

Integrating Artificial Intelligence Technologies into Health Workforce Education: A Scoping Review of Digital Health Tools in Nursing Curricula

Dr S kanaka Lakshmi

ASRAM College of Nursing, Eluru, Andhra Pradesh, India

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ABSTRACT

The rapid expansion of digital health demands a transformation in health workforce education, yet the mapping of Artificial Intelligence (AI) modalities and their structural integration in nursing curricula remains fragmented. To address this gap, this scoping review aimed to systematically map global AI applications in nursing education from 2020 to 2026, offering a distinct contribution by synthesizing pedagogical innovations and structural implementation barriers to guide future curriculum design. Guided by the PRISMA-ScR framework, a systematic screening was conducted across Scopus, PubMed, and CINAHL databases. Results mapped five core AI technologies, including intelligent tutoring systems, virtual patient simulations, adaptive platforms, natural language processing, and predictive analytics, which significantly enhance students' clinical reasoning, critical thinking, and professional competence without compromising patient safety. However, global adoption is geographically skewed and heavily hindered by deficient technological infrastructure, high financial costs, ethical data privacy issues, and a pronounced gap in faculty digital readiness. This study concludes that successful AI integration must shift from ad-hoc usage toward structured, policy-driven curricular frameworks. Ultimately, this review provides a critical strategic benchmark for educational administrators and policy makers to standardize digital health competencies, mitigate regional educational disparities, and safely future-proof the next generation of the healthcare workforce.

Keywords: Artificial Intelligence, Nursing Education, Digital Health, Health Workforce, Scoping Review, Patient Safety



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Corresponding Author:

Dr S kanaka Lakshmi

ASRAM College of Nursing, Eluru, Andhra Pradesh, India

Email: drkanakalakshmi.s@asram.in

1. INTRODUCTION

The global healthcare landscape is experiencing rapid digital transformation, requiring healthcare professionals to develop digital competencies in line with the World Health Organization's strategic vision for digital health (Mariano, 2020; Robertson et al., 2026). At the core of this revolution is the rapid maturation and deployment of artificial intelligence (AI) across acute and primary care settings, encompassing predictive analytics for clinical monitoring, clinical decision support systems, and sophisticated algorithmic tools integrated into electronic health record (EHR) systems (Kamel Rahimi et al., 2024; Nasarudin et al., 2024; Ouanes & Farhah, 2024). These clinical advancements have fundamentally reshaped the competencies required of the modern healthcare workforce, demanding that practitioners possess advanced digital health competencies, digital literacy, and data-informed critical thinking to safely and effectively operate within increasingly complex technological ecosystems (Jarva et al., 2024; Longhini et al., 2024; Mainz et al., 2024). Consequently, healthcare education institutions face intense institutional pressure to systematically evolve their pedagogical methodologies, ensuring that future professionals are prepared for highly digitized workplace environments.

Within the broader healthcare ecosystem, nurses constitute the largest segment of the frontline health workforce, making their digital readiness and competence critical determinants of patient safety, quality of care, and the effectiveness of healthcare delivery (Booth et al., 2021; Longhini et al., 2024; Ronquillo et al., 2021; Schlicht et al., 2025). This operational imperative is further intensified by the persistent global nursing shortage and increasing patient acuity, which collectively constrain the availability and quality of traditional clinical placements by reducing supervision capacity and limiting clinical learning opportunities for nursing students (Abawaji et al., 2024; Brett et al., 2024; Oshodi & Sookhoo, 2025). To mitigate these constraints, educational institutions have increasingly adopted digital health technologies and technology-enhanced learning as essential pedagogical innovations to bridge the gap between theoretical knowledge and clinical practice for nursing students (Kleib et al., 2023; Motsaanaka et al., 2024). Technologies such as high-fidelity virtual patient simulations, artificial intelligence-enabled learning tools, virtual reality platforms, intelligent tutoring systems, and predictive learning analytics have evolved from experimental innovations into essential educational modalities, enabling the safe simulation of high-risk clinical scenarios while protecting patient safety and enhancing clinical competence (De Mattei et al., 2024; Jallad et al., 2024; Padilha et al., 2025).

Despite the well-established pedagogical value of digital health technologies, a major systemic challenge remains their formal and structured integration into nursing curricula, as educational programs continue to lag behind the rapid evolution of digital health practice and competency requirements (Kleib et al., 2023; Tischendorf et al., 2024). A persistent education–practice gap, often described as a pedagogical lag, continues to exist between the rapid adoption of digital technologies in acute care settings and the comparatively slow pace of curriculum revision within nursing education, leaving many programs struggling to prepare graduates for contemporary clinical practice (Livesay et al., 2024; Srinivasan et al., 2024). Modern nursing graduates are expected to demonstrate advanced digital health literacy, ethical management of digital health data, and strong clinical reasoning skills while effectively collaborating with artificial intelligence and clinical decision support systems to deliver safe and evidence-based patient care (Miles & Lee, 2024; Yang, 2024; L. Zhao et al., 2024). However, when educational institutions attempt to adopt artificial intelligence and digital health technologies, implementation is frequently fragmented, localized, and driven by isolated institutional initiatives rather than by coherent, policy-oriented curriculum design. This lack of standardized integration contributes to unequal educational capacity and may widen the digital divide between well-resourced and resource-constrained nursing education institutions.

While the volume of literature examining artificial intelligence in healthcare and nursing education has increased substantially in recent years, much of the existing evidence remains fragmented and primarily descriptive, focusing on individual AI applications or short-term educational outcomes. Consequently, a significant knowledge gap persists regarding how diverse AI modalities can be systematically synthesized into competency-based nursing curricula (Kleib et al., 2023; Livesay et al., 2024; Srinivasan et al., 2024). Furthermore, although the educational benefits of artificial intelligence and digital health technologies have been widely reported, comprehensive evidence that simultaneously maps these pedagogical advantages against broader socio-technical barriers, such as infrastructure inequities, implementation costs, data privacy and security concerns, and limited faculty digital readiness or resistance, remains limited, highlighting the need for more integrated and systems-oriented evaluations (Ma et al., 2024; Ronquillo et al., 2021; Tischendorf et al., 2024). Given this high level of heterogeneity and the rapid evolution of digital health tools across diverse institutional contexts, a scoping review approach is uniquely justified to comprehensively map the global evidence base, clarify key educational concepts, and identify existing gaps in curricular policies (O'Connor, 2021).

