Future Directions for Integrating Artificial Intelligence in Simulation-Based Healthcare Education

SSH
Society for Simulation in Healthcare™

AI Simulation Healthcare Collaborative

Future Directions for Integrating Artificial Intelligence in Simulation-Based Healthcare Education

EDITED BY

Amar P Patel, DHSc, MBA, MS, NRP, CHSE, FSSH
Department of Emergency Medicine,
University of North Carolina School of Medicine,
Chapel Hill, North Carolina, USA
Power of One Consulting,
Myakka City, Florida, USA

Maria Bajwa, PhD, MBBS, MSMS, CHSE
Department of Health Professions Education,
MGH Institute of Health Professions,
Boston, Massachusetts, USA
Nova Southeastern University,
Ft. Lauderdale, Florida, USA

Isabel T Gross, MD, PhD, MPH
Department of Pediatrics, Section of Emergency Medicine,
Yale University School of Medicine,
New Haven, Connecticut, USA

SSH
Society for Simulation in Healthcare™

AUTHORED BY

Amar P Patel, DHSc, MBA, MS, NRP, CHSE, FSSH
Department of Emergency Medicine,
University of North Carolina School of Medicine,
Chapel Hill, North Carolina, USA
Power of One Consulting,
Myakka City, Florida, USA

Maria Bajwa, PhD, MBBS, MSMS, CHSE
Department of Health Professions Education,
MGH Institute of Health Professions,
Boston, Massachusetts, USA
Nova Southeastern University,
Ft. Lauderdale, Florida, USA

Krystle Campbell, DHA, MSMS, CHSE, FACHDM
Simulation Center, Department of Emergency,
University of Texas Southwestern Medical Center,
Dallas, Texas, USA

Jeffrey Huang, MD, MS, CHSE
Department of Anesthesiology and Perioperative
Medicine, Mayo Clinic,
Rochester, Minnesota, USA

Henry S. Park, MD, FAAD
Department of Internal Medicine and Medical Education,
University of South Florida Morsani College of Medicine,
Tampa, Florida, USA
James A. Haley Veterans' Hospital (Tampa VAMC),
Tampa, Florida, USA

Andrew A. Borkowski, MD
Departments of Pathology, Medicine and Surgery,
University of South Florida Morsani College of Medicine,
Tampa, Florida, USA
VA Sunshine Healthcare Network, Tampa, Florida, USA;
National AI Institute, Washington, DC, USA

Julie E. LeMoine, PhD
Interprofessional Center for Experiential Learning and
Simulations (iCELS), Eunice Kennedy Shriver Center
Worcester, Massachusetts, USA
Dept of Psychiatry, Dept of Medicine at UMass Chan
Medical School, Worcester, Massachusetts, USA
My Diji Helper, Inc.,
Watertown, Massachusetts, USA

Eury Hong, MA
Department of Pediatrics,
Yale University School of Medicine,
New Haven, Connecticut, USA

Aaron Calhoun, MD
Department of Pediatrics,
University of Louisville and Norton Children's Hospital
Louisville, Kentucky, USA

Tonya A. Schneidereith, PhD, MBA, CRNP, PPCNP-BC, CPNP-AC, CNE, CHSE-A, ANEF, FSSH, FAAN
SIMPL Simulation, LLC,
Brooklandville, Maryland, USA

Cathleen Deckers, EdD., RN, CNE, CHSE
California State University, Long Beach,
School of Nursing,
Long Beach, California, USA

Alice Martanegara, DNP, RN
Golden West College - School of Nursing,
Huntington Beach, California, USA

Melissa Morris, PhD, RN, CPN, CHSE
Nova Southeastern University,
Ft. Lauderdale, Florida, USA

Nabit Bajwa, MSCS, BSEE
College of Engineering and Computing,
George Mason University,
Fairfax, Virginia, USA

Jennifer Roye, MSN, RN, CNE, CHSE, EdD(c)
University of Texas at Arlington College of Nursing and
Health Innovation,
Arlington, Texas, USA

Leah Mallory, MD
Hannaford Simulation Center,
MaineHealth,
Portland, Maine, USA
Tufts University School of Medicine,
Boston, Massachusetts, USA

Jonathan P. Duff, MD, MEd
Department of Pediatrics, Faculty of Medicine and
Dentistry, University of Alberta,
Edmonton, Canada

Desiree A. Díaz, Ph.D, APRN, FNP-BC, CNE, CHSE-A, ANEF, FSSH, FAAN
University of Central Florida College of Nursing,
Orlando, Florida, USA

Dawn Wawersik, Ph.D, RN, CHSE, CNEcl
Nova Southeastern University,
Ft. Lauderdale, Florida, USA

Matteo Rosati, BS
Yale University School of Medicine,
New Haven, Connecticut, USA

Janice C Palaganas, PhD, APRN, ANEF, FNAP, FAAN, FSSH
Center of Excellence in Healthcare Simulation Research,
MGH Institute of Health Professions,
Boston, Massachusetts, USA

Isabel T Gross, MD, PhD, MPH
Department of Pediatrics, Section of Emergency Medicine,
Yale University School of Medicine,
New Haven, Connecticut, USA

ACKNOWLEDGEMENTS

We gratefully acknowledge the invaluable support and contributions from the Society for Simulation in Healthcare. We would like to acknowledge Mena Khan for assistance in data collection in the initial stages of the project and Michele T. McGinnis for assistance with the literature search.

CONTRIBUTORS' STATEMENTS

Amar P. Patel, Maria Bajwa, and Isabel T. Gross conceptualized the article, authored their respective segments, and coordinated the integration of sections written by all individual authors. All authors critically reviewed and revised the final manuscript; all authors approved the final manuscript as submitted.

FINANCIAL DISCLOSURE

The authors have no financial relationships relevant to this article to disclose.

FUNDING

No funding.

POTENTIAL CONFLICT OF INTEREST

Amar P. Patel is the Co-Founder & Principal of Power of One Consulting, LLC. Tonya A. Schneidereith is the Co-Founder, Chief Executive Officer and Managing Partner of SIMPL Simulation, LLC. Julie E. LeMoine is the Founder & Chief Innovation Officer of My Diji Helper, Inc.

All other authors have no conflicts of interest to disclose.

ISBN 979-8-9920505-0-9 (eBook)

First release edition November 2024.

AI Simulation Healthcare Collaborative is part of CHESI LLC.

SSH Society for Simulation in Healthcare™

AI Simulation Healthcare Collaborative

EXECUTIVE SUMMARY

The improvement of developing technologies, such as artificial intelligence (AI), plays a vital role in advancing the education of healthcare practitioners, significantly enhancing learning via simulation-based activities. This publication presents a guide on how to incorporate AI in healthcare simulations with a thoughtful focus on ethical matters, governance, and the place of AI within education.

