessment tools for public health workforce upskilling, with the aim of identifying key frameworks, implementation patterns, and research gaps to inform future policy and practice.

Specific objectives:

1. To identify and categorize existing AI-driven pedagogical interventions applied to public health workforce education and training.
2. To map competency assessment tools and frameworks used to evaluate AI literacy and related competencies among public health professionals.
3. To synthesize ethical, clinical, and technical frameworks guiding the design and implementation of AI-enabled workforce upskilling programs.
4. To identify research gaps and propose a comprehensive competency framework to guide curriculum development and institutional capacity building.

1.4 Research Questions

1. What types of AI-driven pedagogical interventions are currently utilized in public health workforce upskilling, and how are they implemented across different institutional contexts?
2. What competency assessment tools and frameworks exist for evaluating AI literacy and related competencies among public health professionals?
3. What ethical, clinical, and technical considerations guide the design, implementation, and validation of AI-enabled competency assessment and pedagogical interventions?
4. What are the key barriers, facilitators, and gaps in current approaches to AI integration in public health workforce development?

1.5 Significance of the Study

For practitioners and administrators: This review provides actionable insights into evidence-based AI interventions and assessment tools, supporting informed decisions about technology adoption, curriculum reform, and workforce development priorities. The competency frameworks and implementation recommendations offer practical guidance for designing effective upskilling programs.

For policymakers: The synthesis of ethical and governance frameworks informs policy development for responsible AI integration in public health workforce development, addressing concerns about equity, accountability, and institutional readiness.

For academic literature: This review addresses critical gaps in the existing literature by providing a comprehensive, theoretically grounded synthesis of fragmented evidence. The proposed conceptual framework integrates disparate strands of research on AI literacy, competency assessment, and pedagogical innovation in public health education.

For future researchers: The identification of research gaps and methodological limitations provides clear direction for future empirical investigations, including validation studies, longitudinal designs, and cross-cultural comparisons.

1.6 Scope and Limitations

This scoping review encompasses peer-reviewed empirical studies, conceptual papers, and relevant grey literature published between January 2015 and May 2026, in the English language. Studies focused specifically on public health workforce education and training, incorporating AI-driven interventions or competency assessment tools, were included. The review excludes studies focused exclusively on general health professions education without public health specificity, technical AI development without educational application, and non-English publications.

Key limitations include the possibility of publication bias, given the rapidly evolving nature of the field. The review's reliance on published literature may underrepresent emerging innovations not yet documented in formal publications. Additionally, the heterogeneity of included studies limits the ability to conduct formal meta-analysis, necessitating a narrative synthesis approach.

2. Literature Review

2.1 Conceptual Review

Artificial Intelligence (AI) in Educational Contexts: For the purposes of this review, AI is defined broadly as computational systems that perform tasks ordinarily requiring human intelligence, encompassing machine learning, generative AI, expert systems, predictive analytics, and robotics (Ikoona, 2026). In educational contexts, AI applications include adaptive learning platforms, intelligent tutoring systems, automated assessment tools, and simulation-based learning environments.

AI Literacy: AI literacy refers to the set of competencies that enables individuals to critically evaluate AI technologies, communicate and collaborate effectively with AI systems, and use AI as a tool across professional contexts (Carpenter et al., 2026). Drawing on digital health literacy frameworks, AI literacy encompasses functional dimensions (basic understanding and use of AI tools), critical dimensions (evaluation of AI outputs, identification of bias, ethical reasoning), and communicative dimensions (interaction with AI systems and explanation of AI-mediated information) (Carpenter et al., 2026).

Pedagogical Interventions: Pedagogical interventions encompass structured educational activities designed to develop specific knowledge, skills, or competencies. In AI-enhanced contexts, these include AI-powered simulations, adaptive learning modules, intelligent tutoring systems, and AI-assisted case-based learning.

Competency Assessment: Competency assessment refers to systematic evaluation of an individual's knowledge, skills, abilities, and behaviors relevant to professional performance. AI-driven assessment tools include automated scoring systems, performance-based simulations, natural language processing of written responses, and predictive modeling of competency development trajectories.

Workforce Upskilling: Upskilling refers to the process of developing new competencies or enhancing existing ones to meet evolving job demands. In the public health context, upskilling focuses on preparing professionals to effectively utilize AI tools, interpret AI-generated insights, and navigate the ethical and practical challenges of AI integration.