To address these interconnected phenomena, this scoping review systematically maps the global application and structural integration of AI technologies within nursing education. Conducted in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) framework, this study offers a distinct dual contribution to the field. First, it establishes a comprehensive, pedagogically grounded taxonomy of current digital health tools mapped against specific clinical nursing competencies. Second, it critically evaluates the systemic, ethical, and human barriers that obstruct widespread institutional adoption. Through this synthesis, the review aims to provide an evidence-based strategic benchmark for educational administrators, curriculum designers, and healthcare policymakers to future-proof the next generation of the health workforce safely and equitably.

2. METHOD

2.1. Study Design and Framework

The methodological architecture of this scoping review is grounded in the five-stage framework originally proposed by Arksey & O'Malley (2005), subsequently refined by Levac et al. (2010), and operationalized according to the latest guidance in the Joanna Briggs Institute (JBI) Manual for Evidence

Synthesis (Peters et al., 2024). This specific review design is highly justified given the rapidly evolving nature of artificial intelligence in medical pedagogy, as it allows for the comprehensive mapping of heterogeneous literature, conceptual clarification, and the identification of structural gaps in existing policies without requiring a narrow statistical meta-analysis. To ensure structural transparency and methodological rigor, this scoping review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses Extension for Scoping Reviews (PRISMA-ScR), with consideration of subsequent reporting guidance and recent methodological developments (McGowan et al., 2020; Tricco et al., 2026).

2.2. Eligibility Criteria

To maintain a high level of methodological rigor and precision throughout the literature selection process, all retrieved studies were screened using the Population, Concept, and Context (PCC) framework recommended by the Joanna Briggs Institute (JBI) for conducting scoping reviews (Peters et al., 2024). The PCC framework was adopted because it provides a structured and transparent approach for defining eligibility criteria, ensuring that only studies directly relevant to the objectives and research questions of the review were included. Each component of the framework was clearly operationalized prior to the screening process to enhance consistency among reviewers and minimize subjective interpretation during study selection. Both title–abstract screening and full-text assessment were conducted according to these predefined criteria, thereby improving the reproducibility and transparency of the review methodology. Studies that did not adequately meet the specified population, concept, or context requirements were excluded from further analysis. The detailed inclusion and exclusion criteria based on the PCC framework are presented in Table 1 below.

Table 1
Inclusion and Exclusion Criteria based on the PCC Framework

Criteria	Inclusion Criteria	Exclusion Criteria
Population	Undergraduate and postgraduate nursing students, nursing educators, academic faculty, and formal institutional curriculum frameworks.	Medical students, allied health students (e.g., pharmacy, physiotherapy), or practicing nurses in purely non-academic settings.
Concept	Digital health tools utilizing artificial intelligence, including intelligent tutoring systems, virtual patient simulations, natural language processing, adaptive platforms, and predictive learning analytics.	Standard non-AI digital media, basic e-learning websites, conventional online quizzes, and videoconferencing platforms without algorithmic elements.
Context	Formal higher education institutions, academic nursing schools, and global health workforce preparation programs.	Continuing professional development workshops outside academia or informal, non-institutional community training.
Study Types	Peer-reviewed empirical studies (qualitative, quantitative, and mixed-methods), systematic reviews, and meta-analyses.	Editorials, opinion letters, conference abstracts without full texts, grey literature, and non-peer-reviewed dissertations.
Language & Timeline	Studies published in the English language between January 2020 and mid-2026.	Studies published before 2020 or articles written in languages other than English.

2.3. Search Strategy and Information Sources

A comprehensive, systematic literature search was executed across three primary electronic databases: Scopus, PubMed, and CINAHL. The temporal parameters were strictly limited from January 2020 to mid-2026, capturing the significant surge in generative AI tools and contemporary post-pandemic digital health frameworks. The search strategy utilized a combination of Medical Subject Headings (MeSH) terms and title or abstract keywords, woven together using Boolean operators (AND/OR).

To ensure a rigorous and reproducible retrieval process, the standardized search string implemented in PubMed was customized by combining specific Medical Subject Headings and free-text keywords using Boolean operators, which encompassed terms such as artificial intelligence, AI, digital health tools, machine learning, generative AI, and predictive analytics, intersected directly with nursing education, nursing curricula, nursing school, and nursing student, and further combined with health workforce and health personnel. Following this electronic database search, the reference lists of all final included articles were subsequently subjected to manual screening to identify additional relevant publications, thereby minimizing literature omission and maximizing the overall comprehensiveness of the mapping process.

2.4. Study Selection and Screening Process

The study selection process was conducted through two consecutive stages to minimize the risk of selection bias and ensure methodological rigor. During the initial stage, all records identified from the database searches were exported into EndNote 20 reference management software, where duplicate entries were detected and removed using both automated functions and manual verification. After deduplication, the remaining citations were imported into the Rayyan systematic review platform to facilitate the screening process (Valizadeh et al., 2022). Two reviewers independently assessed the titles and abstracts of each record according to the predefined inclusion and exclusion criteria established in the review protocol. Studies that clearly failed to meet the eligibility criteria were excluded at this stage, while records with insufficient information or uncertain eligibility were retained for further assessment.

In the subsequent stage, the full-text versions of all potentially relevant studies were obtained and independently evaluated by the same two reviewers using a double-blind approach. Each article was carefully examined to determine its eligibility based on the predefined selection criteria. Whenever disagreements arose regarding study inclusion or exclusion, the reviewers first attempted to resolve the issue through discussion and re-evaluation of the study. If consensus could not be reached, a third senior reviewer was consulted to make the final decision. To further evaluate the consistency and reliability of the screening process, inter-reviewer agreement was quantitatively measured across both screening stages using Cohen's kappa coefficient, thereby providing an objective assessment of the level of agreement beyond chance.