The whitepaper is built on the following sections:

- **Section 1 - Introduction**
- **Section 2 - Current Use and Potential Application:** AI in healthcare simulation improves learning across psychomotor, affective, and cognitive domains. It enhances skill assessment, feedback, emotional training, and decision-making through data analysis and virtual simulations. AI also helps educators manage workloads and has potential for AI-driven coaching and decision-support tools.
- **Section 3 - Guiding Principles**
    a. ***Healthcare Simulation & AI Industry Partnership:*** There must be a joint collaboration between an AI professional and a healthcare simulationist for any enhancements of educational solutions using AI. The iterative approach to product development provided by the Software Development Life Cycle (SDLC) helps bring this collaboration to fruition by ensuring that effective AI solutions are built into simulation activities.
    b. ***Usability and Human Factors Analysis:*** Implementing AI within a system must emphasize usability and human factors. This will allow for the efficient use of AI technologies in healthcare education and within the AI industry, ensuring that educators and learners are well-trained to maximize their potential.
    c. ***Governance:*** The responsible governance of the models developed is fundamental to the achievement of ethical values and to compliance with regulations. This principle stipulates the obligation of every healthcare entity to develop appropriate governance practices of protecting data, being accountable for how the AI is utilized, and ensuring just, transparent, and responsible use of AI.
    d. ***Oversight Monitoring to Mitigate Bias:*** Bias in AI systems must be recognized and addressed systematically. To mitigate bias, it is essential to track historical biases represent data across diverse groups, refine measurement practices, customize models for different populations to avoid aggregation bias, and continuously evaluate input data and data drift to ensure it reflects the target population accurately.
    e. ***Transparent Empowerment for Sustainable Change:*** To ensure sustainable AI adoption in healthcare, strong leadership and effective change management are essential to building resilient, empowered teams that can integrate AI despite cultural and infrastructural barriers. Transparency in AI is limited by system complexities, but fostering collaboration, shared decision-making, and continuous leadership commitment can drive innovation, ethical deployment, and resilience in AI adoption.

- **Section 4 - Legislation:** Common challenges in AI healthcare simulation included a lack of AI literacy, curriculum gaps, ethical concerns, governance issues, and the need for legal and regulatory compliance. The whitepaper makes relevant legislative proposals.
- **Section 5 - Future Directions:** The integration of AI in healthcare education is rapidly evolving. To create usable technology, we must enhance interoperability across simulation platforms and develop standardized protocols that will allow for the smooth integration with existing technologies. By developing data-driven customization that addresses ethical implications we advance personalized learning experiences. Lastly, we must foster collaboration amongst stakeholders including AI developers, healthcare educators, simulationists, and healthcare practitioners to overcome cultural resistance and fully integrate AI into educational practices.

Conclusion

This whitepaper is a living document for educators, practitioners, product managers, engineers, and policymakers who wish to incorporate AI in healthcare simulation-based education principally and constructively. When stakeholders want to improve the efficiency of using AI technologies for education, increase the safety of medical interventions, and improve technology development in the field of medical education, review and implementation of these recommendations is essential.

SECTION 1: INTRODUCTION

The rapid advancement of Artificial Intelligence (AI) technologies is transforming healthcare education worldwide [1-5]. Given this evolution, it is crucial to establish a mutual understanding of AI in healthcare education and AI technology, the potential innovations that each presents with and from the other, as well as the identification of stakeholders. Industry players often focus on technological innovation and market penetration, while healthcare institutions and academics prioritize clinical outcomes, educational efficacy, and evidence-based practices. Meanwhile, individuals focus on efficiency-enhancing tools and personal and team advancements, while societal considerations revolve around ethical implications, accessibility, and the equitable distribution of AI-enabled educational resources. Bridging these distinct priorities is crucial for leveraging AI to benefit all stakeholders and improve global healthcare education standards and outcomes. This whitepaper aims to provide guidance and direction for the future development of AI-enabled products, services, and solutions in healthcare simulation-based education. See Table 1 for the terminology used in this paper.

Table 1. Terminology used in this white paper.

Terms	Definitions
Artificial Intelligence (AI)	Systems that learn from data to achieve specific goals through flexible adaptation [6,7].
AI Systems	Machine-based systems that generate outputs like predictions and recommendations based on human-defined objectives [8].
Healthcare AI Systems	AI systems specifically designed for the healthcare industry. [Our definition for this project].
As warranted	Decisions that are justified or appropriate based on the circumstances given the rapidly evolving nature of artificial intelligence technology [Our definition for this project].
Software Development Life Cycle (SDLC)	A formal or informal methodology for designing, creating, and maintaining software (including code built into hardware) [9]. A process used by a development team to design and build software. SDLC is a systemic set of steps that divide the work into tasks [10].
User Acceptance Testing (UAT)	It is the final stage of testing in software development, designed to demonstrate the start-to-end functional capabilities of the software and to evaluate its readiness for operational use. UAT focuses on verifying that the software meets user-defined acceptance criteria and is typically conducted by the user to ensure the system's compliance with their expectations and operational needs [11,12]. Also called beta testing. Involves evaluating software in a real-world environment by the target audience or business representatives. The purpose is to ensure the application meets end-user needs through practical scenarios and real data, instead of pre-set menus [13].

Terms	Definitions
Veteran Administration (VA)	A United States of America government agency responsible for providing healthcare, benefits, and other services to military veterans and their families. It operates a nationwide system of hospitals, clinics, and benefits programs to support the well-being and reintegration of veterans into civilian life [14].
Health Insurance Portability and Accountability Act of 1996 (HIPAA)	A federal law in the United States of America that mandates national standards to safeguard sensitive patient health information from unauthorized disclosure without the patient's consent. It includes the HIPAA Privacy Rule, which sets the guidelines for protecting health information, and the Security Rule, which ensures the protection of electronic health data [15].
Family Educational Rights and Privacy Act (FERPA)	A federal law in the United States of America that protects the privacy of student education records. It grants parents certain rights regarding their children's education records, which transfer to the student when they turn 18 or attend a school beyond the high school level [16].
Machine Learning (ML)	A subset of AI and computer science that centers on using data and algorithms to teach AI systems to learn from experience and progressively enhance their performance. This approach enables machines to make decisions and predictions with increasing precision over time, similar to human learning processes [17]. Machine learning can analyzes procedural workflows to improve deliberate practice and competency assessments [18-20].
Human-machine interface (HMI)	Systems enabling interaction between humans and machines, evolving from basic control panels to advanced interfaces incorporating web visualization, mobile applications, and cognitive spaces — environments where operators interact intuitively with machines through technologies like virtual and augmented reality, using gestures, voice commands, and context-aware responses [21]. A platform, hardware or software, allows users to interact with and control a machine or system. It can vary from simple physical controls, like buttons and lights, to more complex setups, like touchscreens or computers with graphical displays running specialized software [22].