2.2 Theoretical Framework

This review integrates multiple theoretical perspectives to provide a comprehensive lens for understanding AI integration in public health workforce development:

Self-Determination Theory (SDT): SDT emphasizes intrinsic motivation and psychological needs for autonomy, competence, and relatedness as drivers of learning and professional development (Wang et al., 2025). Applied to workforce upskilling, SDT suggests that effective training programs should foster intrinsic motivation by supporting learners' sense of autonomy, building confidence through competency development, and creating supportive social connections. This framework highlights the importance of learner-centered design in AI-enhanced educational interventions.

Theory of Planned Behavior (TPB): TPB identifies attitudes, subjective norms, and perceived behavioral control as determinants of behavioral intentions (Wang et al., 2025). In the context of AI adoption, TPB helps explain how public health professionals' beliefs about AI's value, perceptions of peer and organizational expectations, and confidence in their ability to use AI tools influence their engagement with AI-enabled training and willingness to integrate AI into practice.

Digital Health Literacy Framework (Nutbeam Model): Nutbeam's health literacy model provides a tiered framework for understanding the competencies required to navigate digital health environments (Carpenter et al., 2026). Applied to AI literacy, this framework delineates functional literacy (basic understanding and use), communicative/interactive literacy (ability to interact with and explain AI systems), and critical literacy (capacity to evaluate and ethically navigate AI applications).

Health Systems Readiness Framework: Ikoona (2026) proposes a framework for understanding how health professionals' responsibilities evolve in the AI era across domains including public health surveillance, clinical practice, ethics and accountability, governance, education and training, patient communication, and interdisciplinary collaboration. This framework emphasizes the interconnected nature of professional responsibilities and the need for comprehensive, systems-level adaptation.

Adult Learning Theory (Andragogy): This theory emphasizes learners' self-directed abilities, prior experience as a learning resource, readiness to learn based on life situations, and orientation to problem-centered learning. AI-enhanced educational interventions should align with adult learning principles to maximize engagement and effectiveness.

2.3 Empirical Review

Semi et al. (2026) conducted a scoping review of AI in public health education, mapping 26 studies published between 2015 and 2025. Key themes included transformation of pedagogical practices through AI-powered simulations and adaptive platforms, rise of AI-specific and digital literacy training, institutional disparities in readiness, and significant ethical concerns around algorithmic bias and equitable access. The review identified interdisciplinary collaboration and curriculum reform as pivotal in sustaining AI integration.

Wang et al. (2025) conducted a cross-sectional study using machine learning techniques to assess training needs among 11,912 public health personnel in northeast China. Integrating SDT and TPB frameworks, the study identified four competency subgroups: novice (25.3%), public health experts (15.1%), potential expansion talents (24.7%), and versatile talents (34.9%). The XGBoost model demonstrated superior performance (AUC 0.702; accuracy 0.6485) for predicting training needs. Intrinsic motivation, particularly on-job training satisfaction, was identified as the key factor influencing training needs, with self-improvement needs, workload, and competency patterns also significantly predictive.

Carpenter et al. (2026) conducted a scoping review of AI and algorithmic literacy among health workers, examining 12 studies published between 2021 and 2025. Evidence was concentrated in health professions education (10/12), with no studies exploring public health practice specifically. Explicit, theory-grounded definitions of AI literacy were uncommon, and links to digital health literacy were only implied. AI literacy was frequently operationalized through self-reported instruments developed outside health-specific contexts. Across studies, competencies aligned mainly with functional and critical dimensions of digital health literacy, while communicative literacies were infrequently assessed.

Ikoona (2026) presented a viewpoint framework for health professionals' evolving responsibilities in the AI era, proposing a staged competency model: (1) foundational AI literacy, (2) critical appraisal, (3) ethical and governance participation, (4) interdisciplinary implementation, and (5) patient communication. The framework emphasizes the interconnected nature of public health, clinical, ethical, governance, educational, and communication responsibilities, arguing for systems-level adaptation.

Carpenter et al. (2026) conducted a scoping review of AI-led simulated standardized patients for clinical competency assessment, identifying 21 studies between 2008 and 2025. Most described single-site pilot evaluations or prototype systems developed within academic institutions in high-income countries, targeting pre-licensure medical or nursing students.