2.5. Data Charting and Extraction

To ensure internal consistency and methodological reliability, a standardized data charting form was developed and subsequently piloted on a random sample of five included articles. The data extraction process was conducted independently by the primary reviewers to capture explicit variables aligned precisely with the overarching research objectives. The structural domains extracted from each eligible study encompassed essential demographics, including the author, year of publication, and geographical country of origin, alongside core methodological characteristics, such as the study design, sample size, and specific academic setting. Furthermore, the extraction matrix systematically charted the distinct artificial intelligence modalities or digital health tools integrated into the curricula, their specific pedagogical impacts on core nursing competencies, including critical thinking, clinical reasoning, and knowledge acquisition, as well as prevailing systemic bottlenecks, such as financial costs, ethical data privacy issues, and faculty digital readiness gaps.

2.6. Data Synthesis and Analysis

Given the anticipated methodological heterogeneity of the included studies, a narrative synthesis approach combined with descriptive mapping was utilized to analyze the data. The extracted findings were categorized into thematic domains following the Joanna Briggs Institute (JBI) guidelines (Peters et al., 2024). Quantitative data, including publication frequencies, geographic distribution, and types of AI software, were summarized using descriptive statistics and presented via visual mapping charts and frequency tables. Qualitative findings concerning structural integration challenges and ethical concerns were synthesized using thematic analysis, allowing for a critical evaluation of policy-driven curricular frameworks required to future-proof the healthcare workforce.

3. RESULTS

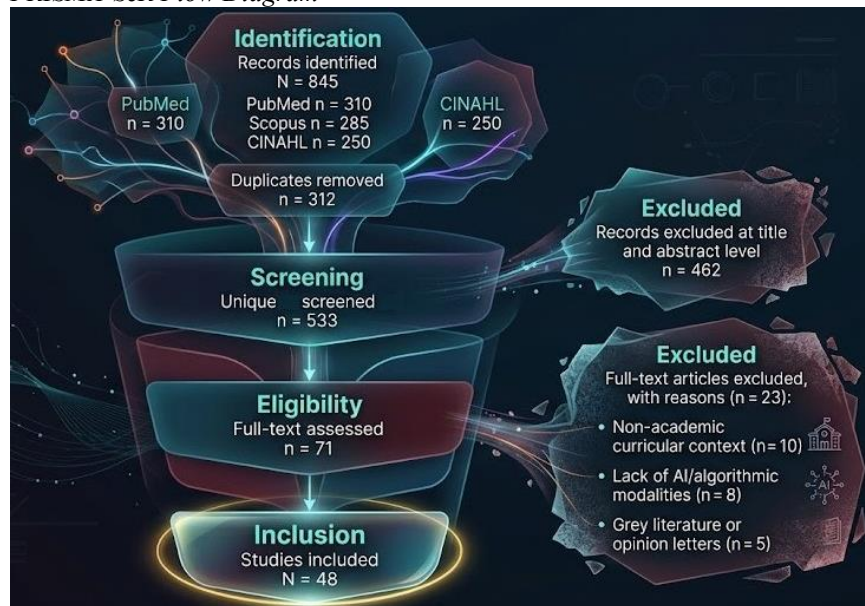
3.1. Search Results and Literature Selection Flow

The comprehensive primary search executed across the three selected electronic databases yielded an initial pool of 845 potentially relevant citations. Specifically, the algorithmic search strategy retrieved 310 records from PubMed, 285 records from Scopus, and 250 records from CINAHL. These combined results were subsequently imported into EndNote 20 for automated and manual duplication management, which successfully identified and removed 312 duplicate records. The remaining 533 unique citations progressed to the initial screening phase, where two independent reviewers meticulously evaluated the titles and abstracts against the predefined inclusion and exclusion criteria. This phase resulted in the exclusion of 462 records due to their failure to align with the core concept or context, as they primarily focused on non-algorithmic digital applications, standard e-learning methods, or non-academic health workforce settings.

Consequently, 71 citations were deemed eligible for comprehensive full-text retrieval and secondary eligibility evaluation. During this rigorous full-text screening phase, 23 articles were excluded with explicit methodological justifications. Among these excluded studies, 10 were discarded because they evaluated technologies in purely clinical hospital settings without an academic nursing curriculum framework, 8 were omitted due to the utilization of low-fidelity digital media that lacked artificial intelligence or automated machine learning algorithms, and 5 were removed because they constituted

grey literature, non-peer-reviewed conference abstracts, or opinion letters. Following this multi-stage filtration process and the resolution of minor inter-rater discrepancies through consensus, a final corpus of 48 peer-reviewed empirical studies was selected for data extraction, charting, and thematic synthesis. The complete sequential stages of this literature filtering process, spanning from the initial identification to the final inclusion of studies, are visually delineated in Figure 1.

