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The Partnership Principle for Healthcare Simulations Using Artificial Intelligence: Simulationists and Techies Need to Communicate!

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Abstract

Integrating artificial intelligence (AI) in healthcare simulation offers significant educational benefits, yet collaboration between simulationists and AI developers remains challenging due to differing expertise and objectives. This study examines the reasons and process of structured partnerships to optimize AI-driven simulations through a hermeneutic narrative review. It identifies critical collaboration points and introduces the AI-Simulation Partnership Framework, which aligns AI capabilities with healthcare simulation and instructional design principles. Key findings emphasize interdisciplinary communication, iterative co-design, and ethical considerations. By standardizing collaboration, the proposed framework can help align simulation development with stakeholders' needs through improved communication. Serving as a critical collaborative checklist and a practical tool, the AI-Simulation Partnership Framework may improve the efficiency and sustainability of AI-driven simulations without causing feature bloat or omission. More targeted and adaptable simulations can, in turn, enhance training quality, which is essential for building clinical competence and improving patient care outcomes.

Categories: AI applications, Ethical AI and Responsible Technology, Data Science Methodologies
Keywords: healthcare simulation, artificial intelligence, ai simulation partnership, interdisciplinary collaboration, simulation ai technology integration, ai scientists and simulation experts collaboration, partnership of ai and simulation experts, industry simulationists partnership

Introduction And Background

Artificial intelligence (AI) has been used in computer technology by organizations with the resources to support advanced systems and experts for decades [1,2]. One subset of AI, generative AI (GenAI), refers to tools and AI capabilities that "generate" new content, such as text, images, video, and audio, based on data upon which the GenAI has been trained [3]. Since 2022, the rise of publicly accessible and free-of-cost tools like ChatGPT has drawn new attention to AI's potential in mainstream education and healthcare [4,5]. In healthcare, GenAI is gaining traction due to its rapid technological evolution, versatility, and ability to enhance education, clinical training, and practice [6]. However, the pace of innovation continues to surpass the development of best practices. As AI becomes more embedded in healthcare education, particularly in simulation, the lack of structured collaboration to ensure purposeful design, development, and deployment of simulation-AI systems between simulationists and AI developers presents real challenges. Poor communication and lack of structured collaboration in the above-mentioned context have led to issues such as unrealistic goals, limited educational relevance with feature bloat or feature scarcity, mismatched user expectations, and unresolved ethical concerns [7,8].

Although current research acknowledges several of these challenges, including technical, pedagogical, and ethical barriers, there is no widely adopted framework to support effective collaboration between simulationists and AI developers. Technically, integration with existing simulation systems often demands significant resources and expertise [9]. Incompatible data formats, proprietary software, and lack of expertise make seamless integration difficult [9,10]. Pedagogically, a major disconnect can occur in balancing AI's analytical capabilities with learner-centered goals. AI developers may focus on algorithmic performance without addressing instructional relevance, which results in outputs that may be clinically accurate but educationally impractical [11,12]. Ethical concerns further limit trust and uptake [13,14]. Simulationists emphasize the need for diverse and representative datasets, while developers may be constrained to use data lacking cultural or clinical nuance [15]. These challenges might become worse by differing development timelines: simulationists work iteratively in slower healthcare educational simulations, while AI developers often operate iteratively in rapid sprint cycles of computer simulations. Moreover, clinicians and educators also express skepticism toward opaque AI tools, especially when

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decision-making processes are not transparent [10-12]. Calls for explainable AI systems are growing, particularly among simulationists who seek human oversight alongside actionable insights [12].

This research examines key considerations for building sustainable, effective partnerships between healthcare simulationists and the AI industry. It proposes a structured framework to guide communication and collaboration, supporting AI integration that aligns with educational priorities, enhances learning outcomes, and improves the sustainability and effectiveness of AI-enhanced healthcare simulation across all stages of application.

Background

At the annual healthcare simulation conference in January 2024 in San Diego, California, a sub-meeting was held to focus on guiding healthcare simulationists in utilizing AI within their workflow. The engaging in-person discussion generated themes for further development. Participants agreed that a sustainable partnership between simulationists and AI experts is one of the fundamental guiding principles for collaborative work, and a team of specialists from healthcare simulation, data science, and AI was assembled for its exploration. This research paper presents detailed insights from the literature review regarding the reasons and processes behind the collaboration between the healthcare simulation and AI systems industries. For AI-related definitions for this research, see Appendix 1.

Research question

We sought to answer the following research questions: 1) Why is it necessary to consider partnerships between healthcare simulationists and technologists, i.e., the healthcare AI systems industry? (The Reasons); and 2) What considerations and strategies are needed to build sustainable partnerships for designing, developing, and deploying AI systems to improve healthcare education simulations regarding quality, efficiency, and effectiveness? (The Process).

Review

Methods

To address the research questions, we conducted a narrative literature review using a hermeneutic framework for knowledge synthesis, a method chosen for its practicality within time and resource constraints [16,17]. This approach allows for the judicious and purposeful selection of the literary evidence iteratively [17,18].

The hermeneutic approach operates through two intertwined cycles: (1) search and acquisition, where relevant literature is identified, sorted, and selected, and (2) analysis and interpretation, where texts are critically examined, themes refined, and further searches conducted as needed [17]. By focusing on concepts and their contextual relationships in an iterative manner, the hermeneutic method aligned well with our research goals, allowing us to explore complex interdisciplinary connections between healthcare simulation and AI while adapting to new findings throughout the process. Initial themes were mapped and refined as the review progressed [17]. The process was conducted for both research questions, with the reasons slightly ahead of the process.

To ensure methodological rigor, we followed the reporting guidelines of the Scale for the Assessment of Narrative Review Articles (SANRA) [19]. The SANRA guidelines comprise six steps, among which the first two steps of (1) justification of the research and (2) statement of concrete aims are described above. The four additional steps described below include (3) describing the literature search, (4) referencing key statements, (5) providing reasoning or evidence for arguments, and (6) presenting data appropriately.

Following hermeneutic review guidelines, we conducted a literature search in two cycles (Figure *1*) [11]. The first cycle, from February to April 2024, identified key literature and guided the initial thematic analysis. In October 2024, a subsequent cycle expanded and refined themes to ensure comprehensive coverage.