SECTION 2: CURRENT USE AND POTENTIAL APPLICATION

Artificial Intelligence (AI) is rapidly transforming learning and skill development in healthcare simulation education [23]. Table 2 summarizes opportunities and challenges with the use of AI in simulation. We explore AI's impact across the three fundamental learning domains: cognitive, psychomotor, and affective [24], highlighting specific opportunities and challenges within each. Illustrative examples demonstrate AI's potential to enhance educational outcomes in healthcare simulation

Table 2. Opportunities and challenges of artificial intelligence in simulation.

Opportunities for Development	**Challenges to Address**
• Content Creation: develop tools to assist educators with writing tasks in scenario development, curriculum design, and education scholarship • Interactivity: design chatbots to enhance learner engagement. • Personalization: train AI using large clinical datasets to enhance simulation fidelity. • Analytics: enhance simulation delivery through AI analytics, feedback, coaching, and assessment. • Professional Development: develop training modules to teach educators how to use AI effectively • Policy templates: create policy templates to guide institutions on appropriate restrictions and oversight procedures based on best practice evidence. • Research methods: learn engineering methods of research, develop modules on how to use AI for research	• Lack of transparency: "Black box" problem limiting end-user understanding of how AI arrives at its output. • Hallucinations: AI can generate convincing inaccuracies. • Biases: AI may propagate existing biases from its training dataset. • Privacy and data security concerns: Data use and data security policies of AI platforms may not properly protect clinical and business-confidential information. • Copyright: AI-generated content may pose tricky ownership problems. • Cost: AI integration may be expensive. • User Training: individuals new to AI need education on best usage practices. • Policies: variability in institutional policies and restrictions on AI use. • Resistance: individual- and institutional-level resistance to the implementation of new technologies and to AI integration into workflows.

Psychomotor

AI can enhance the psychomotor domain in healthcare simulation and may improve the learning and performance of physical tasks and motor skills. Machine learning analyzes procedural workflows to improve deliberate practice and competency assessments [18-20]. It can correlate biometric data, such as EEG tracings, with competency to track learning progression [25]. AI algorithms can analyze images or videos of anatomy and procedures, breaking them into steps for automated feedback and proficiency assessment [26]. Additionally, AI can measure outcomes like intraoperative blood loss and provide feedback [27,28]. This quantification of real-life outcomes can offer objective, on-demand training in areas traditionally relying on direct observation and expert assessment. Challenges include translating data into meaningful automated performance metrics (APMs) and validating machine-based assessments against in-person assessments to integrate these tools into simulators.

Affective

AI applications in the affective domain impact the emotions and attitudes of simulation participants. AI can improve training by providing automated feedback through personalized tutoring [29,30]. AI chatbots offer practice opportunities and immediate feedback. Opportunities include enhancing advanced communication skills, like delivering bad news, discussing care goals, de-escalating challenging situations, addressing professionalism lapses, and responding to discrimination or harassment.

AI enhances workflows for healthcare educators, reducing stress and burnout while increasing job satisfaction, productivity, and efficiency [31,32]. It also helps cultivate values, such as learning empathy [33], managing emotions [34], recognizing social disparities, and understanding bias in AI models [35].

A key challenge in healthcare simulation is incorporating emotions, tones, cultural nuances, and linguistic sensitivity into AI-based simulations while safeguarding patient or learner privacy and mitigating bias in AI databases [30]. When selecting patient records for AI datasets, it's essential to carefully curate data to ensure that the AI can authentically replicate the emotions and tone of a real patient while maintaining privacy. For instance, the dataset should include comprehensive notes, images, descriptions, specific situations, and the emotions elicited to enable AI systems to reflect the intended emotions and tone accurately.

Cognitive

In the cognitive domain, AI applications enhance mental processes like knowledge acquisition, problem-solving, decision-making, and critical thinking. AI is used in clinical practice for risk stratification, severity assessments, and clinical decision support by analyzing vital signs and other clinical data points [36-38]. These algorithms offer opportunities in healthcare simulation education, such as presenting learners with virtual cases and providing feedback on clinical decision-making [39], and developing decision-making skills in virtual reality [40].

Simulation labs are ideal for AI-based assessment of cognitive skills like clinical decision-making, enabling standardized, reproducible, and observable encounters [41]. Future opportunities include exploring and integrating AI coaches and feedback systems to enhance training and using simulation labs to create and test AI-informed clinical decision-support tools. AI can change healthcare education by shifting the cognitive load [34]. To better integrate AI into healthcare simulation education, it is essential to understand how AI data is derived, tested, and applied.

SECTION 3: GUIDING PRINCIPALS

Artificial Intelligence (AI) has the potential to enhance healthcare outcomes and streamline workflows for practitioners by offering tools for clinical decision support, predictive modeling, and adaptive tutoring, which require collaboration between industry, academia, and healthcare experts [42,43]. Practitioners need education in areas such as machine learning, data management, and AI model transparency to optimize their ability to care for patients and ensure patient safety [44,2,3]. The goal is to supplement, not replace, practitioners, ensuring AI systems operate effectively and safely [42,1]. These guiding principles for AI adoption in healthcare education and simulation are interconnected, each supporting the other to ensure AI's ethical and effective integration.

Principle 1 emphasizes communication and collaboration between AI experts and simulationists to define goals and maintain alignment. Principle 2 focuses on usability and human factors, promoting transparency and education to enhance AI literacy. Principle 3 highlights governance, integrating regulatory standards and ethical principles to safeguard data and ensure responsible AI use. Principle 4 highlights oversight and bias mitigation, essential for continuously monitoring AI systems to maintain fairness and effectiveness. Principle 5 advocates for transparent empowerment, stressing the need for strategic leadership and team collaboration to foster sustainable change and adaptation to AI technologies in healthcare.

Together, these principles form a comprehensive framework that fosters safe, transparent, and impactful AI applications in healthcare simulations, essential for navigating the complexities of AI integration while ensuring patient safety and ethical standards are upheld.

GUIDING PRINCIPLE 1 (GP1): HEALTHCARE SIMULATION & HEALTH AI INDUSTRY PARTNERSHIP

Overview

A strong partnership between healthcare AI industry experts (AI and other software experts) and healthcare simulationists during the lifecycle of simulations using AI (AI-based products or services) will potentially improve patient outcomes. General and stage-specific stakeholder collaboration, from setting goals to deployment and support, is crucial for achieving established goals, staying within budgets and timelines, avoiding scope creep, and protecting users.

The Software Development Life Cycle (SDLC) [45] model, commonly recognized in the software and AI industries, emphasizes iterative steps and feedback, providing an excellent framework for maintaining this partnership. Bajwa et al. [44] overlay AI expert/simulationist partnership areas onto SDLC stages, identifying opportunities for information sharing, agreements, and other key activities. See Table 3.