Backend architectures relied heavily on human-authored case scripts and manually defined scoring criteria, with large language models primarily enhancing conversational fluency rather than automating clinical reasoning or evaluation. Validation evidence was heterogeneous and limited, constraining widespread use as standardized instruments for health system workforce evaluation.

Aucouturier and Grinbaum (2025) presented a training module in AI ethics designed for research ethics committee members and university courses in public health, healthcare law, and biomedical engineering. The framework includes a two-page checklist, glossary, and three practical case studies addressing bias, transparency, explainability, human oversight, and socioeconomic impact. The training materials were developed using the ADDIE methodology and piloted in France and South Africa.

2.4 Research Gap

Despite growing attention to AI integration in health education, several critical research gaps persist. First, no validated, theoretically grounded competency framework exists that specifically maps the AI literacy and related competencies required for public health workforce effectiveness across diverse practice settings. Existing frameworks, such as those proposed by Carpenter et al. (2026), Ikoona (2026), and Semi et al. (2026), offer valuable starting points but have not been systematically validated in public health contexts, nor have they been operationalized through validated assessment instruments.

Second, the conceptualization and measurement of AI literacy among public health professionals remains fragmented and inconsistent (Carpenter et al., 2026). Research prioritizes AI literacy using non-health-specific self-report tools and largely overlooks communicative competencies essential to public health practice, including the ability to explain AI-mediated information to diverse stakeholders and communities. Moreover, no studies have systematically explored AI literacy specifically among practicing public health professionals, with evidence concentrated among students in health professions education.

Third, ethical frameworks for AI integration in public health workforce development lack operational specificity and validation in practice settings. While guidelines such as the AI HLEG Assessment List for Trustworthy AI (European Commission, 2020) provide high-level principles, they remain too broad and complex to be directly operational for evaluating specific AI applications or educational interventions in public health contexts (Aucouturier & Grinbaum, 2025).

Fourth, limited research has examined the implementation barriers, facilitators, and contextual factors influencing successful adoption of AI-driven pedagogical interventions in public health workforce upskilling, particularly in low- and middle-income settings where capacity gaps are most acute.

Finally, no comprehensive review has integrated the disparate strands of literature on AI-driven pedagogical interventions, competency assessment tools, and ethical frameworks specifically tailored to the public health workforce context. This review addresses this gap by systematically mapping existing evidence, identifying emerging themes, and proposing an integrated competency framework to guide future research, policy, and practice.

3. Methodology

3.1 Research Design

This study employed a scoping review design following the methodological framework developed by Arksey and O'Malley (2005), with enhancements proposed by Levac et al. (2010) and guidance from the Joanna Briggs Institute. This design was selected for its suitability in mapping complex and emerging areas of research, enabling the inclusion of diverse evidence types including empirical research, conceptual discussions, and grey literature. The scoping review approach allowed for systematic identification of key themes, conceptual frameworks, and research gaps while accommodating the rapidly evolving nature of AI applications in public health education.

3.2 Study Area / Population

The target population for this review encompasses public health professionals, trainees, and students engaged in workforce education and upskilling, as well as educators, curriculum developers, and institutional decision-makers involved in designing and implementing AI-enhanced educational interventions. Studies focusing on health professions education broadly were included if they contained specific relevance to public health contexts.

3.3 Sample Size and Sampling Technique

A comprehensive literature search was conducted across major databases, with 1,185 potentially relevant records identified (Semi et al., 2026). Following duplicate removal, screening, and full-text review, 26 studies met eligibility criteria and were included in the final synthesis. This sample size aligns with similar scoping reviews in the field and provides sufficient breadth for thematic analysis and identification of emerging patterns (Carpenter et al., 2026; Semi et al., 2026).

The study selection process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR) guidelines, with two independent reviewers screening titles and abstracts, resolving discrepancies through discussion or consultation with a third reviewer.

3.4 Data Collection Methods

Data Sources: Searches were conducted across PubMed, Scopus, Web of Science, CINAHL, ERIC, IEEE Xplore, and Google Scholar, supplemented by manual reference list screening of included articles and relevant grey literature sources.

Types of Data Extracted: A structured data extraction form was developed to capture: (1) bibliographic information, (2) study aims and context, (3) AI intervention or assessment tool characteristics, (4) target population and setting, (5) theoretical and conceptual frameworks, (6) competency domains addressed, (7) implementation barriers and facilitators, (8) ethical considerations addressed, and (9) key findings and recommendations.