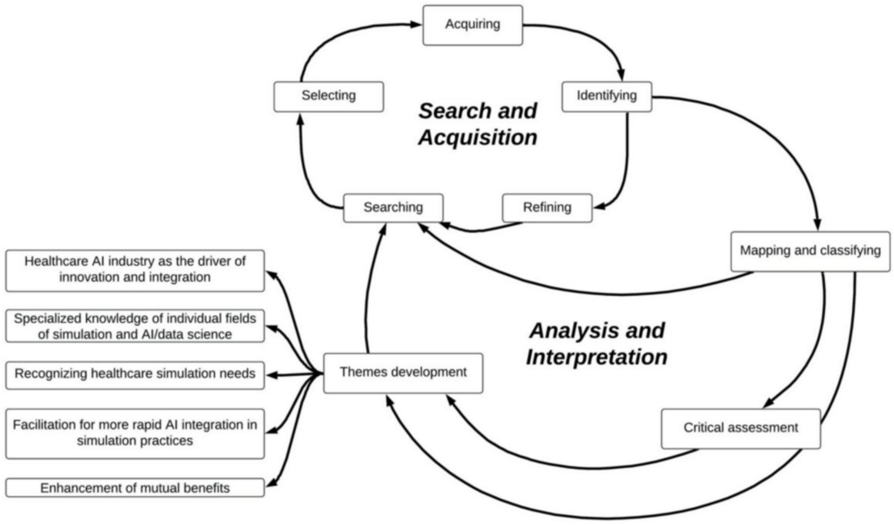

FIGURE 1: Two Intertwined Cycles of Hermeneutic Review Conducted

Our research questions intersected multiple educational fields, complicating access to several databases within a limited timeframe. Additionally, many of the latest findings in the AI field have not been published in peer-reviewed journals. Therefore, we utilized Google Scholar and Google Search for their broad multidisciplinary access, ability to bypass institutional paywalls, and access to gray literature. While we acknowledge that search algorithms influence results based on individual search histories, we leveraged this variability to maximize coverage conducted by different authors.

For the first research question regarding the reasons, the search terms for the initial cycle included “healthcare partnership and AI,” “AI health application and education,” “artificial intelligence industry, healthcare education,” “AI industry, healthcare education,” “AI and healthcare simulation partnership,” and “AI, healthcare collaboration.” We collected 140 gray literature sources and 140 peer-reviewed articles by reviewing the first 20 search results for each search term, as we noticed that after the first 20 or so articles, the frequency of pertinent articles dropped significantly. During the screening phase, we included peer-reviewed journal articles, organizational documents, government reports, and white papers while excluding advertisements, AI-related organization websites, promotional content, AI course offerings, non-substantive materials, and non-English sources without translations. Based on these criteria, we excluded 80 gray literature sources and 66 peer-reviewed articles. The remaining 60 gray literature sources and 74 peer-reviewed articles underwent further review, leading to the inclusion of 20 gray literature sources and 31 peer-reviewed articles (Figures *2* and 3). Any disagreements in selection were resolved through discussion among the authors until a consensus was reached.

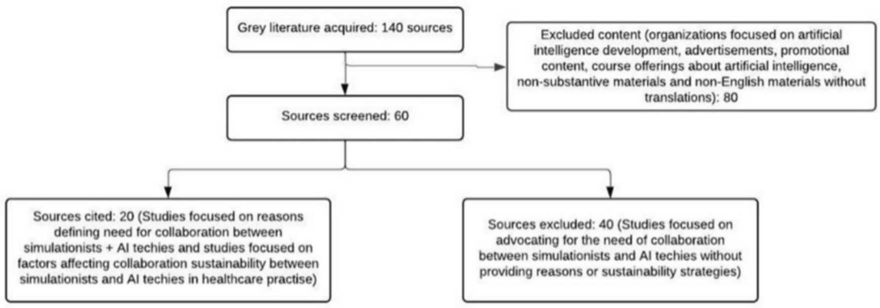

FIGURE 2: Gray Literature Search for Hermeneutic Narrative Review

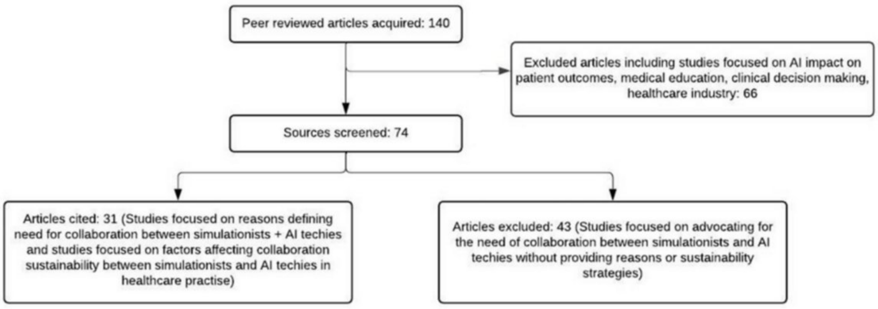

FIGURE 3: Peer-Reviewed Literature Search for Hermeneutic Review

Two researchers conducted independent searches, summarizing findings separately before comparing results to identify common themes and unique insights. Any disagreements were discussed until a consensus was reached. Articles deemed relevant were discussed collaboratively, allowing themes to emerge organically rather than being predefined. To refine the themes, a third researcher was brought in to review the initially identified themes, helping to consolidate and structure them. A fourth author then independently reviewed the final themes and provided feedback, which was incorporated into the synthesis. This multi-step review process ensured rigor, reduced bias, and enhanced the reliability of the final thematic framework.

For the second research question regarding the "process," we leveraged the authors' expertise in simulation, AI, and computer science during the first two steps of the hermeneutic cycle and progressed to the third step. We mutually agreed to identify a theoretical or conceptual framework that could provide structure. In the third step of "identifying," we compiled a list of key theories, models, frameworks, and conceptual ideas, along with the associated literature.

Next, to verify the author-made list, we searched Google Scholar and Google Search using the following terms: "simulation framework," "educational theories in simulation," "life cycle of AI applications," "theoretical models in computer science," "Software Development Lifecycle Management (SDLC) models," "Agile vs. Waterfall vs. V-shaped SDLC," "AI software development models," "SDLC for AI," "AI software development frameworks," and "successful partnerships with business case owners in software development." In the refining phase, we held multiple synchronous discussions from March to October 2024. During these discussions, researchers critically evaluated the strengths and weaknesses of various models and consulted relevant literature. Through this process, we identified four key frameworks that informed the framework proposed in this study.

Results

First, we present the AI-Simulation Partnership Principle, the core of our research. Then, we describe the results of both research questions that informed the development of the AI-Simulation Partnership Framework, which drives the principle. The AI-Simulation Partnership Principle is as follows:

"To establish sustainable partnerships between the healthcare AI industry and healthcare simulationists for educational and training needs lasting the lifecycle of an AI-based product or service. Of particular importance are effective product/service designs that meet the intended goals, are viable and affordable to create and maintain, do not exceed required feature sets, and afford the necessary protections for users, critical in healthcare simulation."

Research Question 1: The Reasons for Partnership

The critical analysis of articles from our dataset resulted in five themes: 1) Healthcare AI industry as the driver of innovation and integration, 2) Specialized knowledge of individual fields of simulation and AI/data science, 3) Recognizing healthcare simulation needs, 4) Enhancement of mutual benefits, and 5) Facilitation for more rapid AI integration in simulation practices.