Limitations

The lack of cohesive communication and vernacular between simulationists and AI industry experts hinders AI's adoption in simulation-related activities. Significant increases in simulations using AI due to its democratization and limited collaborative research amplify this issue. Divergent fields, knowledge gaps, and insufficient software/technical AI and healthcare simulationist subject matter experts lead to misalignment in expectations, staffing, and funding. New and shared terminology, controls, and training are essential.

Recommendations

Table 3 shares the recommendations for collaboration under the classic simulation software development framework.

Table 3. Partnership model.

SDLC Stage	Goal of Simulationists/AI Expert Collaboration	Recommended Areas of Collaboration Between AI Experts/Simulationists
Requirements	• To enable a shared understanding of use case goals/objectives and AI's role in supporting them. This enables AI experts to gather necessary data and understand its characteristics.	• Simulation/Use Case Details • Intended use /Impact of AI, e.g., how AI surfaces in the HMI • Required AI Data/ Sources • Other Critical Topics: Metrics, Performance (e.g., Speed, Accuracy)
Design	• To support AI experts in data preparation, model selection, and plan for tuning and ongoing maintenance.	• Data labeling, typing, grouping • Data pre-processing: agree on how to manage missing data, validation of data and testing data, data bias, and others • Support AI model and tools selection & design via ongoing Q&A (Intent, HMI, metrics, etc.) • Feedback/input during rounds of prototyping • Computational Costs/Feasibility • Data and Model Maintenance
Implementation (Coding, Training)	• To ensure that AI supports simulationists in attaining use case goals, particularly concerning controlling requirements and ensuring required data accuracy • The AI Expert will create and train the model and create the designed HMI access to the AI services.	• Ongoing Feedback/Input, discussions, Q&A • Unit Testing Support, if applicable • Continued trade-off decision-making, e.g., Costs/Feasibility
Testing	• To ensure the AI is properly designed and adapted to the context of a particular educational setting. • The AI Expert will tune the model and data.	• End-to-End AI/Sim Testing Support & Tuning Insights • Continued Tradeoff Decision making, e.g., Costs/Feasibility
Deployment or Installation	• To ensure that Simulationists share user feedback and issues with AI Experts. • The AI Expert will tune the model and data.	• Recruiting for UAT/Initial Launch • Support, Review, Respond in Initial & Follow-on Launch
Maintenance	• To ensure that Simulationists and AI Experts continue to maintain and improve the AI services within the simulation. • The AI Expert will adjust the tuning and work with the simulationists to update, acquire, or adjust the data if appropriate for the model/data.	• Ongoing discussions of tuning via hyperparameters, new data, etc.

GUIDING PRINCIPLE 2: USABILITY AND HUMAN FACTORS ANALYSIS

Overview

Usability and human factors analysis are crucial in using AI in healthcare simulation or vice versa to ensure that AI systems are designed with the end-user in mind, promoting safe, effective, and user-centered technologies that support intended educational outcomes. Similarly, healthcare simulation must be carefully considered and constructed to assess AI outcomes best. Educational programs should collaborate with AI industry leaders to develop appropriate AI applications in healthcare education to ensure usability, e.g., using simulation to develop effective assessment tools as per the SLDC framework (GP 1 & GP 5). Strategic partnerships are essential for regulatory oversight, i.e., accessing de-identified data (GP 1, GP 3), testing model accuracy, providing human factors testing, and monitoring models for degradation and drift [2]. Integrating AI literacy curricula fosters dataset validation and risk management skills, with simulation as a key methodology for assessing AI and promoting ethical adoption in clinical settings through enhanced testing [44,2,3].

Limitations

Several current curricula lack practical AI literacy and infrastructure for human factor testing through simulation. Cultural resistance to AI poses challenges [44,2]. Effective change management and strategic industry partnerships are essential for enhancing the usability of AI, further discussed in GP 5 [3].

Recommendations

Academic programs should partner with AI industry leaders to understand usability and ensure human factors integration to assess AI accuracy, provide human factors training, and monitor for model degradation (GP 1, GP 5) [2,3]. Overcoming cultural resistance to AI as an enhancement, not a replacement, requires effective change management and continuous education on AI benefits and limitations (GP 5) [44,2].

GUIDING PRINCIPLE 3: GOVERNANCE

Overview

Responsible AI governance in healthcare must acknowledge and incorporate local regulations like the Health Insurance Portability and Accountability Act (HIPAA) and Family Educational Rights and Privacy Act (FERPA), ethical AI principles, and high-reliability organizational (HRO) practices. In the United States, HIPAA ensures the privacy of patients' health information, while FERPA protects student education records [46]. Learners and educators should understand AI's workings, its impact on them, and its trustworthiness [46]. The Veteran Administration's (VA) Trustworthy AI principles advocate for purposeful, safe, secure, fair, and accountable AI systems benefiting patients and clinicians [47]. Combining these principles with HRO practices, such as leadership commitment and patient-centeredness, enhances AI's safety and reliability [46,47]. Healthcare organizations should align AI governance with local privacy and ethical standards and regulations, embedding Trustworthy AI principles and HRO practices [46,47].

Health education and simulation can be used to evaluate AI tools, ensuring they meet regulatory and ethical standards [46,47]. Regular audits, security controls, and algorithm adjustments should be implemented to maintain fairness and effectiveness, fostering systemic accountability and patient-focused care [46,47].

Limitations

The complexity of integrating regulations, ethical principles, and HRO practices challenges the implementation of comprehensive AI governance. Maintaining rigorous testing, bias assessment, and ongoing system security is also difficult [46]. Additionally, cultural and organizational resistance to these frameworks can hinder effective adoption and compliance [46].

Recommendations

To ensure responsible AI governance, healthcare organizations should integrate personal and private information laws and regulations, such as HIPAA and FERPA, in the United States, ethical AI principles, and HRO practices. Aligning healthcare education and simulation AI guiding principles with the VA's Trustworthy AI principles ensures the promotion of safe, secure, fair, and accountable AI systems. Simulation can evaluate AI tools, ensuring they meet regulatory and ethical standards. Organizations must conduct regular audits, implement security controls, and adjust algorithms to maintain fairness and effectiveness. Overcoming the complexity of integrating these elements requires strong leadership, continuous education, and a culture of compliance and accountability.

GUIDING PRINCIPLE 4: OVERSIGHT/MONITORING TO MITIGATE BIAS

Overview

Bias in AI arises when algorithms produce unfair outcomes due to biased input data. Bias can come from many different sources through machine learning and AI process. It can be helpful to organize sources of bias as either statistical (those secondary to sampling errors and measurement bias) or societal (representing potentially objectionable social structures in the data) [5]. Suresh and colleagues [48] categorized bias (See Table 4). Other authors have classified bias based on the interaction between data, the algorithm, and the user [49].

Table 4. Classification of sources of bias in machine learning [49, 50].