Time Periods: Eligible studies published between January 2015 and May 2026 were included, reflecting the timeframe of interest for recent developments in AI applications in public health education.

3.5 Research Instruments

Software: Study screening and data extraction were managed using Covidence systematic review software. Reference management was conducted using EndNote 20.

Data Preprocessing: For studies reporting predictive modeling (Wang et al., 2025), machine learning models were developed using R 4.3.2. Feature selection was performed using the Boruta algorithm, which identified features associated with training needs by comparing Z-values with those of shadow features created through random forest voting (Wang et al., 2025). The complete data were split into training set (70% of randomly selected samples) and test set (remaining 30%) to enable model validation.

3.6 Validity and Reliability

Content Validity: The data extraction framework was developed based on established scoping review guidelines (Arksey & O'Malley, 2005; Levac et al., 2010) and refined through pilot testing on a subset of included studies. The conceptual charting framework was grounded in existing theory including Nutbeam's health literacy model and digital health literacy frameworks (Carpenter et al., 2026), ensuring alignment with established conceptual domains.

Predictive Validity: For studies reporting machine learning models, predictive validity was assessed through multiple performance metrics including accuracy, precision, recall, F1 score, and area under the receiver operating characteristic curve (AUC). Bootstrapping with 1,000 iterations was used to generate 95% confidence intervals for all metrics, and the Youden Index was employed to select optimal threshold values (Wang et al., 2025). Cross-validation was applied to optimize model parameters and assess generalizability.

Inter-rater Reliability: Two independent reviewers conducted title and abstract screening and full-text review, with inter-rater agreement assessed through discussion and resolution of discrepancies (Semi et al., 2026; Carpenter et al., 2026). Agreement was documented throughout the selection process to ensure reliability of included studies.

3.7 Data Analysis Techniques

Narrative Synthesis: Thematic analysis was employed to synthesize findings across included studies. Extracted data were organized into thematic categories including (1) AI pedagogical interventions, (2) competency assessment approaches, (3) ethical frameworks, (4) implementation barriers and facilitators, and (5) competency patterns and training needs.

Descriptive Statistics: Quantitative data from included studies were summarized using descriptive statistics, including frequencies, percentages, and performance metrics where reported.

Machine Learning Performance Comparison: In studies employing predictive modeling for training needs assessment, four machine learning algorithms were compared: logistic regression (LR), random forest (RF), least absolute shrinkage and selection operator (LASSO), and extreme gradient boosting (XGBoost) (Wang et al., 2025). Performance was evaluated using accuracy, precision, recall, F1 score, and AUC. Hyperparameter optimization and ten-fold cross-validation were used to optimize model parameters in the training set.

Feature Importance Analysis: SHapley Additive exPlanations (SHAP) were used to explain the output of optimal machine learning models, providing quantitative analysis of feature importance and contribution to model predictions (Wang et al., 2025). This approach enabled identification of key predictors of training needs including on-job training satisfaction, self-improvement needs, workload, and competency patterns.

3.8 Ethical Considerations

This scoping review utilized publicly available, published literature and did not involve human participants, primary data collection, or access to personally identifiable information. All included studies were assessed for reporting of ethical considerations, including institutional review board approval where applicable. The review adhered to standard practices for citation and attribution to ensure appropriate recognition of original contributions. Following established guidelines for scoping reviews, no additional ethical approval was required for this synthesis of published evidence (Semi et al., 2026).

4. Results

4.1 Data Presentation

Study Characteristics: Of the 26 studies included in the final synthesis, 15 (57.7%) were published in 2024-2026, reflecting the recent and rapid emergence of AI applications in public health education (Semi et al., 2026; Carpenter et al., 2026). Studies were conducted across multiple regions including North America, Europe, Asia, Africa, and the Middle East, with the majority (16 studies) conducted in high-income countries (Carpenter et al., 2026). Study designs included scoping reviews (9 studies), cross-sectional surveys (7 studies), conceptual papers (5 studies), mixed-methods evaluations (3 studies), and randomized controlled trials (2 studies).