1. Healthcare AI Industry - The Driver of Innovation and Integration

AI has been identified as one of the key domains in the fourth technological and industrial revolution [20,21]. The rapid growth of the global AI market heightens the need for partnerships between simulationists and technologists. Valued at $196.63 billion in 2023, the AI market is projected to expand at a compound annual growth rate (CAGR) of 37.3% through 2030 [22]. A report from Fortune Business

Insights (2025) forecasts further growth of the AI industry from $294.16 billion in 2025 to $1.77 trillion by 2032, with a CAGR of 29.2%. As the AI industry evolves, insights from the healthcare simulation community are vital to ensuring that AI solutions are both innovative and practical, effectively meeting the needs of healthcare education [23,24].

Historically, the technology industry has played a major role in technological and industrial revolutions [20]. For example, in the pharmaceutical industry, AI systems have been aiding healthcare by analyzing data sets for decades [25]. As technology for data analysis evolved, so did the ability to capture and retain more data for analysis, leading to AI and data systems saving millions of lives, creating new drugs, and developing new ways of tracking patient issues and treatments [25,26]. Therefore, it is reasonable to expect the AI industry to be a driver of the healthcare AI industry and its experts to be major stakeholders in healthcare simulation [27]. For this reason, healthcare simulation and the AI industries ought to learn from, with, and about each other as GenAI becomes more and more viable within healthcare education simulations [26].

2. Specialized Knowledge of Individual Fields - Simulation and Artificial Intelligence/Data Science Perspectives

Both simulationists and AI professionals possess specialized knowledge in their respective fields. Simulation as an instructional modality employs diverse frameworks, principles, and theories from andragogical and pedagogy, as well as from instructional and game design domains. Simulationists and their teams in education must have a comprehensive understanding of the art, science, and ethics of effective simulation-based learning [28]. Key conceptual models include the Healthcare Simulation Standards of Best Practices, Bauman's gaming theory, Kern's curriculum design, ADDIE's instructional design approach, Benner's model, and Kirkpatrick's model of learning evaluation [28-33].

AI is a subfield of computer science and data science, comprising practitioners focused on designing, developing, or enhancing AI systems and machines to perform tasks that typically require human intelligence [34,35]. AI draws from various disciplines beyond computer and data science, including mathematics, linguistics, psychology, neuroscience, and philosophy, to formulate algorithms and systems that can simulate intelligent behavior [36]. Therefore, for software systems that utilize AI techniques, a team of software developers may need to include a diverse range of specialists, such as data scientists, AI research scientists, and AI/machine learning engineers. These professionals contribute their expertise in statistical analysis, machine learning algorithms, data management, research, and AI-specific software engineering to ensure the safe, accurate, effective, and scalable implementation of AI models and techniques [34,37]. Addressing the lack of intersectionality between these two distinct fields and bridging the knowledge gap provides an impetus for their collaboration [38].

3. Recognizing and Addressing Healthcare Education Simulation Needs

The healthcare educational simulation community has expertise that positions them as essential collaborators in shaping AI-driven solutions aligned with the needs of simulation-based learning and evidence-based practices, such as, AI in three-dimensional (3D) printing [39]. As subject matter experts, simulationists understand the sector's specific requirements, ensuring AI applications remain relevant, efficient, and adaptable to evolving healthcare needs, such as a pandemic [40]. Additionally, it is crucial for both sides to intentionally consider the ethical implications of AI-driven educational activities, such as the trustworthiness, safety, privacy, explainability, fairness, and human oversight of AI tools and AI-driven simulations [14,15,26,41].

Collaboration between simulationists and AI developers is necessary to mitigate feature bloat, where excessive, non-essential functionalities compromise usability, and feature scarcity, where missing critical capabilities limit effectiveness [35,42,43]. Both issues affect the reliability and applicability of AI-driven simulation tools. Just as pharmaceutical experts guide AI innovations in drug development, simulation specialists must oversee AI integration into healthcare simulation education to ensure hardware compatibility, scalability, and long-term impact [44]. Without this collaboration, AI solutions risk misaligning educational objectives, leading to inefficiencies, reduced adoption, and limited practical value [23].

4. Enhancement of Mutual Benefits

AI software and techniques will either enable new capabilities or enhance existing software and hardware functions [38]. To fully realize the potential of AI technology, all stakeholders, including AI-driven simulation developers, healthcare professionals, and legislators, must engage in collaborative relationships to address ethical, legal, and technological challenges [45,46]. These partnerships ensure that the decision-making processes of AI systems remain transparent and comprehensible [47]. Moreover, explaining the process is a key factor in fostering trust and optimizing mutual benefits. When AI-driven simulations articulate their decision-making processes to end users, including learners, educators, and stakeholders, trust is strengthened [48]. As an additional benefit, this communication reduces feature overload, improves data interpretation accuracy, and creates a feedback loop that benefits all involved [47].

High-quality data is essential for improving the accuracy of AI systems. Healthcare has recorded data across genetics, pharmaceuticals, and clinical practice for years, tracking medical professionals, technicians, patients, and clinical outcomes [25,49]. From a data perspective, a necessary and mutually beneficial relationship exists between simulationists and AI developers; AI relies on large datasets from diverse modalities to achieve accuracy, effectiveness, and utility [47]. These datasets should not be limited to organizations developing simulations but should also incorporate contributions from other entities within the healthcare AI ecosystem. However, ensuring data relevance is critical to mitigating bias. For example, using data from a metropolitan population to construct AI-driven simulations for rural healthcare settings could misalign training models with real-world conditions, leading to ineffective or biased outcomes [23].

5. Facilitating Rapid Uptake of Beneficial AI in Simulation Practices

Establishing partnerships between simulationists and AI scientists is significant because it may facilitate the rapid adoption of AI in healthcare education simulation, thanks to its ability to provide efficient solutions to simulationists' everyday responsibilities [50]. Integrating AI into healthcare simulation might help improve efficiency and learning, as adaptive learning has been shown to be beneficial to learners [37].

Zhang et al. [23] suggested that a possible reason AI has not yet been widely applied to practical teaching in healthcare is the disciplinary gap between developers and end-users. Healthcare simulation education and AI do not routinely intersect, leading to a scarcity of proficient professionals in both areas and a lack of reported collaborations between these disciplines [23].

Research Question 2: The Process of Partnership

To address the second research question, we reviewed and analyzed theories and frameworks from educational simulation and software development, identifying significant differences in their approaches. These differences were evident as one emphasized learner-centered education while the other focused on technology to address field-specific issues. Frameworks from either field alone failed to account for the unique requirements of interdisciplinary collaboration in developing AI-driven educational simulations.

We considered foundational concepts from educational simulation, including Kolb's Experiential Learning Theory, the ADDIE framework, Kern's six-step approach to curriculum development, and the Healthcare Simulation Standards of Best Practice (HSSBP) [28,30,51,52]. Among these, ADDIE and Kern's models emerged as the most suitable for interdisciplinary collaboration between AI and simulation education. Their structured yet flexible design allows integration with AI and data science methodologies. We found other approaches, such as Kolb's and HSSBP, to be more prescriptive and less adaptable to the iterative and data-driven requirements of AI integration.