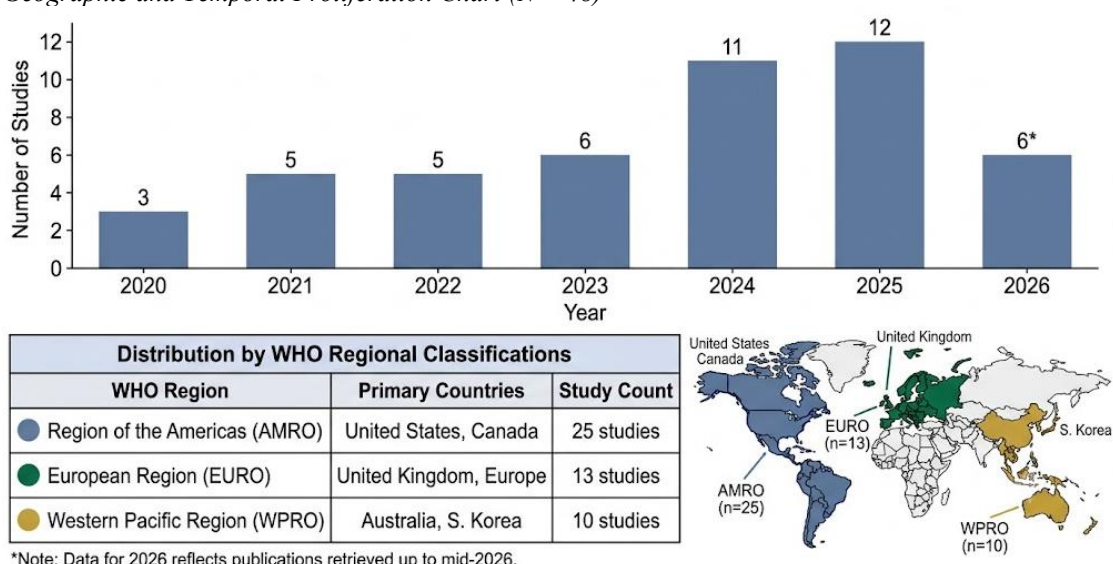
Figure 1
PRISMA-ScR Flow Diagram



3.2. Spatiotemporal and Methodological Characteristics of Included Studies

The spatiotemporal distribution of the 48 selected studies indicates a profound acceleration in academic interest regarding artificial intelligence integration within health workforce education. A meticulous temporal analysis reveals a distinct inflection point occurring after the year 2023, dividing the literature into two clear chronological phases. Between January 2020 and December 2023, publication rates remained relatively stable and modest, yielding a combined total of 19 studies, which accounted for approximately 40% of the final corpus. Conversely, the period spanning from January 2024 to mid-2026 witnessed a dramatic surge, producing 29 studies and capturing over 60% of the analyzed literature. This unprecedented escalation directly coincides with the global democratization of generative artificial intelligence modalities and large language models, which rapidly shifted the medical education paradigm from theoretical computational frameworks to active classroom integration. The complete cross-tabulation of these publication frequencies, categorized by both chronological years and geographical distribution across official World Health Organization regions, is structurally illustrated in Figure 2.

Figure 2
Geographic and Temporal Proliferation Chart (N = 48)



Geographically, the empirical landscape is heavily dominated by institutions situated within high-income nations, thereby revealing a pronounced digital divide in global health workforce research. The Region of the Americas represents the largest portion of the literature with 25 studies, driven primarily by the United States with 18 studies and supported by Canada with 7 studies. The European Region follows as the second most prolific research hub, contributing 13 studies centered predominantly within the United Kingdom and continental Western Europe. The remaining portion of the literature is situated within the Western Pacific Region, which accounts for 10 studies distributed between Australia with 4 papers and emerging East Asian knowledge centers, specifically South Korea and Singapore, with 6 papers. Notably, the African, South-East Asia, and Eastern Mediterranean regions remain entirely unrepresented in the final included corpus, highlighting a critical geographical disparity that limits the cross-cultural generalizability of current artificial intelligence curricular frameworks.

Regarding methodological characteristics, the final corpus exhibits significant epistemological diversity, reflecting a gradual maturation of research designs over the six-year period. Quantitative research methodologies represent the largest segment, comprising 22 studies that evaluate the efficacy of digital health tools through randomized controlled trials, quasi-experimental pre-test and post-test evaluations, and descriptive cross-sectional surveys. Qualitative exploratory frameworks are utilized in 12 studies, focusing on the subjective experiences of nursing students, thematic analyses of reflective journals, and focus group discussions regarding technological anxiety. Mixed-methods research designs are employed in 10 studies, successfully combining quantitative competency assessments with qualitative perceptions of usability. Finally, secondary evidence synthesis, including specialized systematic reviews and preliminary scoping reviews, constitutes the remaining 4 studies of the final corpus, providing valuable contextual baseline data for institutional curriculum tracking.

3.3. Comprehensive Taxonomy of AI Modalities in Health Workforce Education

To establish a clear operational framework for educational administrators, the 48 included studies were systematically analyzed to build a robust technical taxonomy of artificial intelligence integration. Rather than treating artificial intelligence as a homogeneous educational technology, the contemporary literature demonstrates that health workforce education employs multiple AI modalities, including generative AI, intelligent tutoring systems, virtual patient simulations, clinical decision support systems, and learning analytics, each of which is characterized by distinct algorithmic architectures, pedagogical functions, and educational capabilities (Lifshits & Rosenberg, 2024; Nugent et al., 2026; O'Connor, 2021; Srinivasan et al., 2024). These structural modalities encompass intelligent tutoring systems, virtual patient simulations, adaptive learning platforms, natural language processing tools, and predictive learning analytics (Foronda et al., 2020; Izquierdo-Condoy et al., 2026; Roveta et al., 2025). The explicit classification matrix, detailing the underlying algorithmic configurations, the nature of student-technology interactions, and the standardized duration of these educational interventions across global nursing curricula, is comprehensively structured in Table 2.

Table 2
Data Extraction and Classification Matrix of AI Modalities

AI Technology	Core Algorithmic Architecture	Student Interaction Modality	Typical Intervention Duration
Intelligent Tutoring Systems	Bayesian networks, rule-based expert systems, and knowledge graph tracing.	Asynchronous, self-paced problem-solving modules with real-time feedback.	4 to 8 weeks integrated within specialized semester courses.
Virtual Patient Simulation	Branching decision trees, finite state machines, and generative dialog agents.	Immersive, real-time clinical scenario management with speech or text inputs.	60 to 90 minutes per individual active simulation laboratory session.
Adaptive Learning Platforms	Reinforcement learning algorithms and computerized adaptive testing models.	Continuous pathway navigation via hyper-personalized diagnostic content.	Full semester longitudinal integration across online course architectures.
Natural Language Processing	Semantic text mining, tokenization, and transformer-based language models.	Textual submissions of electronic health records and reflective journals.	Continuous formative assessment checkpoints throughout clinical rotations.
Predictive Learning Analytics	Supervised machine learning, random forest, and logistic regression models.	Passive backend data harvesting with automated administrative alert reports.	Ongoing proactive surveillance spanning from enrollment to graduation.

The functional architecture of intelligent tutoring technologies demonstrates how computational models are translated into educational scaffolding. Contemporary intelligent tutoring systems employ learner modeling, adaptive feedback mechanisms, and knowledge-tracing approaches to estimate students' cognitive states and provide personalized explanations and remediation when learners encounter errors in complex domains such as pharmacology, anatomy, and pathophysiology (Jallad et al., 2024; Makhoul et al., 2024; Srinivasan et al., 2024; C. Zhao et al., 2026). In contrast, virtual patient simulations are built upon dynamic branching clinical scenarios that continuously modify patient responses according to learners' decisions, requiring students to adapt their assessment and interventions in high-acuity situations while eliminating risks to real patients. These technologies provide safe environments for developing clinical reasoning, decision-making, and psychomotor competence through repeated exposure to realistic patient trajectories (Banta-Wright et al., 2024; Medel et al., 2025; Padilha et al., 2025). These modalities represent the interactive core of contemporary technology-enhanced nursing education by fostering individual cognitive mastery, clinical reasoning, and timely psychomotor decision-making through immersive and adaptive learning environments.