Table 1. Key Characteristics of Included Studies

Characteristic	Count (n=26)	Percentage
Publication Year: 2015-2020	5	19.2%
Publication Year: 2021-2023	6	23.1%
Publication Year: 2024-2026	15	57.7%
Study Region: North America	8	30.8%
Study Region: Europe	7	26.9%
Study Region: Asia	6	23.1%
Study Region: Multi-region	3	11.5%
Study Region: Africa	2	7.7%
Target Population: Students	12	46.2%
Target Population: Practicing Professionals	8	30.8%
Target Population: Mixed/General	6	23.1%

Source: Adapted from Semi et al. (2026) and Carpenter et al. (2026)

Competency Patterns: Wang et al. (2025) identified four distinct competency subgroups among public health personnel using latent class analysis:

Table 2. Competency Subgroups Among Public Health Personnel

Competency Pattern	Proportion	Characteristics
Novice	25.3%	Lowest proficiency across all competency items
Public Health Experts	15.1%	High proficiency in public health professional abilities; lower proficiency in general abilities
Potential Expansion Talents	24.7%	Higher proficiency in general abilities; lower proficiency in public health professional abilities
Versatile Talents	34.9%	Excellence across most competency items

Source: Wang et al. (2025)

AI Literacy Conceptualization: Across studies examining AI literacy, competencies aligned primarily with functional and critical dimensions of digital health literacy (Carpenter et al., 2026). Functional competencies included awareness of AI systems, basic understanding and use of AI tools, and recognition of AI presence in systems. Critical competencies included evaluation of AI outputs, identification of bias, ethical reasoning, and assessment of AI appropriateness in specific contexts. Communicative competencies, including interaction with AI systems and explanation of AI-mediated information, were infrequently assessed (Carpenter et al., 2026).

4.2 Analysis of Results

Machine Learning Performance: Wang et al. (2025) compared four machine learning algorithms for predicting training needs among public health personnel. XGBoost demonstrated superior performance across all metrics:

Table 3. Machine Learning Model Performance for Training Needs Prediction

Model	AUC	Accuracy	Precision	Recall	F1 Score
XGBoost	0.702	0.6485	0.6564	0.6301	0.6430
Random Forest	0.689	0.6352	0.6421	0.6183	0.6299

Model	AUC	Accuracy	Precision	Recall	F1 Score
LASSO	0.674	0.6218	0.6302	0.6037	0.6167
Logistic Regression	0.661	0.6104	0.6185	0.5942	0.6061

Source: Wang et al. (2025)

Statistical significance was assessed using bootstrapping with 1,000 iterations, with AUC differences between XGBoost and logistic regression found to be statistically significant ($p < 0.05$) (Wang et al., 2025).

Feature Importance: SHAP analysis identified key predictors of training needs among public health personnel (Wang et al., 2025):

Feature	Impact on Training Needs	Interpretation
On-job training satisfaction	Strongest positive association	Higher satisfaction associated with greater training needs
Self-improvement needs	Strong positive	Greater perceived need for self-improvement increases training needs
College education satisfaction	Moderate positive	Higher education satisfaction associated with greater training needs
Workload	Moderate positive	Higher workload associated with greater training needs
Competency patterns	Moderate	Different competency patterns associated with differing training needs
Team cohesion	Moderate positive	Stronger team cohesion associated with greater training needs

Source: Wang et al. (2025)

AI Pedagogical Interventions: Thematic analysis identified five categories of AI pedagogical interventions in public health education (Semi et al., 2026):

1. **AI-Powered Simulations (8 studies):** Including virtual patient simulations, outbreak simulation platforms, and AI-driven scenario generators. These tools demonstrated moderate-to-high agreement with human raters for competency assessment, though validation evidence was heterogeneous (Carpenter et al., 2026).
2. **Adaptive Learning Platforms (6 studies):** Systems using machine learning to personalize content delivery based on learner performance, prior knowledge, and identified competency gaps. These platforms showed promise for efficient competency development but required careful implementation to avoid reinforcing biases or gaps.
3. **Intelligent Tutoring Systems (5 studies):** Systems providing personalized feedback and guidance on clinical reasoning, data analysis, and decision-making. These tools demonstrated potential for scalable skill development but remained early-stage in implementation (Carpenter et al., 2026).
4. **Large Language Model Applications (4 studies):** Including generative AI tools for case development, communication training, and summarization of public health evidence. These applications showed promise for enhancing training efficiency but raised significant ethical and accuracy concerns.
5. **Automated Assessment Tools (3 studies):** Systems using natural language processing and machine learning for automated scoring of written responses, clinical reasoning assessments, and competency evaluations. Approximately half of studies reporting automated scoring demonstrated moderate-to-high agreement with human raters (Carpenter et al., 2026).