In software development, frameworks such as the software development life cycle (SDLC), a long-standing standard, provide a comprehensive roadmap for project development [53,54]. We observed that emerging AI-specific models, such as the AI life cycle and the AI Guide for the U.S. Government, focus on AI processes but often fail to integrate traditional SDLC stages [55,56]. This misalignment can hinder communication and collaboration between AI developers and software teams. Ethical and trust-focused frameworks for AI, still in their infancy, also need further development for effective application in educational simulations [23].

To address these challenges, we propose a hybrid framework that combines key elements from healthcare simulation and software development. Below is a short description of the individual constituent frameworks and the hybrid framework.

1. Kern's Model of Simulation and Curriculum Design

Kern's model for curriculum design is a widely used six-step approach in healthcare education, particularly in simulation designs across various healthcare disciplines for several decades [30,57,58]. The steps involve problem identification, targeted needs assessment, establishing goals and objectives, developing educational strategies, implementation, and evaluation and feedback. Its focus on iterations made it an ideal candidate for our model.

2. ADDIE's Instructional Design

The ADDIE model, comprising Analysis, Design, Development, Implementation, and Evaluation, is a foundational framework used in instructional design [59]. It systematically guides the creation of effective educational experiences by addressing learner needs, developing and delivering content, and evaluating outcomes in AI-driven simulations, such as virtual reality environments [52]. Its adaptability and focus on learners made the ADDIE model an ideal candidate for our proposed model.

3. SDLC

The most well-known process in the software industry is the Software Development Life Cycle (SDLC) model [60]. The SDLC model includes six stages, which are progressed through in order or iterated in single or combinations of stages before progressing: 1) Requirements or Requirements Analysis, 2) Design, 3) Implementation or Coding, 4) Testing, 5) Deployment or Installation, and 6) Maintenance. These stages are often presented in a circle to reinforce the SDLC as an ongoing or iterative life cycle process within which software system creators continue to assess and update the system through these stages to establish, then evolve, and maintain systems for their users or goals.

4. Clarifying the Role of AI in Simulation Software Development

There are multiple types of AI, and using AI is a software effort that involves specific data science efforts. AI development in simulation follows a process: (1) Establishing goals through requirements analysis, (2) Acquiring relevant data, (3) Designing the AI functions and selecting an appropriate model, (4) Preparing data via various methods as required, which can include preprocessing or cleansing added data well as bias analysis, and validation set creation, (5) Implementing the use of the AI capabilities and conducting any necessary training, grounding and tuning, if required, the model to optimize performance, and (6) Iteratively refining the model based on results and feedback [61].

The use of AI is increasing in healthcare simulations. Similar to simulations that utilize databases, the data science aspect of AI focuses on establishing data and methods to access, adjust, and maintain this data. For example, leveraging GenAI capabilities in a simulation involves using large or small language models (LLMs or SLMs, henceforth referred to as LLMs) for conversational services and algorithms to access these LLMs on behalf of the simulation. Simulation projects may find that utilizing pre-existing AI models, such as ChatGPT4.X, is more beneficial than developing new models from scratch [62]. Employing these pre-existing models can save both time and money. Thus, reusing existing models emphasizes the importance of control techniques for established AI models. Examples of these control techniques include grounding data access through Retrieval-Augmented Generation and rubric techniques [63]. These methods add knowledge or topic-focused assets to help regulate outputs from general-purpose GenAI models, ensuring that responses from an LLM are relevant to the simulation. This combination of well-designed controls employed with pre-existing models enhances the viability of AI in simulations for a broader range of projects.

5. Our Proposed Model

AI capabilities in educational simulations depend on extensive datasets to train and maintain models, necessitating adaptive functionality to meet the evolving educational needs of healthcare educational needs. Effective simulations incorporating AI must focus on two key areas: 1) designing and integrating AI functionalities ethically, and 2) managing data models throughout their lifecycle, including structure, access, testing, and adjustment. These tasks require ongoing collaboration between simulation experts and technology professionals, relying on effective information sharing and coordinated activities to ensure the success of AI-powered simulations.

As a collaborative approach, we propose a lifecycle-centered framework as a foundation for fostering meaningful partnerships at critical stages of an AI-driven simulation. This framework identifies key collaboration areas per development stage of AI-driven simulation and outlines critical topics for bilateral communications. It serves as a practical checklist to ensure that essential discussions and decisions occur at the appropriate points throughout the project. This strategy integrates conceptual models familiar to both the simulation and AI communities and aligns with established guidelines [56,64]. Software models such as SDLC correspond with evidence-based practices in healthcare simulation and provide opportunities for structured collaboration, including data validation, functionality testing, and user feedback [30,59,60]. By leveraging these stages, simulationists and developers can effectively address challenges related to AI integration and lifecycle management.

Our proposed AI-Simulation Partnership Principle framework consists of two scaffolded steps: 1) the AI-Critical Collaboration Focus (AI-CCF) Model by LeMoine for AI and Data Science, and 2) the Hybrid AI Lifecycle in Simulation (HAILS) Overlay Framework while applying AI-CCF.

1) AI and Data Models Focus - AI-CCF Model

The first step of the AI-Simulation Partnership Framework is the integration of the AI workflow with

SDLC. The first three AI workflow steps - requirements, identifying, and acquiring data - and the selection of the AI model are often performed simultaneously due to their interdependence, which can require multiple iterations. This type of intra-cycle iteration within a framework is also common when using the SDLC model [60]. AI workflow steps 4-6 focus on preparing the AI model and data to support the goals of the simulation. Moreover, creating the software logic that effectively calls the AI capabilities to meet the simulation objectives is another task that demands AI expertise. Figure 4 illustrates the first step toward a valuable partnership framework by positioning these AI workflow steps within the stages of the SDLC. This initial overlay of AI workflow steps onto the SDLC stages addresses a model gap between generalized and AI-specific project management frameworks, laying the foundation of the AI-CCF model.