Bias Type	Goal of Simulationists/AI Expert Collaboration	Recommended Areas of Collaboration Between AI Experts/Simulationists
Historical	Data used to train the AI system is no longer accurate - may reinforce stereotypes and misrepresent historically under-represented groups	Gender pay gap, though still an issue, is improving yearly, and systems using historical data may not be accurate
Representation	Parts of the input space are underrepresented	Sampling methods using smartphone apps may under-represent lower income groups
Measurement	Use of a proxy variable instead of the outcome of interest. Quality of data varies between groups.	Women are more likely to be misdiagnosed if "self-reported pain" is one of the symptoms of interest
Aggregation	Use of a one-size-fits-all model across groups	Rates of complications of diabetes can vary across ethnicities
Evaluation	Input data does not represent the target population	Facial recognition software that was built with very few dark-skinned female faces

Limitations

Bias or unfairness can be introduced throughout any SDLC stage [45,48,51]. Several guidelines have been developed for the safe and fair use of AI systems (see GP 2 & GP 3) [51,52]. However, these guidelines often have flaws. Hagendorff [53] reviewed and compared 22 major guidelines of AI ethics across multiple contexts. Although some common topics were shared across the guidelines (such as accountability, privacy, and fairness), there was little demonstrated accountability or details on how existing technical solutions could be brought to bear for each problem. Several institutional ethics boards review research but not educational interventions [54]. As such, these guiding principles highlight the importance of the most common guiding principles' themes across all models, with heightened recognition of the importance of monitoring and mitigating bias.

Recommendations

Detecting and preventing bias in AI systems requires continuous oversight throughout the AI lifecycle—from data processing and model training to deployment. Several strategies, such as algorithmic bias mitigation, Dataset size, transparency, and review for biases, are employed to enhance AI system reliability [53,54].

Table 5. Strategies for migrating bias.

Strategy for Mitigation	Explanation
Dataset size	Increasing the data pool from which their inputs are drawn can improve data diversity and provide a broader representation of learners. However, simply increasing the size does not guarantee increased diversity [55].
Transparency	The internal algorithms of AI systems can be obscure. These algorithms are costly to develop and are often kept private as proprietary intellectual property. Sometimes, e.g. complex neural networks, these algorithms are difficult for even their designers to understand - the so-called “black box” problem [56]. Khosravi and colleagues [5] proposed a framework that considers stakeholders, potential pitfalls, the design of tools, benefits, approaches to presenting explanations, and the AI models being used.
Generalizability	AI systems, while often perceived as inherently accurate, are only as reliable as their input data, creators, and training. They excel in specific contexts but falter outside these areas. AI systems must be re-trained, akin to traditional assessment tools, to ensure appropriate performance [57].
Reviewing for Bias	Bias in AI outputs can be mitigated using various techniques. Gardner's Absolute Between-ROC Area (ABROCA) assesses predictive models for bias in student performance [58]. Similarly, Sha's method evaluates predictions in online forum posts [59]. These approaches are essential for reviewing outputs, especially when models handle sensitive data.

GUIDING PRINCIPLE 5 TRANSPARENT EMPOWERMENT FOR SUSTAINABLE CHANGE

Overview

Transparent empowerment for sustainable change in AI is crucial with the healthcare sector's historical resistance to technology adoption [60-66]. The gap between new technology and resistance from healthcare teams demands effective change management and strong leadership to build resilient, empowered teams [67].

Leaders must foster resilience and team culture to withstand disruptive changes [67-69] and empower multidisciplinary teams using best-practice change management principles [70]. Empowerment requires leaders who understand their teams' diverse perspectives and can design strategic plans for integrating AI effectively while overcoming barriers like complex infrastructures and organizational culture [67-71].

Limitations

Transparency in AI requires communicating objectives, training data, usage, and decision-making processes, yet AI systems complexities can limit transparency and interoperability [66]. Balancing transparency with data privacy and intellectual property concerns is challenging [66]. Resource constraints and cultural resistance also hinder the implementation of comprehensive transparency measures [66,67].

Recommendations

Effective AI deployment in healthcare requires strong leadership and resilient teams [67-69]. Establishing constructive cultures with shared decision-making among diverse experts, including data scientists, is imperative (GP1) [67-70]. Leadership training empowers teams to collaborate, leverage diverse expertise, and align AI initiatives with organizational goals and ethical standards [67-69]. This collaborative approach fosters innovation and resilience in adopting AI technologies within complex healthcare environments [67-69]. Change Management principles, like Kotter's 8-step change management model [70], empower change champions and align AI initiatives with organizational values, enhancing team culture and supporting effective change adoption [67,69]. This approach promotes informed decision-making and transparency through enhanced communication and shared governance and fosters psychological safety within teams [67-70]. Continuous monitoring through culture surveys and sustained leadership commitment is crucial for overcoming resistance and ensuring the ethical deployment of AI in healthcare settings [66-70].

SECTION 4: LEGISLATION

Our analysis of the current legislation and regulatory frameworks from the United States, Europe, and the World Health Organization identified several common challenges related to AI in healthcare simulation.

1. **Lack of AI Literacy:** Continuous professional development is needed to enhance AI literacy among faculty, staff, and students to ensure they understand and can effectively use AI technologies in healthcare education [72-74].
2. **Curriculum Gaps:** Existing curricula often lack comprehensive modules on AI applications, ethical implications, and legal frameworks, necessitating periodic updates to stay aligned with the latest industry and educational standards [72-74].
3. **Ethical Concerns:** The use of AI in simulations must be ethical and transparent, requiring regular reviews and discussions on ethics and biases and embedding ethical considerations into simulation scenarios [72-78].
4. **Governance and Risk Management:** Robust governance policies and risk management strategies are needed to balance innovation with regulation and ensure that AI applications are safe and effective [72-76,79].
5. **Legal and Regulatory Compliance:** Educators and learners need to be familiar with national and international AI regulations to ensure compliance and mitigate legal risks associated with AI applications in simulations [72-78].
6. **Professional and Collaborative Growth:** Engagement with professional communities and continuous learning opportunities are essential for staying at the forefront of AI advancements in healthcare education [72,73,80].

Recommendations

We provide legislative recommendations for AI-based simulations in healthcare education tailored for educators and healthcare learners.

1. **AI Integration into Teaching & Learning**
    a. Mandate continuous professional development in AI in simulation technologies for faculty, staff, and students.
    b. Require a routine update as warranted of modules on AI applications, and their ethical implications, in alignment with legal frameworks and the latest industry and education standards and practices for faculty, staff, and students.
    c. Enforce interactive AI-enhanced simulation scenarios that provide hands-on experience with everyday and complex healthcare situations, emphasizing critical thinking, ethical decision-making, and regulatory compliance.
2. **Ethical and Transparent Use of AI**
    a. Introduce reviews and discussions as warranted with faculty, staff, and students on AI-related ethical issues and biases using real-world cases and simulation.
    b. Implement comprehensive documentation to maintain transparency in AI-driven decisions and outcomes.
    c. Develop guidelines that mandate the inclusion of scenarios aligned with evidence-based practices for simulation, incorporating ethical dilemmas and potential bias recognition related to AI use.