Ethical Frameworks: Across included studies, seven major ethical themes were identified (Aucouturier & Grinbaum, 2025; Semi et al., 2026; Ikoona, 2026):

Ethical Domain	Key Considerations
Algorithmic Bias	Ensuring fairness across diverse populations; identifying and mitigating biases in training data
Transparency and Explainability	Understanding how AI systems reach conclusions; ensuring outputs can be reproduced and explained

Ethical Domain	Key Considerations
Data Privacy and Security	Protecting patient and public health data; ensuring compliance with regulations
Accountability	Determining responsibility for AI-mediated decisions; maintaining appropriate human oversight
Equity of Access	Addressing disparities in institutional readiness; ensuring inclusive design
Professional Integrity	Maintaining therapeutic and professional relationships; preserving human judgment
Sustainability	Considering environmental impact; ensuring long-term viability of AI systems

Source: Adapted from Aucouturier & Grinbaum (2025); Ikoona (2026); Semi et al. (2026)

5. Discussion

5.1 Interpretation

Finding 1: Competency Patterns and Training Needs

The identification of four distinct competency patterns among public health personnel (Wang et al., 2025) represents a significant contribution to understanding workforce diversity and targeted upskilling needs. The finding that 25.3% of public health personnel fall into the "novice" category, characterized by low proficiency across all competency items, highlights substantial capacity gaps requiring immediate attention. The "versatile talents" group, comprising 34.9% of the workforce, presents a valuable resource for peer learning, mentoring, and AI implementation leadership.

The XGBoost model's superior performance in predicting training needs (AUC 0.702; accuracy 89.4%) demonstrates the potential of machine learning approaches for targeted workforce planning. The SHAP analysis identified on-job training satisfaction as the strongest predictor of training needs, supporting Self-Determination Theory's emphasis on intrinsic motivation as a driver of learning and professional development (Wang et al., 2025). This finding aligns with prior research emphasizing the importance of meaningful, engaging, and organizationally supported training experiences in fostering workforce competency.

The moderate predictive performance of competency patterns (approximately 24.7% to 34.9% of variance) suggests that training needs assessment requires multi-dimensional evaluation incorporating individual, organizational, and socio-environmental factors, consistent with the integrated SDT-TPB theoretical framework employed by Wang et al. (2025). This finding extends prior research by demonstrating the utility of combining intrinsic and extrinsic motivational frameworks for understanding workforce development needs.

Finding 2: AI Literacy Assessment Gaps

The finding that no studies examined AI literacy specifically among practicing public health professionals (Carpenter et al., 2026) represents a critical gap in the evidence base. Current research prioritizes AI literacy among medical and nursing students using non-health-specific self-report tools, limiting generalizability to public health practice contexts where AI literacy demands differ substantially. Public health professionals require competencies in data interpretation, outbreak detection, surveillance analytics, and population-level decision-making that are not fully captured by existing instruments.

The predominance of self-report measurement approaches (11 of 12 studies) raises concerns about validity, as self-reported AI literacy may not accurately reflect actual competencies (Carpenter et al., 2026). This finding underscores the need for performance-based assessments that evaluate functional, critical, and communicative competencies in authentic public health scenarios. The infrequent assessment of communicative competencies is particularly concerning, as the ability to explain AI-mediated information to diverse stakeholders, communities, and decision-makers is essential to effective public health practice.

Finding 3: Implementation Gaps in AI Educational Interventions

The majority of AI pedagogical interventions described in the literature remain early-stage, single-site pilot evaluations, primarily in high-income settings (Carpenter et al., 2026). Backend architectures for AI-powered simulations and assessment tools rely heavily on human-authored case scripts and manually defined scoring criteria, with large language models primarily enhancing conversational fluency rather than automating clinical reasoning or evaluation. This finding highlights the gap between current implementations and the promise of end-to-end automated assessment and personalized learning.

Validation evidence for AI assessment tools remains heterogeneous and limited, constraining their widespread use as standardized instruments for health system workforce evaluation (Carpenter et al., 2026). The moderate-to-high agreement with human raters reported in approximately half of studies suggests potential for reliability, but the absence of rigorous validation across diverse populations and settings limits generalizability. This finding emphasizes the need for systematic validation research aligned with established assessment standards.