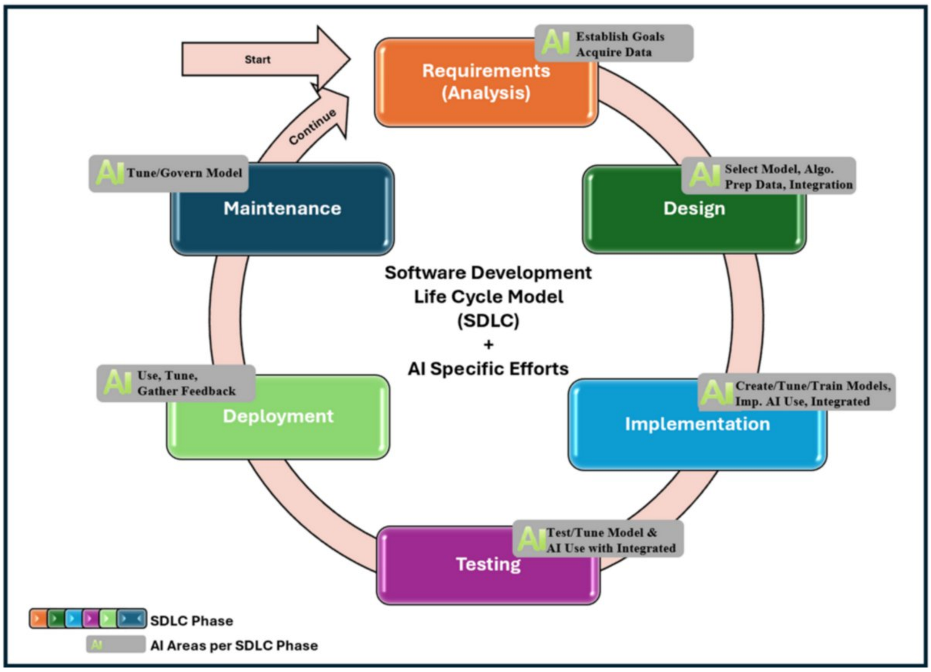

FIGURE 4: LeMoine SDLC With AI

Figure 5 presents the recommended discussion and collaboration points between AI experts and simulationists. The result is a single management framework that includes an ordered set of AI-specific efforts that fit within the overall creation effort for simulations, along with areas of critical collaboration that can be used to guide successful projects. These collaborations include the why, how, and for what purpose the AI services are called upon, and overtly calls out topics, such as rubrics and RAG (Figure 5).

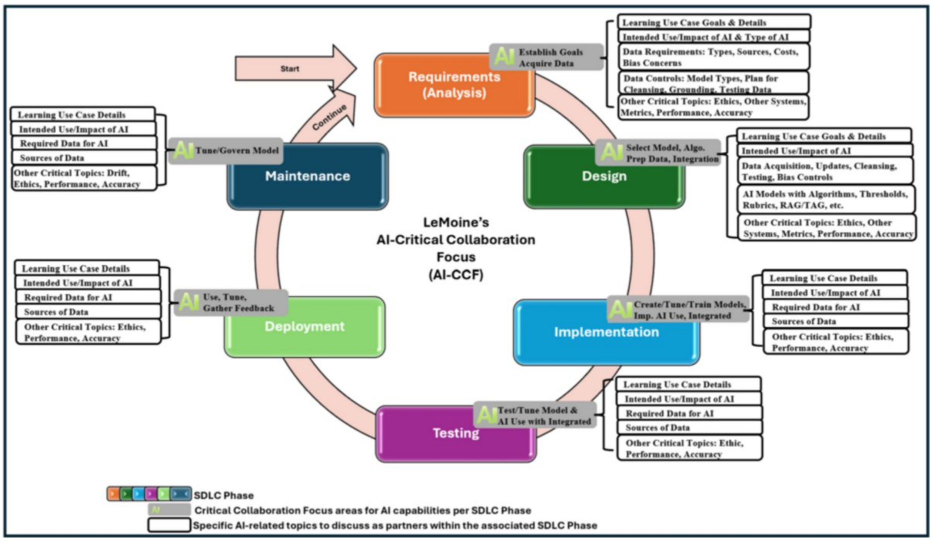

FIGURE 5: LeMoine AI-CCF Model

Before outlining the goals of each area of critical collaboration highlighted in the AI-Critical Collaboration Focus (CCF) model, we will connect the stages of the SDLC model to models that may be more familiar to simulationists and are used more frequently in their simulation practices.

2) HAILS Overlay Framework

To bridge the gap between technologists and simulationists, we introduce the Hybrid AI Lifecycle in Simulation (HAILS) Overlay Framework as the second step of the AI-Simulation Partnership Framework. In this framework, the HAILS technique identifies inflection points which are key collaborative areas between simulationists and AI experts. These inflection points, highlighted by the AI-CCF in Figure *5*, represent essential areas for discussion and decision-making, ensuring a structured and sustainable partnership between these fields of science. By aligning the adaptability of ADDIE and Kern's models with the structured approach of AI-CCF, the HAILS technique establishes a scalable, systematic methodology for AI-driven educational simulations. As an example, we present a HAILS of the CCE inflection points for the Kern and ADDIE frameworks. Both Kern and ADDIE are widely used instructional frameworks in educational simulations. These examples provide teams familiar with the Kern and ADDIE frameworks with the ability to understand when the AI-CCF inflection points should be raised and addressed to mitigate misalignment and feature bloat. Given the distinct origins of these two frameworks, the HAILS framework strategically applies AI-CCF stages alongside its critical collaboration across multiple steps in simulation-based instructional models.

As described earlier, the ADDIE framework has five stages. The first four flow in this order: Analyze, Design, Development, and Implementation. The Implementation stage flows back into the "Analyze" stage, completing this cycle. Each of these stages can also flow into the Evaluation stage. The Kern framework consists of six states, arranged in a clockwise order: Problem Identification, Needs Assessment, Goals and Objectives, Educational Strategies, Implementation, and Evaluation and Feedback. While the Kern model or framework offers a cycle that progresses from Problem Identification through Evaluation and Feedback, each state is fully interconnected, allowing for transitions from one state to another.

Table *1* presents a HAILS overlay that identifies the AI-CCF's stages for each ADDIE and Kern's state. This overlay allows users of ADDIE or Kern models to use the identified areas of collaboration to aid their efforts when using AI in their projects.

AI-CCF (SDLC Stage)	ADDIE State	Kern's State
Requirements	Analyze	Problem Identification; Needs Assessment; Goals & Objectives
Design	Design	Design
Implementation (Coding, Training)	Development	Implementation
Testing	Evaluation	Implementation; Evaluation & Feedback
Deployment (Install and Use)	Implement	Implementation
Maintenance	Analyze (Post-Implement)	Evaluation & Feedback

TABLE 1: HAILS Technique Overlay of AI-CCF Stages Onto ADDIE and Kern's States

AI-CCF, Artificial Intelligence-Critical Collaboration Focus; SDLC, Software Development Life Cycle; HAILS, Hybrid AI Lifecycle in Simulation

Figures *6* and 7, respectively, reflect the HAILS technique, which overlays the AI-CCF model stages onto Kern and ADDIE's frameworks.