3. Governance and Risk Management

a. Mandate professional development for faculty and staff periodically on AI applications, according to the most updated evidence, focusing on developing, critiquing, and improving governance policies to balance innovation and regulation.

b. Enforce risk management protocols that require institutes to conduct regular assessments of AI applications in simulations, including risk identification and periodic professional development sessions on risk identification, assessment, and mitigation related to AI applications. Ensure that governance policies account for potential risks and have clear management strategies.

c. Require that the educational institutions to establish protocols for evaluating AI-based simulation tools, training, and instructional practices for educational accuracy, relevance, and ethical compliance. These protocols should implement regular risk assessments as part of the quality assurance process to identify and mitigate potential issues with AI-based tools and practices.

4. Legal and Regulatory Compliance

a. Mandate healthcare education programs that train faculty, staff, and students with national and international AI regulations, such as the EU AI Act and other governing AI-based simulation practices.

b. Require that the integration of legal compliance and risk management training modules as part of the compliance training focusing on legal risks associated with AI, such as data privacy breaches, algorithmic bias, and liability issues.

5. **Professional and Collaborative Growth**

a. Allocate resources and funding for faculty, staff, and students to participate in AI and healthcare simulation forums, conferences, and workshops.

b. Provide incentives for faculty, staff, and students to participate in these communities to enhance shared learning, networking opportunities, and professional development.

These recommendations offer practical steps to effectively incorporate AI into healthcare simulations balancing the compliance and innovation for professionals to be AI-ready to practice within their scope.

SECTION 5: FUTURE DIRECTION & CONCLUSION

AI integration in healthcare education has made significant strides, yet the potential for growth and advancement remains vast. Future directions should focus on enhancing the interoperability of AI systems across different simulation platforms, ensuring that AI tools can seamlessly integrate with existing educational technologies. This will require the development of standardized protocols and guidelines that promote the consistent application of AI in various simulation environments.

Moreover, fostering collaboration between AI developers, educators, and healthcare practitioners will be essential to drive innovation. Building multidisciplinary teams that can bridge the gap between technology and education will ensure that AI solutions are technically advanced, pedagogically sound, and clinically relevant. This collaborative approach will be vital in overcoming the cultural and institutional resistance to AI adoption and ensuring that these technologies are effectively integrated into healthcare education practices.

Another area for future exploration is the ethical implications of AI in healthcare education will continue to be a critical area of focus. Future research should aim to create robust frameworks that address bias, transparency, and the ethical use of AI, ensuring that these technologies are applied fairly and equitably. This includes the ongoing refinement of AI algorithms to mitigate potential biases and implementing continuous oversight mechanisms to monitor AI's impact on learners and patients when applicable.

Finally, the personalization of learning experiences through AI. By leveraging large datasets and advanced machine learning techniques, AI has the potential to revolutionize healthcare education by providing highly customized educational experiences tailored to individual learners' needs, thus enhancing learning outcomes. The development of AI-driven adaptive learning systems that dynamically adjust content and difficulty based on real-time learner performance will be pivotal. To fully realize this potential, it will be essential to increase AI literacy among educators and learners, ensuring they have the knowledge and skills to engage effectively and benefit from these advanced educational tools.

Conclusion

In conclusion, AI will continue to rapidly change the healthcare education landscape, and continuous communication with industry stakeholders will be essential to driving innovations relevant to our field. We trust that this whitepaper will serve as a foundational document that will support the implementation of AI solutions in healthcare simulation education, guide ethical education practices and research, and support policy-making.This is precision learning.

REFERENCES

1. Lomis K, Jeffries P, Palatta A, Sage M, Sheikh J, Sheperis C, Whelan A. Artificial intelligence for health professions educators. NAM Perspect. 2021;2021.

2. Gray K, Annabell L, editors. AI education for health workforce: survey of approaches and needs. JMIR Med Educ. 2022;8(2):e35223. doi: 10.2196/35223.

3. Charow A, Krever C, Shi M. AI education programs for health professionals - scoping review. JMIR Med Educ. 2021;7(4):e31043. doi: 10.2196/31043.

4. Zhang W, Cai M, Lee HJ, Evans R, Zhu C, Ming C. AI in medical education: global situation, effects and challenges. Educ Inf Technol. 2024;29(4):4611-33.

5. Khosravi H, Shum SB, Chen G, Conati C, Tsai YS, Kay J, et al. Explainable artificial intelligence in education. Comput Educ Artif Intell. 2022;3:100074.

6. Kaplan A, Haenlein M. Siri, Siri, in my hand: who's the fairest in the land? On the interpretations, illustrations, and implications of artificial intelligence. Bus Horiz. 2019;62(1):15-25. doi: 10.1016/j.bushor.2018.08.004.

7. Federal Register. Executive Order 14110: Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence. Fed Regist. 2023 Nov 1.

8. OECD.AI. What is AI? Can you make a clear distinction between AI and non-AI systems? Organization for Economic Co-operation and Development (OECD). 2023. Available from: https://oecd.ai/en/wonk/definition.

9. Souppaya M, Scarfone K, Dodson D. Secure software development framework (SSDF) version 1.1. NIST Spec Publ. 2022 Feb;800:218. doi: 10.6028/NIST.SP.800-218.

10. Amazon AWS. What is SDLC? - software development lifecycle explained. Amazon Web Services; 2024. Available from: https://aws.amazon.com/what-is/sdlc/. Accessed Sep 2, 2024.

11. Leung HK, Wong PW. A study of user acceptance tests. Softw Qual J. 1997;6(2):137-49. doi: 10.1023/A:1018503800709.

12. Paiva TM, Oliveira TC, Pillat RM, Alencar PS. Supporting the automated generation of acceptance tests of process-aware information systems. In: Proceedings of the International Conference on Web Information Systems and Technologies (WEBIST). 2023. p. 128-39.

13. Stanford University. User acceptance testing. Available from: https://uit.stanford.edu/pmo/UAT. Accessed Sep 2, 2024.

14. U.S. Department of Veterans Affairs. About the Department. Washington, DC: U.S. Department of Veterans Affairs; 2023. Available from: https://department.va.gov/about/.

REFERENCES

15. Centers for Disease Control and Prevention (CDC). Health insurance portability and accountability act of 1996 (HIPAA). Atlanta, GA: CDC. Available from: https://www.cdc.gov/phlp/php/resources/health-insurance-portability-and-accountability-act-of-1996-hipaa.html.

16. U.S. Department of Education. Family educational rights and privacy act (FERPA). Washington, DC: U.S. Department of Education; 2021. Available from: https://www2.ed.gov/policy/gen/guid/fpco/ferpa/index.html.

17. IBM. What is machine learning (ML)?. Armonk, NY: IBM; 2021 Sep 22. Available from: https://www.ibm.com/topics/machine-learning.