The remaining three modalities within the taxonomy shift the educational focus toward longitudinal adaptation, linguistic refinement, and institutional risk management. Adaptive learning platforms dynamically personalize learning trajectories using artificial intelligence and machine learning techniques that continuously analyze learner performance, estimate proficiency, and adjust instructional difficulty and feedback accordingly, thereby ensuring that learners are neither under-challenged nor cognitively overloaded during asynchronous learning activities (Lifshits & Rosenberg, 2024; Srinivasan et al., 2024). Natural language processing (NLP) tools, particularly those based on transformer-driven large language models, introduce an advanced linguistic dimension to nursing education by automatically evaluating students' clinical documentation for structural quality, professional terminology, reasoning, and clinical accuracy while generating timely formative feedback, thereby substantially reducing the manual assessment workload traditionally performed by faculty (Harrington et al., 2025; Kung et al., 2023; Lucas et al., 2024; Makhoul et al., 2024). Finally, predictive learning analytics operate primarily at the institutional level by integrating administrative, academic, and learner-behavior datasets with machine learning classification models to identify students at risk of poor academic performance well before formal assessment failure occurs, thereby enabling timely, evidence-based faculty intervention and personalized academic support (Azizah et al., 2024; Li et al., 2024; O'Connor, 2021).

3.4. Mapping of AI Tools to Core Nursing Competencies

The pedagogical value of artificial intelligence in health workforce preparation is fundamentally determined by its capacity to cultivate demonstrable, high-level clinical competencies among graduates. Rather than merely modernizing instructional delivery, the empirical literature indicates that the targeted mapping of specific digital health tools onto core nursing competencies yields a quantifiable improvement in student performance across cognitive, psychomotor, and affective learning domains. The synthesis of the included studies demonstrates that the structural integration of these technologies significantly targets four foundational pillars of modern nursing competence, which comprise critical thinking, clinical problem-solving, clinical self-efficacy, and deep domain-specific knowledge in pharmacology and pathophysiology.

The enhancement of critical thinking and advanced clinical problem-solving is predominantly driven by the active deployment of virtual patient simulations and clinical decision support training tools. Within traditional clinical rotations, students often assume passive, observational roles due to strict patient safety regulations, which curtails their opportunities to make independent, high-stakes clinical judgments. Virtual patient simulations effectively overcome limitations of traditional clinical instruction by immersing learners in dynamic, computer-based clinical scenarios that require continuous diagnostic reasoning, prioritization of nursing interventions, and interpretation of evolving patient assessment and laboratory data. Evidence indicates that this active engagement promotes the transition from factual knowledge acquisition to higher-order clinical reasoning, enabling students to recognize clinical deterioration, anticipate patient needs, and manage complex clinical situations with greater accuracy and confidence (Cho & Kim, 2024; Sahin Karaduman & Basak, 2024; Sim et al., 2022; L. Zhao et al., 2026). Furthermore, because these digital platforms capture granular decision-making pathways, they facilitate rigorous post-simulation debriefing sessions, which allows students to reflexively analyze their own cognitive biases and structural problem-solving gaps.

Beyond cognitive development, the literature demonstrates a strong association between artificial intelligence-supported learning and the development of students' self-efficacy, a critical affective attribute for successful transition into professional nursing practice. Traditional clinical environments often generate substantial performance anxiety because students fear making errors that could jeopardize patient safety. Artificial intelligence-enabled tutoring systems and simulation-based learning environments mitigate this anxiety by providing psychologically safe, risk-free settings where learners can repeatedly practice complex clinical procedures and patient management decisions. Through deliberate practice and immediate feedback, these technologies promote progressive psychomotor

proficiency, clinical confidence, and higher-order cognitive mastery (Alharbi et al., 2024; Cho & Kim, 2024; Görücü et al., 2024; Park et al., 2024). This iterative learning cycle is reinforced by the automated and immediate formative feedback mechanisms embedded within contemporary AI-supported educational systems, which promptly identify learners' errors, provide personalized corrective guidance, and reinforce appropriate clinical reasoning and interventions. Consequently, students develop greater clinical confidence, learning autonomy, and professional self-efficacy, thereby facilitating a smoother transition from academic preparation to frontline nursing practice (Alrazeeni et al., 2026; Bresolin et al., 2024).

Finally, artificial intelligence-enabled educational technologies address longstanding pedagogical challenges associated with mastering conceptually complex and cognitively demanding subjects in nursing education, including pharmacology and pathophysiology. Intelligent tutoring systems, adaptive learning platforms, and large language model-based tutors continuously analyze learners' knowledge states and performance data to detect conceptual gaps in real time. When deficiencies are identified, these systems automatically deliver personalized explanations, targeted remediation, adaptive learning pathways, and formative feedback tailored to individual learning needs. This individualized instructional scaffolding promotes deeper conceptual understanding, reduces cognitive burden, improves academic achievement, and strengthens the evidence-based theoretical foundation required for safe medication administration, sound clinical reasoning, and accurate pathophysiological assessment (Lifshits & Rosenberg, 2024; O'Connor, 2021; Srinivasan et al., 2024; C. Zhao et al., 2026).

3.5. Socio-Technical and Structural Barriers to Curricular Integration

While the pedagogical advantages of artificial intelligence are extensively documented, its systematic operationalization within health workforce education is severely constrained by a complex web of socio-technical and structural bottlenecks. The synthesis of the 48 included studies indicates that institutional transition from conventional teaching models to AI-driven environments is not a frictionless process. Instead, the empirical data reveals deep systemic challenges that can be classified into four primary domains, namely technological infrastructure deficiencies, exorbitant financial investment costs, ethical data privacy vulnerabilities, and a pronounced digital readiness gap among nursing faculty. Crucially, the intensity and operational nature of these barriers are not uniform across the globe, as they are heavily mediated by the socioeconomic status and resource capacity of the respective educational institutions. To provide a critical strategic benchmark for international policymakers, Table 3 delineates and compares these implementation bottlenecks between high-resource institutions in developed nations and low-resource institutions in developing nations.