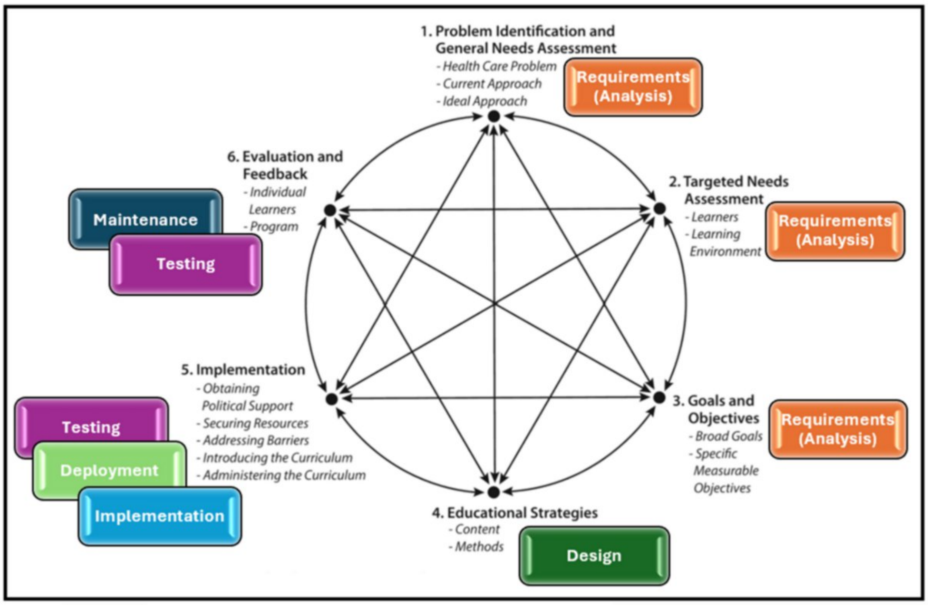

FIGURE 6: HAILS Technique Overlay on Kern's Model

HAILS, Hybrid AI Lifecycle in Simulation

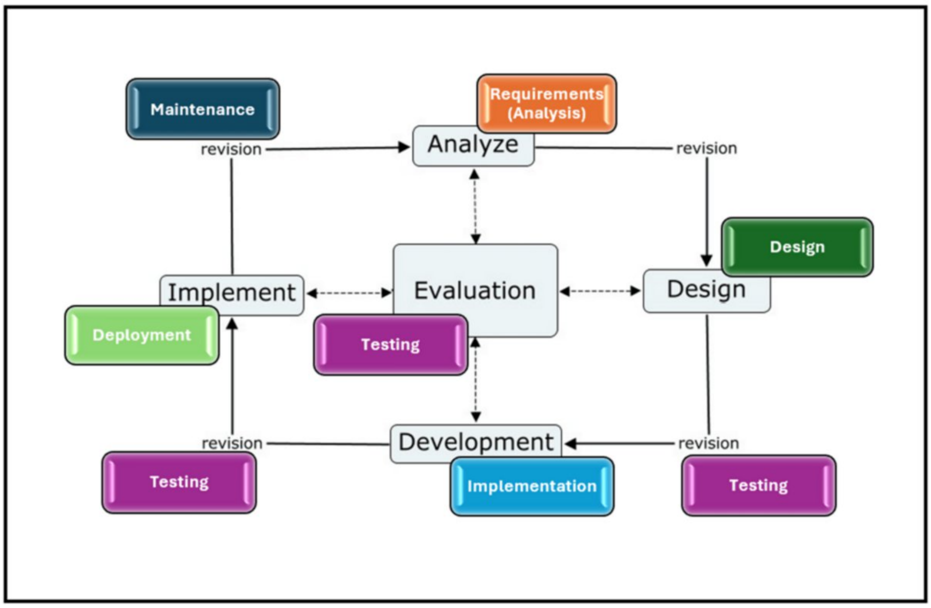

FIGURE 7: HAILS Technique Overlay on ADDIE

HAILS, Hybrid AI Lifecycle in Simulation

HAILS ensures that each of the six AI-CCF stages is included, aligning the critical AI-CCF stages with established simulation and instructional design frameworks. This provides simulationists a structured method to track progress and share feedback with AI product developers. In the ADDIE framework, for example, parts of the AI-CCF testing stage occur at three key stages: Design, Implementation, and Evaluation (Figure 7). Similarly, parts of the AI-CCF Requirement (Analysis) stage map onto Kern's Problem Identification, Needs Assessment, and Goal Setting (Figure 7). This structured integration enhances interdisciplinary collaboration by bridging the gaps between simulationists and AI experts.

Table 2 summarizes each area at each inflection point in the AI-CCF, along with the Kern and ADDIE models' counterparts. It also outlines the summary goal and specific topic area for each inflection point. This table can be used and extended with project-specific additions, resulting in a checklist to guide critical collaboration discussions and track shared agreements as they are established by the team.

Inflection Points	Goals of Simulationists/AI Expert Collaboration	Recommended Areas of Collaboration Between AI Experts/Simulationists
AI-CCF: Requirements; ADDIE: Analyze; Kern: Problem ID, Needs Assessment, Goals & Objectives	To enable a shared understanding of use case goals/objectives and AI's role in supporting them. This allows AI experts to gather the necessary understanding of the project to understand models and data characteristics.	· Simulation/Use Case Details · Intended use /Impact of AI, e.g., how AI surfaces in the HMI · Data Requirements: Types, Sources, Costs, Bias Concerns · Data Controls: Model types, plan for cleansing, grounding, testing · Other Critical Topics: Ethics, Other Systems, Metrics, Performance, Accuracy
AI-CCF: Design; ADDIE: Design; Kern: 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 including data and model maintenance plan · Other Critical Topics Continue
AI-CCF: Implementation (Coding, Training); ADDIE: Development; Kern: Implementation	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 · Other Critical Topics Continue
AI-CCF: Testing; ADDIE: Evaluation; Kern: Implementation, Evaluation & Feedback	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 Trade Off Decision making, e.g., Costs/Feasibility · Other Critical Topics Continue
AI-CCF: Deployment (install and use); ADDIE: Implement; Kern: Implementation	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 · Other Critical Topics Continue
AI-CCF: Maintenance; ADDIE: Analyze (Post-Implement); Kern: Evaluation & Feedback	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. · Other Critical Topics Continue

TABLE 2: AI Simulation Partnership Framework

AI-CCF, Artificial Intelligence-Critical Collaboration Focus; SDLC, Software Development Life Cycle; HMI, Human-Machine Interface; Q&A, Questions and Answers; UAT, User Acceptance Testing

Discussion

This study addressed two research questions about the reasons for and the process of a meaningful and sustainable partnership between healthcare simulationists and the AI healthcare industry. Findings revealed the AI healthcare industry's pivotal role in driving simulation innovation and the value of integrating specialized knowledge from both fields. This study also provided a hybrid framework that aligns AI capabilities with simulation-based learning and fosters collaboration between simulationists and AI developers.

The Necessity of Collaboration

Collaboration between simulationists and AI experts is essential, but is currently lacking due to the absence of standardized methodologies that bridge AI development with simulation practices. Existing frameworks, such as ADDIE and Kern's curriculum design, emphasize learner-centered instructional design, whereas AI development prioritizes data acquisition, algorithmic optimization, and computational performance [30,52,55]. Furthermore, these AI priorities do not always align with the software development processes utilized to establish simulations. This fundamental disconnect in priorities and workflows leads to inefficiencies and misaligned goals, which are exhibited by either feature bloat or feature scarcity and resource allocation issues [65]. Kern's and ADDIE's concepts also emphasize the importance of appropriately aligning simulations with goals to enhance effectiveness and efficiency [57,59].