18. Rogers MP, DeSantis AJ, Janjua H, Barry TM, Kuo PC. The future surgical training paradigm: virtual reality and machine learning in surgical education. Surgery. 2021;169(5):1250-2. doi: 10.1016/j.surg.2020.09.040.

19. Siddiqui A, Zhao Z, Pan C, Rudzicz F, Everett T. Deep learning model for automated trainee assessment during high-fidelity simulation. Acad Med. 2023;98(11):1274-7. doi: 10.1097/ACM.0000000000005290

20. Reich A, Mirchi N, Yilmaz R, Ledwos N, Bissonnette V, Tran DH, et al. Artificial neural network approach to competency-based training using a virtual reality neurosurgical simulation. Oper Neurosurg (Hagerstown). 2022;23(1):31-9. doi: 10.1227/ons.0000000000000173.

21. Papcun P, Kajáti E, Koziorek J. Human-machine interface in concept of Industry 4.0. In: Proceedings of the IEEE International Conference on Industry 4.0. IEEE; 2020. p. 289-96. doi: 10.1109/ICPC47212.2020.9117329.

22. National Institute of Standards and Technology (NIST). Human-machine interface - glossary: CSRC. Available from: https://csrc.nist.gov/glossary/term/human_machine_interface. Accessed Sep 2, 2024.

23. Lie M, Rodman A, Crowe B. Harnessing generative artificial intelligence for medical education. Acad Med. 2024 May;10.1097/ACM.0000000000005760. doi: 10.1097/ACM.0000000000005760.

24. Bloom BS, Engelhart MD, Furst EJ, Hill WH, Krathwohl DR, editors. Taxonomy of educational objectives, handbook I: the cognitive domain. New York: David McKay Co Inc.; 1956.

25. Natheir S, Christie S, Yilmaz R, Winkler-Schwartz A, Bajunaid K, Sabbagh AJ, et al. Utilizing artificial intelligence and electroencephalography to assess expertise on a simulated neurosurgical task. Comput Biol Med. 2023 Jan;152:106286. doi: 10.1016/j.compbiomed.2022.106286. Epub 2022 Nov 15. PMID: 36502696.

26. Hisey R, Camire D, Erb J, Howes D, Fichtinger G, Ungi T. System for central venous catheterization training using computer vision-based workflow feedback. IEEE Trans Biomed Eng. 2022 May;69(5):1630-8. doi: 10.1109/TBME.2021.3124422. Epub 2022 Apr 21. PMID: 34727022; PMCID: PMC9118169.

27. Chan J, Pangal DJ, Cardinal T, Kugener G, Zhu Y, Roshannai A, et al. A systematic review of virtual reality for the assessment of technical skills in neurosurgery. Neurosurg Focus. 2021 Aug;51(2). doi: 10.3171/2021.5.FOCUS21210. PMID: 34333472.

REFERENCES

28. Alotaibi FE, AlZhrani GA, Sabbagh AJ, Azarnoush H, Winkler-Schwartz A, Del Maestro RF. Neurosurgical assessment of metrics including judgment and dexterity using the virtual reality simulator NeuroTouch (NAJD Metrics). Surg Innov. 2015 Dec;22(6):636-42. doi: 10.1177/1553350615579729. Epub 2015 Apr 7. PMID: 25851146.

29. Khumrin P, et al. DrKnow: a diagnostic learning tool with feedback from automated clinical decision support. AMIA Annu Symp Proc. 2018;2018:1348-57.

30. Patel CR, et al. Perspectives of ChatGPT in pharmacology education and research in health care: a narrative review. J Pharmacol Pharmacother. 2023.

31. Liu J, et al. The application of Chat Generative Pre-trained Transformer in nursing education. Nurs Outlook. 2023;71(6):102064.

32. Sallam M. The utility of ChatGPT as an example of large language models in healthcare education, research, and practice: systematic review on future perspectives and potential limitations. medRxiv. 2023.

33. Kobayashi M, et al. Simulated communication skills training program effects using augmented reality with real-time feedback: a randomized control study. Alzheimers Dement. 2022;18(S8).

34. Fazlollahi AM, Bakhaidar M, Alsayegh A, Yilmaz R, Winkler-Schwartz A, Mirchi N, et al. Effect of artificial intelligence tutoring vs expert instruction on learning simulated surgical skills among medical students: a randomized clinical trial. JAMA Netw Open. 2022;5(2). doi: 10.1001/jamanetworkopen.2021.49008.

35. Gurnani B, Kaur K. Leveraging ChatGPT for ophthalmic education: a critical appraisal. Eur J Ophthalmol. 2023.

36. Dziadzko MA, Novotny PJ, Sloan J, Gajic O, Herasevich V, Mirhaji P, et al. Multicenter derivation and validation of an early warning score for acute respiratory failure or death in the hospital. Crit Care. 2018 Oct 30;22(1):286. doi: 10.1186/s13054-018-2194-7. PMID: 30373653; PMCID: PMC6206729.

37. Herasevich S, Pinevich Y, Lipatov K, Barwise AK, Lindroth HL, LeMahieu AM, et al. Evaluation of digital health strategy to support clinician-led critically ill patient population management: a randomized crossover study. Crit Care Explor. 2023 May 3;5(5). doi: 10.1097/CCE.0000000000000909. PMID: 37151891; PMCID: PMC10158897.

38. Jansson M, Rubio J, Gavaldà R, Rello J. Artificial intelligence for clinical decision support in critical care, required and accelerated by COVID-19. Anaesth Crit Care Pain Med. 2020 Dec;39(6):691-3. doi: 10.1016/j.accpm.2020.09.010. Epub 2020 Oct 21. PMID: 33099016; PMCID: PMC7577289.

39. Wang M, Sun Z, Jia M, Wang Y, Wang H, Zhu X, et al. Intelligent virtual case learning system based on real medical records and natural language processing. BMC Med Inform Decis Mak. 2022 Mar 4;22(1):60. doi: 10.1186/s12911-022-01797-7. PMID: 35246134; PMCID: PMC8895690.

40. Higazy O, Ali A, Hakami E, Awad A, Taha E, Egaili K, et al. Exploring transformative role of virtual reality technology in nursing education and patient care: a narrative review. Rawal Med J. 2023;48. doi: 10.5455/rmj.20230828092451.

REFERENCES

41. Weinger MB, Banerjee A, Burden AR, McIvor WR, Boulet J, Cooper JB, Steadman R, Shotwell MS, Slagle JM, DeMaria S Jr, Torsher L, Sinz E, Levine AI, Rask J, Davis F, Park C, Gaba DM. Simulation-based assessment of the management of critical events by board-certified anesthesiologists. Anesthesiology. 2017 Sep;127(3):475-89. doi: 10.1097/ALN.0000000000001739. PMID: 28671903.