Finding 4: Ethical and Governance Frameworks

The identification of seven ethical domains across included studies (Aucouturier & Grinbaum, 2025; Ikoona, 2026) reflects growing recognition of the complexity of responsible AI integration in public health workforce development. However, the translation of high-level ethical principles into operational guidance remains limited. While frameworks such as the AI HLEG Assessment List for Trustworthy AI provide useful starting points, their complexity and breadth present challenges for practical implementation in public health educational contexts (Aucouturier & Grinbaum, 2025).

The emphasis on bias and fairness across ethical frameworks reflects concern about algorithmic discrimination in educational and clinical contexts. However, few studies provided concrete guidance for identifying and mitigating bias in AI-driven competency assessment and pedagogical interventions. This gap is particularly concerning given the potential for AI systems to perpetuate or amplify existing disparities in public health workforce development.

5.2 Implications

Academic Implications

This review extends theory in three significant ways. First, by integrating SDT, TPB, and digital health literacy frameworks within a comprehensive analytical lens, the study provides a theoretically grounded foundation for future research on AI integration in public health workforce development. Second, the identification of four distinct competency patterns offers a nuanced understanding of workforce heterogeneity and the need for targeted, tailored upskilling strategies. Third, the synthesis of ethical, clinical, and technical frameworks provides a foundation for developing integrated competency models that encompass the full range of competencies required for AI-ready public health professionals.

The review introduces three new constructs for future investigation: **pragmatic AI competency** (the ability to operationalize AI tools in real-world public health settings), **communicative AI literacy** (the capacity to explain and navigate AI-mediated information with diverse stakeholders), and **adaptive AI readiness** (the ability to continuously adapt to evolving AI technologies and applications). These constructs extend existing digital health literacy frameworks and provide a foundation for instrument development and validation research.

Practical Implications

The findings support actionable recommendations for public health administrators, educators, and policymakers:

1. **Targeted Training Based on Competency Patterns:** Organizations should implement stratified training programs tailored to identified competency subgroups. For "novice" personnel (25.3% of the workforce), foundational AI literacy training is urgently needed. For "public health experts" and "potential expansion talents," training should address complementary competencies to create well-rounded professionals. For "versatile talents," leadership development and peer mentoring roles should be prioritized.
2. **Priority on On-Job Training Quality:** Given that on-job training satisfaction was the strongest predictor of training needs, organizations should invest in high-quality, engaging, and relevant training experiences. This includes incorporating adult learning principles, providing opportunities for application and practice, and ensuring training is aligned with professional development goals and organizational needs.
3. **Performance-Based AI Literacy Assessment:** Moving beyond self-report instruments, organizations and educators should develop and implement performance-based assessments that evaluate functional, critical, and communicative AI literacy in authentic public health scenarios. This includes simulated outbreak detection, AI-assisted surveillance, and communication of AI-generated findings to diverse stakeholders.
4. **Ethical Framework Integration:** AI-enabled educational interventions should incorporate explicit attention to ethical considerations throughout design, implementation, and evaluation. This includes systematic bias assessment, transparency and explainability features, human oversight mechanisms, and attention to equity of access and outcomes.
5. **Monitoring Metrics:** Organizations should monitor the following key indicators to support successful AI integration:

Indicator	Target	Monitoring Frequency	Expected Lead Time
AI literacy competency scores	≥70% proficiency	Quarterly	6-12 months
Training satisfaction ratings	≥4.0/5.0	Per training event	3-6 months
AI tool utilization rates	≥80% of eligible personnel	Monthly	3-6 months

Indicator	Target	Monitoring Frequency	Expected Lead Time
Competency assessment reliability	≥0.80 inter-rater agreement	Annual	12-24 months
AI-related workforce gaps	≤10% of identified gaps	Semiannual	6-12 months

5.3 Limitations

Limitation 1: Study Selection and Publication Bias. The search was limited to English-language publications indexed in selected databases, potentially excluding relevant studies published in other languages or emerging in non-traditional venues. Given the rapidly evolving nature of AI in education, publication bias may overrepresent positive findings and underrepresent implementation challenges or failed interventions.

Limitation 2: Heterogeneity of Included Studies. The diverse methodologies, populations, and outcome measures across included studies limited the ability to conduct formal meta-analysis. While the scoping review design was appropriate for mapping the broad landscape, future systematic reviews with more focused research questions may enable quantitative synthesis.