Interdisciplinary partnerships offer an opportunity to co-create AI-driven simulation tools that are both technically sound and educationally effective. For instance, AI-enhanced adaptive learning systems can tailor training experiences to individual learners while avoiding unnecessary features that create cognitive overload [8,44,47]. Intentional collaboration ensures AI systems align with simulation-based objectives rather than functioning as standalone technological advancements.

The Scaffolded AI-CCF Model and HAILS Framework

To address the foundational issues of various workflow challenges, this study introduced the scaffolded AI-Sim partnership framework, which integrates AI-specific and computer science methodologies with established educational frameworks that can be applied to simulation-based training. Supported by the HAILS technique, the framework pinpoints critical collaboration points, such as requirements analysis, design, and implementation, where simulationists and AI experts must align their efforts. This scaffolding approach enables iterative improvements, ensuring that AI components, like data collection, model training, and testing, are effectively integrated into simulation environments while considering institutional and legal considerations.

Despite its potential, integrating AI into simulation frameworks presents persistent challenges [23]. Our lived experience and in-depth discussions revealed that divergent terminologies, workflows, and expectations create communication barriers, with simulationists prioritizing pedagogical outcomes and AI experts focusing on technical optimization. Additionally, the rapid democratization of AI technologies has increased the demand for AI-driven simulations. Still, this demand has outpaced the availability of technical and pedagogical expertise in the healthcare education sector [66]. We foresee several obstacles to effective collaboration between simulationists and AI experts. Table *3* outlines these challenges and suggests corresponding solutions.

Challenges	Recommendations
Limited communication between simulationists and AI experts, leading to misalignment in goals.	Establish structured communication channels and shared terminology to align goals and expectations early in development.
Lack of clear guidelines for integrating AI into simulation design and development.	Develop a project level and organization-approved standardized framework that defines collaboration points, decision-making processes, and best practices.
Knowledge gaps between simulationists and AI experts, resulting in misinterpretations of requirements.	Provide cross-disciplinary training and joint workshops to bridge technical and domain-specific knowledge gaps.
Data privacy, data bias, and ethical concerns in handling sensitive healthcare data.	Establish organization-specific and local law-abiding policies for data and AI governance. Implement these policies strictly, including privacy protection measures and ethical AI guidelines.
Limited understanding of AI capabilities and constraints among simulationists. Reluctance to include and be advised by AI Experts.	Involve AI experts early in planning to clarify AI's potential and limitations in accessible terms. Recognize AI Experts may have worked on similar projects.
Technical issues such as model drift and system scalability post-deployment.	Establish ongoing monitoring and iterative updates to address model drift, performance degradation, and scalability.
Insufficient feedback mechanisms during testing and deployment stages.	Implement structured feedback loops with end-users to refine AI-driven simulations throughout development and post-deployment.
Reluctance to fund iterative improvements. Early failures can erode executive confidence, leading to stalled adoption, limited resources, and premature abandonment. Lack of leadership buy-in and sustained investment.	Leadership buy-in and a structured funding extension plan should be developed in advance, outlining sustainable financial models, potential funding sources, and contingency strategies to support long-term innovation and scalability. Recognize that newer AI techniques can be new for simulationists and AI experts. Trial and error will be required.

TABLE 3: Challenges and Recommendations With Scaffolded Partnership Model

AI as an Enabler and Enhancer

Our research revealed that AI serves as both an enhancer and enabler in healthcare simulations. It enhances existing workflows through automation and enables new capabilities such as real-time feedback and adaptive learning [44,49]. Additionally, AI-driven simulations can both enhance and enable pre-existing simulations by personalizing training experiences and fostering critical thinking and complex problem-solving skills [47,49].

Despite its potential, AI in healthcare simulation remains underutilized, possibly due to a lack of awareness. As the saying goes, "You don't know what you don't know." Many simulationists and technologists may not fully grasp AI's capabilities or applications. Expanding this understanding through self-learning or collaboration with AI technologists is essential to keeping AI applications goal-driven and user-centered. More real-world use cases are needed to explore AI's enhancing and enabling features, ensuring its full potential in healthcare education.

Building Sustainable Partnerships

Successful partnerships occur when teams adopt co-design methodologies, involving clinicians and educators throughout development cycles to align technical capabilities with educational objectives [5,11,26]. Building lasting partnerships between healthcare simulationists and AI experts requires strategies beyond initial collaboration. Simulationists conduct needs assessments and provide ongoing feedback, while AI specialists translate educational goals into technical solutions and maintain them over time. Sustainability depends on mutual agreement on shared interests, continuous engagement, adaptability to evolving technologies, and long-term commitment [67-69]. Kotter's culture change principles may offer a framework for fostering long-term engagement and guiding teams through necessary shifts in the organizational culture for AI integration in healthcare simulation [68]. Structured engagement aligns stakeholders with a shared vision, ensures AI-driven simulations are rooted in evidence-based methodologies, and fosters a culture of continuous learning, trust, and adaptability [68].

In parallel with building strong internal partnerships, ensuring ethical and regulatory oversight is also essential for long-term success. Lomis et al. [26] emphasize that effective AI integration in health professions education depends on coordinated planning among educators, health systems, and technical stakeholders to align training with evolving clinical and technological contexts. However, persistent gaps in regulatory frameworks for AI-driven simulations create uncertainty around liability and accountability, eroding long-term trust and adoption [12,14]. Addressing these gaps requires coordinated strategies that foster collaboration and embed ethical review and regulatory alignment into the design process, principles that inform the framework proposed in this study.

Key Implications for Practice

This proposed framework provides a rich avenue to develop and implement learner-centric AI-driven simulations. Table *4* discusses the findings, which have broad implications across multiple domains.

Stakeholder Group	Key Implications for Practice
Healthcare Simulationists	AI can create adaptive, learner-centered tools that enhance training and improve patient safety outcomes. Simulationists must collaborate with AI developers to define clear goals and evaluation metrics. Further, simulationists should consider their AI experts as critical contributors during the early stages of any simulation project and ensure their insights are heard while framing goals and plans.
AI Developers	Partnering with simulationists ensures AI solutions are aligned with the needs of healthcare education. This reduces feature overload, improves usability, and addresses practical simulation challenges [32,41]. Further, AI experts should share similar use case's successes and challenges if applicable. Focus should always remain on the project goals and not on AI as a technology [51].
Policymakers & Healthcare Organizations	Support for interdisciplinary partnerships is essential. Funding, guidelines, and policies should encourage collaboration and address ethical concerns such as data privacy, inclusivity, and bias prevention [16].
Ethical Considerations	AI systems must be developed with transparency, fairness, and accountability. Datasets should be representative to prevent biases that could lead to ineffective or harmful training models [17,41].