42. American Nurses Association. The ethical use of AI in nursing practice. ANA Statement. 2022.

43. Hwang GJ, Chang PY, Tseng WY, Chou C-A, Wu CH, Tu YF. Research trends in AI-associated nursing activities based on a review of studies published from 2001–2020. Comput Inform Nurs. 2022.

44. Bajwa M, Le Moine J, Morris M, Bajwa N. Collaboration principles for healthcare simulations using AI: simulationists and the techies need to communicate. [Manuscript in preparation]. 2024.

45. Ruparelia NB. Software development lifecycle models. ACM SIGSOFT Softw Eng Notes. 2010;35(3):8-13.

46. Hu L. Inside AI maturity model – 5 steps to transform with data-centric AI engineering. Towards Data Sci. 2022.

47. VA National AI Institute. Trustworthy AI principles. 2023.

48. Mitchell S, Potash E, Barocas S, D'Amour A, Lum K. Algorithmic fairness: choices, assumptions, and definitions. Annu Rev Stat Appl. 2021;8:141-63.

49. Suresh H, Guttag JV. A framework for understanding unintended consequences of machine learning. arXiv preprint arXiv:1901.10002. 2019.

50. Australian Human Rights Commission. Technical paper: addressing algorithmic bias [Internet]. Sydney: Australian Human Rights Commission; 2021 [cited 2024 Sep 16]. Available from: https://humanrights.gov.au/our-work/technology-and-human-rights/publications/technical-paper-addressing-algorithmic-bias

51. Mehrabi N, Morstatter F, Saxena N, Lerman K, Galstyan A. A survey on bias and fairness in machine learning. ACM Comput Surv. 2021;54(6):1-35.

52. Kizilcec RF, Lee H. Algorithmic fairness in education. In: The ethics of artificial intelligence in education. Routledge; 2022. p. 174-202.

53. Hagendorff T. The ethics of AI ethics: an evaluation of guidelines. Minds Mach. 2020;30(1):99-120.

54. Masters K. Ethical use of artificial intelligence in health professions education: AMEE Guide No. 158. Med Teach. 2023;45(6):574-84.

55. Bender EM, Gebru T, McMillan-Major A, Shmitchell S. On the dangers of stochastic parrots: can language models be too big? In: Proceedings of the 2021 ACM conference on fairness, accountability, and transparency. 2021. p. 610-23.

REFERENCES

56. Von Eschenbach WJ. Transparency and the black box problem: why we do not trust AI. Philos Technol. 2021;34(4):1607-22.

57. Gillani N, Eynon R, Chiabaut C, Finkel K. Unpacking the "black box" of AI in education. Educ Technol Soc. 2023;26(1):99-111.

58. Gardner J, Brooks C, Baker R. Evaluating the fairness of predictive student models through slicing analysis. 2019. Available from: https://doi.org/10.1145/3303772.3303791.

59. Sha L, Rakovic M, Whitelock-Wainwright A, Carroll D, Yew VM, Gasevic D, Chen G. Assessing algorithmic fairness in automatic classifiers of educational forum posts. In: Lecture notes in computer science. 2021. p. 381-94. doi: 10.1007/978-3-030-78292-4_31.

60. Phrampus PE. Simulation and integration into patient safety systems. Simul Healthc. 2018;13(4):225-6.

61. Campbell K, Gardner A, Scott DJ, Johnson J, Harvey J, Kazley A. Interprofessional staff perspectives on the adoption of or black box technology and simulations to improve patient safety: a multi-methods survey. Adv Simul. 2023;8(1):24.

62. Gallant JN, Brelsford K, Sharma S, Grantcharov T, Langerman A. Patient perceptions of audio and video recording in the operating room. Ann Surg. 2022;276(6).

63. Yarbrough AK, Smith TB. Technology acceptance among physicians: a new take on TAM. Med Care Res Rev. 2007;64(6):650-72.

64. Grzybicki DM. Barriers to the implementation of patient safety initiatives. Clin Lab Med. 2004 Dec 1;24(4):901-11.

65. MacRae CA, Deo RC, Shaw SY. Ecosystem barriers to innovation adoption in clinical practice. Trends Mol Med. 2021;27(1):5-7.

66. Goasduff L. Barriers to AI adoption. Gartner. Available from: https://www.gartner.com/smarterwithgartner/3-barriers-to-ai-adoption/. Accessed 2024 Aug 3.

67. Deloitte. The future of health: innovation is blurring traditional health care boundaries [Internet]. Deloitte; 2021 [cited 2024 Feb 28]. Available from: https://www2.deloitte.com/us/en/pages/life-sciences-and-health-care/articles/future-of-health.html.

68. Brown B. Dare to lead: brave work, tough conversations, whole hearts. Random House; 2018.

69. Chima A, Gutman R. What it takes to lead through an era of exponential change [Internet]. Harvard Business Review; 2020 [cited 2024 Feb 28]. Available from: https://hbr.org/2020/10/what-it-takes-to-lead-through-an-era-of-exponential-change.

70. Kotter J. Leading change. Primento Publishing; 2011.

REFERENCES

71. Ibuki T, Ibuki A, Nakazawa E. Possibilities and ethical issues of entrusting nursing tasks to robots and artificial intelligence. Nurs Ethics. 2023.

72. Federal Register. Executive Order 13960: Promoting the use of trustworthy artificial intelligence in the federal government. Federal Register; 2020 Dec 03.

73. Federal Register. Executive Order 14110: Safe, Secure, and Trustworthy Development and Use of Artificial Intelligence. Federal Register; 2023 Oct 30.

74. World Health Organization. Ethics and governance of artificial intelligence for health: guidance on large multi-modal models. Geneva: World Health Organization; 2024 Jan 18.

75. Coalition for Health AI. Blueprint for trustworthy AI implementation guidance and assurance for healthcare, v.1. 2023 Apr 4. Available from: https://healthaipartnership.org/alignment-with-standards.

76. European Commission. EU AI Act: first regulation on artificial intelligence. 2023 Aug 6. Available from: https://www.europarl.europa.eu/topics/en/eu-ai-act.

77. Healthcare AI Partnership. Alignment with standards. 2023. Available from: https://healthaipartnership.org/alignment-with-standards.

78. Matheny M, Thadaney Israni S, Ahmed M, Whicher D, editors. Artificial intelligence in health care: the hope, the hype, the promise, the peril. NAM Special Publication. Washington, DC: National Academy of Medicine; 2019.

79. World Health Organization. Regulatory considerations on artificial intelligence for health. Geneva: World Health Organization; 2023.

80. American Medical Association. Principles for augmented intelligence development, deployment, and use. 2023 Nov 14. Available from: https://www.ama-assn.org/press-center/press-releases/ama-issues-new-principles-ai-development-deployment-use.

ISBN 979-8-99205-050-9

www.aisimhealthcollab.org

AI Simulation Healthcare Collaborative

SSH
Society for Simulation in Healthcare™