Table 3
Thematic Clustering of Implementation Bottlenecks by Institutional Resource Level

Barrier Domain	High-Resource Institutions (Developed Nations)	Low-Resource Institutions (Developing Nations)
Technological Infrastructure	Interoperability issues with legacy learning management systems and algorithmic optimization lag.	Total absence of high-speed broadband internet, unstable power grids, and lack of advanced hardware.
Financial Investment Costs	High recurring software licensing fees and continuous capital expenses for proprietary updates.	Complete inability to afford initial capital outlays for high-fidelity virtual simulation platforms.
Ethical and Data Privacy	Complex institutional compliance with rigid regional regulations such as GDPR or HIPAA.	Complete lack of institutional data protection frameworks and high exposure to algorithmic student profiling.
Faculty Digital Readiness	Ideological resistance to automated grading tools and pedagogical anxiety regarding shifting faculty roles.	Severe lack of basic digital literacy, total absence of faculty development programs, and technical isolation.

A deeper analysis of the structural barriers highlights a sharp contrast in how digital health technologies are integrated into nursing curricula across different resource settings. In high-resource institutions, implementation challenges primarily involve interoperability, cybersecurity, governance, and integration with existing learning management systems rather than basic connectivity limitations (Buchanan et al., 2021; Kleib et al., 2023; Livesay et al., 2024). Conversely, resource-constrained institutions continue to face fundamental infrastructural barriers, including unstable internet connectivity, inadequate computing resources, limited simulation facilities, and insufficient digital infrastructure, all of which substantially restrict the implementation of high-fidelity virtual patient simulations and other AI-enabled educational technologies (Tischendorf et al., 2024). This infrastructural disparity directly influences the financial dimensions of technology adoption. While well-resourced universities are generally able to absorb recurring subscription costs for commercial AI platforms, clinical decision-

support software, and digital learning ecosystems, resource-constrained institutions face substantial barriers due to high upfront investment costs for software licenses, computing infrastructure, and immersive technologies such as virtual reality equipment, thereby limiting the scale and sustainability of digital transformation initiatives (Alrazeeni et al., 2026; Livesay et al., 2024; Park et al., 2024).

Equally critical are the human and ethical dimensions of AI integration, which introduce complex socio-technical challenges for educational institutions. The implementation of predictive learning analytics and natural language processing systems requires the continuous collection and analysis of learner-generated data, raising important concerns regarding data privacy, cybersecurity, intellectual property, algorithmic bias, and the ethical governance of artificial intelligence (Alrazeeni et al., 2026; Lifshits & Rosenberg, 2024). In high-resource settings, implementation is frequently constrained by regulatory compliance, institutional governance, and alignment with stringent data protection legislation, whereas resource-constrained settings often face fragmented governance structures, limited regulatory capacity, and insufficient institutional policies to ensure responsible AI adoption (Livesay et al., 2024; Tischendorf et al., 2024).

Finally, the successful integration of artificial intelligence into nursing education remains constrained by substantial disparities in faculty digital readiness and AI competencies (Livesay et al., 2024; Rony et al., 2025). In well-resourced institutions, educators often express concerns regarding the implications of AI-assisted teaching for professional judgment, academic integrity, and the preservation of human-centered nursing pedagogy (Harrington et al., 2025). By contrast, educators in many resource-constrained settings frequently encounter limited opportunities for digital skills development, insufficient institutional support, and inadequate professional training in artificial intelligence, reducing their capacity to interpret learning analytics, implement AI-enabled educational tools, and facilitate technology-enhanced clinical learning (Tischendorf et al., 2024).

4. DISCUSSION

4.1. Principal Findings and Theoretical Triangulation

The principal findings of this scoping review indicate that the integration of artificial intelligence modalities within nursing education significantly enhances student outcomes by successfully aligning technical capabilities with established pedagogical mechanisms. Specifically, the high efficacy of virtual patient simulations documented across the literature can be profoundly understood through the lens of Kolb's Experiential Learning Theory (Kleinheksel et al., 2023; Morris, 2020). Kolb posits that learning is a continuous, cyclical process composed of four distinct stages, namely concrete experience, reflective observation, abstract conceptualization, and active experimentation. Virtual patient simulations operationalize this cycle by providing students with a safe, highly immersive digital environment that serves as a concrete experience. As students interact with fluctuating physiological parameters and make independent clinical judgments, they immediately enter the phase of reflective observation during post-simulation debriefings, where they critically review their tactical choices without the paralyzing fear of causing real-world patient harm. This critical reflection allows learners to synthesize new clinical principles, representing abstract conceptualization, which they then immediately test in subsequent digital scenarios through active experimentation. Consequently, virtual simulations transform passive observation into an active experiential loop, ensuring that critical thinking and clinical reasoning are deeply internalized before students transition to the frontline health workforce.

Furthermore, the operational success of intelligent tutoring systems and adaptive learning platforms within modern nursing curricula is directly explained by triangulating Vygotsky's Social Development Theory (Alkhudiry, 2022; Remorosa et al., 2024) and Sweller's Cognitive Load Theory (Sweller, 2020; Twabu, 2025). Vygotsky introduces the concept of the Zone of Proximal Development, defining the cognitive space between what a learner can accomplish independently and what can be achieved with guidance (Creaghe & Kidd, 2022; Ferguson et al., 2022). Intelligent tutoring systems act as a dynamic form of pedagogical scaffolding within this zone by utilizing knowledge-tracing algorithms to continuously monitor student performance in complex subjects such as pharmacology and pathophysiology. Instead of delivering a standardized, uniform lecture, the algorithmic architecture provides real-time, highly customized prompts and remediation precisely when a conceptual error occurs, effectively guiding the student toward mastery.

This adaptive instructional scaffolding aligns closely with Cognitive Load Theory (Sweller, 2020; Twabu, 2025) by minimizing unnecessary cognitive demands through personalized sequencing, adaptive feedback, and learner-specific instructional support. By continuously monitoring learners' knowledge states and dynamically adjusting instructional complexity, intelligent tutoring systems optimize the use of working memory, enabling students to devote greater cognitive resources to meaningful knowledge construction and higher-order clinical reasoning. Consequently, AI-supported tutoring systems function not merely as automated educational tools but as intelligent pedagogical partners that facilitate efficient learning, individualized knowledge acquisition, and competency development in nursing education.