TABLE 4: Implications for Individual Stakeholders

Strengths and Limitations

This study has several strengths. This use of a hermeneutic review framework, although less frequently used in healthcare, enabled an iterative and contextually rich synthesis of the literature, allowing themes to emerge organically rather than being predefined. The interdisciplinary approach, incorporating expertise from healthcare simulation, AI, education, and computer science, strengthened conceptual alignment across fields. A structured multi-step review process, including independent searches, cross-checking, and final validation, enhances rigor and reliability. Additionally, the combination of peer-reviewed and gray literature provided a comprehensive perspective, while adherence to SANRA guidelines ensured methodological transparency.

This study has several limitations. Despite its strengths, due to time constraints, the study's reliance on Google Scholar and Google Search was practical; however, it excluded specialized databases such as PubMed and IEEE Xplore, which may have led to the omission of relevant field-specific research. Although explicit inclusion and exclusion criteria were applied, the emphasis on conceptual relevance rather than exhaustive coverage may introduce selection bias. Algorithmic variability in search results, though reduced by independent researcher searches, still represents a limitation. Additionally, while key theoretical and conceptual frameworks were identified, they require empirical validation. Finally, the absence of translations for non-English sources may limit the study's global applicability.

Future Research Opportunities

Future research opportunities are summarized in Table *5*. Moreover, AI, particularly GenAI, is rapidly evolving. AI-related advances, such as the more readily adopted multi-agent AI systems [70], emerging agentic-AI [71], GenAI prompting Command Line Interfaces (CLI) [72], and Vibe Coding techniques [73], may necessitate adjustments and additions to the proposed AI-CCF.

Research Focus	Description
Empirical Validation	Conduct and publish retrospective and new projects that rigorously study and validate the AI-CCF model and HAILS technique across diverse healthcare simulation contexts to ensure effectiveness and applicability. Use these concrete efforts to assess the generalizability and effectiveness of the model's approach.
Standardization	Develop standardized terminologies and guidelines to facilitate interdisciplinary collaboration and seamless integration of AI-driven simulations in healthcare training.
Training Programs	Design and implement both individual and joint training programs to equip simulationists and AI professionals with the necessary skills for effective collaboration, using the AI-CCF model.
Ethical Governance	Investigate and establish governance frameworks to address ethical concerns related to bias, privacy, and accountability in AI-driven simulations.
Longitudinal Impact Assessment	Conduct long-term studies to evaluate the sustained effects of AI-driven simulations on learning outcomes and clinical performance over time.
Scalability and Accessibility	Explore strategies to enhance the scalability of AI-driven simulations, ensuring equitable access across diverse healthcare settings and institutions.

TABLE 5: Future Research Opportunities

AI-CCF, Artificial Intelligence-Critical Collaboration Focus; HAILS, Hybrid AI Lifecycle in Simulation

Conclusions

AI integration in healthcare education simulations requires structured collaboration between simulationists and AI developers. This study establishes a guiding principle for meaningful and sustainable partnerships between AI technologists and simulationists, emphasizing practical, evidence-based technology aligned with educational objectives. The AI-Simulation Partnership Framework, comprising LeMoine’s AI-CCF model and the HAILS framework, utilizes the overlay technique to provide a structured approach for bridging disciplinary gaps by combining AI’s computational capabilities with simulation’s experiential learning. This framework can be a critical collaboration checklist to help guide AI-driven simulations. Sustained collaboration throughout an AI product’s lifecycle ensures alignment with educational goals, considers ethical concerns, prevents feature bloat or scarcity, and supports usability. Future research should focus on empirically validating the framework in applied healthcare simulation contexts to assess its impact on collaboration quality, simulation effectiveness, and learner outcomes. By treating AI and simulation as complementary systems, this approach supports the development of practical and effective AI-driven simulations, advancing healthcare education, and potentially improving patient care outcomes.

Appendices

Terms	Definitions
Artificial Intelligence	Alan Turing’s definition from 1950: Science and engineering of making intelligent machines, especially intelligent computer programs (Turing, 1950). A system’s ability to correctly interpret external data, to learn from such data, and to use those learnings to achieve specific goals and tasks through flexible adaptation [Kaplan 2019; #5 from the manuscript references]. ISO/IEC 22989: 2022 standard defines AI in the following way: “Artificial intelligence is a technical and scientific field devoted to the engineered systems that generates outputs such as content, forecasts, recommendations or decisions for a given set of human-defined objectives.”
Generative AI	The term “generative AI” refers to the class of AI models that emulate the structure and characteristics of input data to generate derived synthetic content. This content can include images, videos, audio, text, and other digital content (Federal Register 2023). GenAI refers to AI capabilities that can be used to create new content, including text, images, and audio by learning based on existing data which the GenAI has been trained. It “generates” new content on its own (Goodfellow, et al., 2014; Hamet &Tremblay, 2017).
AI Systems	An AI system is a machine-based system that can, for a given set of human-defined explicit or implicit objectives, infer, from the input it receives, how to generate outputs such as predictions, content, recommendations, or decisions that can influence physical or virtual environments (Organization for Economic Co-operation and Development, OECD.AI, 2023). OR These include models that attempt to mimic human reasoning for problem-solving and others that rely solely on large volumes of data to generate frameworks and integrate elements of human reasoning without requiring accurate modeling of human processes (Methany, 2019. p. 14).
Healthcare AI Systems	For this project, AI systems dealing with health and the healthcare industry are called the health AI systems industry, or the health AI

Industry	industry for short.
Large Language Models (LLMs)	Large Language Models are models that can understand and generate human-like communication. They use transformative models, are trained on billions of data assets, and use algorithms to predict the next best sequence of words to provide. LLMs are critical to the cutting-edge of GenAI systems (Clusmann et al., 2024).
Healthcare Education Simulationist	A person who is involved, full-time or part-time, in modeling or simulation activities" for example, develops models to be used for simulation purposes; performs simulation studies; develops simulation software; manages simulation projects; advertises and/or markets simulation products and/or services; maintains simulation products and/or services; promotes simulation-based solutions to important problems; advances simulation technology; and advances simulation methodology and/or theory (Lopreiato, n.d., p. 36).
AI/Software Experts	Throughout this paper, we are defining AI Industry or AI/Software Industry Experts as the AI technology experts that design, develop, test, deploy and tune the healthcare educational simulations discussed in this work. It is important to note that no simulation is simply AI or GenAI, they are software and sometimes software and hardware solutions that offer educational experiences. Most require multiple software and hardware experts to design, create and maintain. In terms of this work, these AI and other software/hardware experts work with educationally focused simulationists.
AI Industry	The AI industry are the companies and organizations that are creating and offering AI components, models, APIs and hosted services such as the GenAI LLMs, capabilities from OpenAI or StabilityAI. These capabilities and services are used and or licensed by AI/Software experts when they create simulations.

TABLE 6: Appendix 1: Essential Definitions

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Additional Information

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