Limitation 3: Limited Clinical and Field Validation. The review identified few studies with rigorous validation of AI-driven competency assessment tools or pedagogical interventions across diverse populations and settings. Most implementations remain single-site pilots with limited generalizability, particularly to low- and middle-income contexts.

Limitation 4: Assumption of Historical Pattern Stability. The findings from predictive modeling studies (Wang et al., 2025) assume that patterns of training needs and competency distributions remain stable over time. However, rapid technological change and workforce evolution may alter these patterns, requiring continuous monitoring and model updating.

Limitation 5: Conceptual Underdevelopment. AI literacy and related constructs remain underdeveloped in the public health context, with few studies providing explicit, theory-grounded conceptual definitions (Carpenter et al., 2026). This conceptual fragmentation limits cross-study comparison and synthesis.

5.4 Future Research Directions

1. **Validation of AI Literacy Instruments in Public Health Contexts:** Future research should develop and validate performance-based AI literacy assessment instruments

specifically designed for public health professionals, incorporating functional, critical, and communicative competencies in authentic practice scenarios.

2. **Longitudinal Studies of AI Workforce Development:** Longitudinal designs are needed to examine how AI literacy and related competencies develop over time, how training interventions affect workforce capacity, and how AI integration in practice influences professional role evolution.
3. **Implementation Science Research in Low-Resource Settings:** Research examining implementation barriers and facilitators for AI-driven pedagogical interventions in low- and middle-income settings is critically needed, including studies of local adaptation, contextual factors, and equity implications.
4. **Integrated AI Ethics Training Evaluation:** Research should evaluate the effectiveness of AI ethics training modules (Aucouturier & Grinbaum, 2025) in improving public health professionals' ability to identify and address ethical challenges in AI implementation.
5. **Cross-Cultural Adaptation and Validation:** Studies should examine how AI literacy constructs and competency assessment approaches require adaptation across cultural contexts, and how AI tools can be designed to mitigate biases and support equitable workforce development.
6. **AI-Assisted Competency Assessment Validation:** Validation studies of AI-assisted assessment tools should examine reliability, validity, and fairness across diverse populations, settings, and competency domains, comparing AI-based approaches to traditional human-based assessment.
7. **Comparative Effectiveness Research:** Studies comparing AI-driven pedagogical interventions to traditional approaches should examine effectiveness, cost-effectiveness, equity implications, and implementation feasibility in varied public health workforce contexts.
8. **Organizational Readiness Assessment:** Research should develop and validate instruments for assessing organizational readiness for AI integration, including institutional capacity, infrastructure, policy alignment, and workforce attitudes.

6. Conclusion

This scoping review systematically mapped existing literature on AI-driven pedagogical interventions and competency assessment tools for public health workforce upskilling, synthesizing evidence from 26 studies across multiple regions and settings. The findings demonstrate that AI integration in public health education holds significant promise for personalized, scalable, and effective workforce development, yet current implementations remain early-stage, heavily human-dependent, and narrowly validated. The review identified four distinct competency patterns among public health personnel—novice (25.3%), public health experts (15.1%), potential expansion talents (24.7%), and versatile talents (34.9%)—highlighting the importance of targeted, stratified upskilling approaches. The XGBoost machine learning model demonstrated superior predictive performance for identifying training needs (AUC 0.702; accuracy 89.4%), with on-job training satisfaction identified as the strongest predictor.

The review's main contribution is the integration of disparate evidence strands into a comprehensive competency framework encompassing functional, critical, and communicative literacy dimensions, alongside a staged competency model for AI literacy development. This framework provides a foundation for curriculum design, competency assessment, and institutional capacity building efforts.

For public health administrators, the findings underscore the critical importance of investing in high-quality, engaging on-job training experiences, moving beyond self-report assessment to performance-based evaluation, and systematically integrating ethical considerations into AI-enhanced education and practice. For policymakers, the review highlights the need for intentional, equity-focused AI implementation strategies that address institutional readiness gaps and ensure fair access to training opportunities across workforce segments.

As AI technologies continue to rapidly evolve, the public health workforce must develop not only technical AI literacy but also the critical reasoning, ethical judgment, and communicative competencies essential to translating AI insights into effective population health action. The path forward requires sustained investment in validation research, implementation science, and workforce development partnerships to ensure that AI serves as a tool for health equity rather than a source of disparity.

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