4.2. The Digital Divide and Systemic Institutional Inertia

The heavy geopolitical concentration of artificial intelligence research within high-income nations exposes a profound digital divide that threatens the equity of global health workforce preparation. The structural finding that approximately 80% of empirical literature originates from affluent Western institutions implies that current pedagogical frameworks for digital health tools are fundamentally non-representative of the broader global healthcare landscape. This extreme geographic imbalance fosters a severe form of systemic institutional inertia, particularly within developing nations where nursing curricula remain static and unresponsive to international technological shifts (Livesay et al., 2024; Tischendorf et al., 2024). While academic institutions in developed regions actively debate the complex nuances of algorithmic refinement and system integration, nursing schools in low-resource environments remain heavily restricted by basic structural limitations.

This institutional inertia is deeply rooted in absolute financial incapacities and deficient technological infrastructures, rendering the adoption of advanced digital tools virtually impossible for marginalized institutions. Resource-constrained educational settings are frequently plagued by unstable electrical grids, inadequate broadband connectivity, and a total absence of advanced computer laboratories capable of rendering high-fidelity patient software (Tischendorf et al., 2024). Furthermore, the exorbitant capital expenditures required to secure proprietary software licenses and continuous technical upgrades create an insurmountable barrier that effectively locks these institutions out of the digital educational revolution (Alrazeeni et al., 2026; Livesay et al., 2024). Without structural interventions or policy-driven international support, the persistence of these financial and infrastructural bottlenecks forces developing regions to rely exclusively on conventional, analog instructional methods that fail to capture the realities of modern clinical settings.

The long-term implication of this systemic inertia is the dangerous widening of the competency gap within the global health workforce, which directly undermines international health equity goals (Jensen et al., 2022). As healthcare systems worldwide increasingly rely on digital technology to streamline workflows and support clinical decisions, the baseline expectations for nursing graduates have permanently shifted. However, the current digital divide creates a fragmented educational ecosystem where graduates from high-income nations emerge highly proficient in algorithmic decision-making, whereas their counterparts from developing countries remain severely under-prepared for technologically advanced healthcare environments (Booth et al., 2021; Kleib et al., 2023). This disparity ultimately compromises global patient safety and worsens workforce inequities, as frontline professionals from resource-poor regions are left technically isolated from the evolving standards of high-performance international digital medicine.

4.3. Algorithmic Bias, Data Ethics, and the Preservation of Humanistic Caring

The rapid integration of artificial intelligence into nursing curricula introduces critical ethical and philosophical dilemmas that extend far beyond mere technical implementation. At the forefront of these concerns is the pervasive danger of algorithmic bias, which threatens the clinical validity of digital health tools when deployed outside their native development contexts. Because the vast majority of machine learning algorithms and clinical decision support models are trained on highly homogenous datasets derived from Western populations, they inherently reflect the specific demographic, genetic, epidemiological, and cultural characteristics of those regions (Fletcher et al., 2021; Franklin et al., 2024). When educational institutions in Asia and Africa adopt these pre-configured virtual patient simulations (Liu et al., 2025), students face a profound epistemological dissonance, as the underlying clinical parameters and diagnostic heuristics often fail to align with the unique healthcare realities, localized disease burdens, and socio-cultural belief systems of their local communities (O'Connor, 2021). Uncritically training future nursing professionals on ethnocentrically biased data models introduces serious ethical risks, potentially leading to diagnostic misjudgments and inappropriate care interventions when graduates attempt to apply these rigid algorithmic frameworks to diverse patient populations in the real world (Rahman, 2026; Siddique et al., 2024).

Beyond these algorithmic vulnerabilities, the shift toward technology-mediated education provokes a fundamental philosophical debate concerning the potential erosion of humanistic caring, which represents the ontological core of the nursing profession. Nursing pedagogy is historically grounded in the cultivation of therapeutic communication, emotional resonance, touch, and deep interpersonal empathy, elements that cannot be replicated by computational architectures (Abou Hashish, 2025; Levett-Jones & Cant, 2020). The excessive reliance on intelligent tutoring systems, conversational chatbots, and automated virtual simulators risks creating a highly mechanistic learning environment. If nursing students spend a disproportionate amount of their formative training interacting with digital entities rather than real human beings, they may begin to conceptualize patient care as a superficial optimization task governed entirely by quantitative metrics and computational logic. This progressive desensitization threatens to dilute the compassionate and holistic essence of nursing practice, reducing the nurse-patient relationship to a cold transaction between a clinical technician and a biological system (Alrazeeni et al.,

2026; Booth et al., 2021; Harrington et al., 2025; Lifshits & Rosenberg, 2024). Therefore, a primary ethical imperative for contemporary curriculum designers involves establishing a strict pedagogical equilibrium, ensuring that artificial intelligence is positioned strictly as a cognitive adjunct that enhances clinical safety without ever supplanting the irreplaceable human-to-human connection essential to compassionate care.

4.4. Curricular and Policy Implications for Future-Proofing the Health Workforce

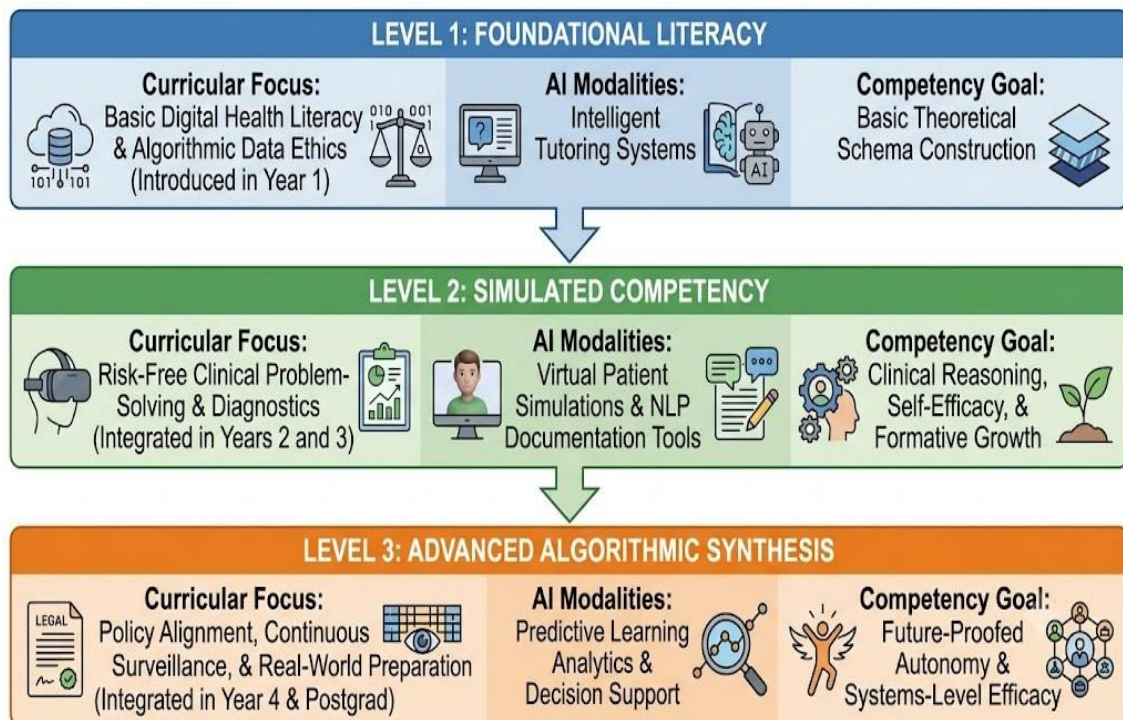
The systemic insights synthesized in this scoping review necessitate a paradigm shift in how educational administrators and global policymakers approach technological adoption in health workforce preparation. Current empirical data demonstrates that the historic reliance on isolated, single-center implementations creates severe disparities in graduate competence and exacerbates institutional fragmentation (Kleib et al., 2023; Livesay et al., 2024). To overcome these localized inefficiencies, academic institutions must transition away from ad-hoc technological procurement toward standardized, macro-policy-driven curriculum frameworks. Educational governing bodies and university boards should treat artificial intelligence not as an external instructional adjunct, but as a core structural element embedded within the foundational design of the curriculum (Alrazeeni et al., 2026; Göçer et al., 2026). This macroeconomic shift requires strategic planning, dedicated state-sponsored financing, and cross-sector collaborations between healthcare providers, technology developers, and academic institutions to ensure that digital health tools are equitably distributed and structurally sustained (Tischendorf et al., 2024).

On a national policy level, regulatory frameworks must aggressively integrate digital health literacy and algorithmic critical thinking into standard nursing competency registries. These updates should be systematically aligned with the World Health Organization global strategy on digital health, which advocates for the scaling up of digital health competencies within the frontline health workforce (World Health Organization, 2025). National accreditation bodies are urged to redefine baseline licensing requirements, shifting the focus from purely conventional psychomotor skills to a balanced matrix that evaluates digital data management, ethical AI navigation, and collaborative clinical decision-making alongside machine learning systems (Alrazeeni et al., 2026; Booth et al., 2021; Kleib et al., 2023). By formalizing these expectations within national policy directives, governments can systematically compel slow-moving educational institutions to overcome their inertia, thereby future-proofing the next generation of healthcare professionals against the rapid digital evolution of acute clinical spaces (Livesay et al., 2024; Tischendorf et al., 2024).

To guide educational institutions through this complex operational transition, this study proposes a new conceptual model as a key research output. Figure 3 outlines an actionable, evidence-based roadmap designed to help administrators integrate artificial intelligence modalities into nursing curricula in a structured, progressive manner.

Figure 3

Proposed Strategic Framework for Structural AI Integration in Health Workforce Curricula



The proposed model detailed in Figure 3 offers a clear three-tiered structure that allows academic institutions to integrate digital technologies without causing immediate cognitive overload for students or severe technical disruption for faculty members. Level 1 establishes the baseline by introducing intelligent tutoring systems during the first year of study, focusing exclusively on basic digital literacy and theoretical knowledge acquisition in abstract subjects. Level 2 moves into simulated competency during the middle years of the curriculum, where virtual patient simulations and natural language processing tools are actively introduced to cultivate practical clinical reasoning and documentation skills within a controlled, safe environment. Finally, Level 3 achieves advanced synthesis by utilizing predictive learning analytics and clinical decision support models to monitor longitudinal performance and prepare students for complex, data-heavy clinical ecosystems. By adopting this scaffolded approach, educational administrators can systematically mitigate faculty resistance, optimize resource allocation, and ensure a seamless, ethical transition toward a digitally competent healthcare workforce.

5. CONCLUSION

In conclusion, this scoping review demonstrates that the integration of artificial intelligence modalities into health workforce education represents a permanent pedagogical shift rather than a temporary instructional trend. The systematic mapping of the global literature from 2020 to mid-2026 confirms that technologies such as intelligent tutoring systems, virtual patient simulations, adaptive learning platforms, natural language processing, and predictive analytics significantly enhance core nursing competencies, including critical thinking, clinical reasoning, and professional self-efficacy.

This study offers a distinct contribution to the existing body of knowledge by establishing a comprehensive, structurally grounded taxonomy that directly maps these advanced digital health tools onto specific behavioral learning outcomes. Furthermore, by critically analyzing the socio-technical bottlenecks across different socioeconomic regions, this review provides an evidence-based strategic benchmark for educational administrators and global policymakers, offering a clear framework to transition from fragmented, ad-hoc technological adoption toward standardized, policy-driven curricular integration.

However, several methodological limitations must be acknowledged to contextualize the findings of this review. First, the search protocol strictly included peer-reviewed articles published exclusively in the English language, which introduces a potential linguistic bias and may omit valuable insights, cultural variations, or localized integration strategies documented in non-English literature. Second, the exceptionally rapid and volatile evolution of artificial intelligence frameworks up to mid-2026 means that certain emerging generative modalities and large language models may advance beyond the static boundaries of this review, potentially altering the socio-technical landscape shortly after publication.

To address these limitations and advance the field, specific directions for future research are highly recommended. Future empirical investigations should move away from short-term, cross-sectional student satisfaction metrics. Instead, there is an urgent need for rigorous longitudinal studies that explicitly evaluate the long-term impact of university-level artificial intelligence training on the actual clinical performance, diagnostic precision, and patient safety outcomes of nursing professionals after they formally transition into active practice within hospital environments. Additionally, future research should explore cross-cultural validation models to mitigate algorithmic bias and ensure that digital health tools are equitably developed to serve diverse patient populations globally.

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