Title: New technology everywhere: What else is on the Horizon?

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Introduction

Simulation technology has advanced significantly in recent years, enhancing the quality of simulation-based education and simulation-based research. Simulation-based education (SBE) leverages technology to enhance the knowledge, skills and behaviors of individuals and teams. The utilization of high-quality healthcare simulation has been shown to positively influence learners by providing opportunities for skill development within a controlled and risk limited environment (Jeffries et al., 2015).

In addition to using technology-enhanced simulation in SBE, technology can also expand the use of simulation as a methodology for assessment of practice or processes and for healthcare delivery research, providing insights that can improve healthcare delivery systems. Examples of current applications that combine simulation and technology include the development of digital twins, assessment of interactions between the physical environment and technical aspects of surgical procedures interact with surgical team movement, analysis of video recordings of nurses' responses to physiological monitor alarms, and the use of eye tracking to understand healthcare information display (Doberne et al., 2015; Macmurchy et al., 2017; Taaffe et al., 2023).

This "chapter" provides tantalizing glimpses into the applications of technology-enhanced simulation that are both challenging and important, forming part of a series of exploratory chapters initiated by the Society for Simulation in Healthcare. Topics in this chapter include applications of technology in education, medication safety, clinical decision making, and digital twinning, and the importance of digital literacy. While some examples highlight nurse trainees, who have unique clinical responsibilities and educational requirements, many of these principles can be broadly applied to benefit the diverse range of healthcare executives, professionals and support staff who work together to optimize patient care.

Implementation of Technologies in Simulation-based Education

Technological advancements have transformed simulation-based education (SBE) by enhancing interactivity, immersion, and realism (Al-Ansi et al., 2023; Higham, 2020 May 22). Learners benefit from increasingly sophisticated experiences that mimic real-world scenarios, promoting clinical judgment, and providing opportunities for the practical application of knowledge and skills (Padilha et al., 2019).

The challenge for educators is to guide learners through progressive levels of learning, from learning how to use a tool in a simulated environment to being able to recognize the need for and optimally utilize a similar tool in patient care settings. In SBE, educators often incorporate simulated tools that mimic those found in patient care, including physical instruments and digital applications. Learner familiarity with clinical procedures and equipment is enhanced through hands-on activities, such as assembling and disassembling a cystoscope for obstetric/gynecologic medical residents or donning and doffing personal protective equipment (PPE) to improve novice clinician confidence and preparedness while decreasing the incidence of contamination (Greaves et al., 2023, March 1; Shah et al., 2022).

The most obvious challenge of using technology with in-person SBE is the significant cost of purchasing, maintaining, and training facilitators to use specialized clinical equipment (Elendu et al., 2024, July 5). This can create an environment of inequity among educational settings. In addition, it can be difficult for simulation centers to keep up with equipment changes made in clinical facilities or to stock multiple versions of a specific piece of equipment (e.g., infusion pumps) as different facilities may use different brands or models. In such cases, the key challenge is to train learners to understand the core function of the equipment and apprise them of the need to remain flexible when encountering something different in clinical settings.

As an alternative to in-person SBE, hybrid simulation offers potentially more flexible options if the resources are available. Le Lous et al. (2020, March 1) describe hybrid simulation as using at least two different simulation modalities within the same simulation (e.g., manikin and augmented reality). Brown et al. (2022) describe how hybrid simulation can include cost-effective options such as wearable technology for trained standardized patients. Burk (2024) utilized Quick Response (QR) codes in simulation as an access point for learners to a knowledge refresher, a visual image of a wound, a how-to guide related to the equipment being used, or even a concept embedded in the scenario. Additionally, QR codes can be used to simulate medication scanning in resource limited areas (Meginniss et al., 2024, August 19).

At the core of all educational efforts is the need to articulate clear learning objectives and design activities aligned with frameworks such as the Healthcare Simulation Standards of Best Practice (Watts et al., 2021). Utilizing Bloom’s taxonomy modified for digital learning (Hogel, n.d.) enables educators to transition from instructing learners on the use of a specific tool in simulated environments to fostering an understanding of the tool’s role in patient care. This approach promotes the development of flexibility in selecting among various tool options for the creation and implementation of care plans that prioritize optimal patient safety and outcomes. Integrating digital literacy into health education is essential for adequately preparing future healthcare professionals (American Association of Colleges of Nursing, 2024; Tietze & Thomas, 2024).

Increasing Digital Literacy to Improve Medication Safety

Electronic Health Records (EHR) and Bar-Coded Medication Administration (BCMA) systems are prevalent in 96% of modern hospital settings; however, fewer than 10% of nursing programs utilize an

EHR system in simulation (Tietze et al., 2024, January 19). These technologies must be integrated consistently into simulation-based learning experiences to adequately prepare future nurses for real-world clinical data systems (Wyman et al., 2024).

Addressing technostress

Technostress refers to the mental or emotional strain that can result from interactions with the ever-expanding applications of technology in healthcare. Effective management of technostress, through a robust technology-oriented nursing education curriculum supported by academic-practice partnerships, is critical to the well-being of both current and future nurses (Nursing, 2021). In addition to promoting well-being among nurses, healthcare organizations benefit directly, as nurses become well-positioned to contribute meaningfully to the overall strategic goals of the organization. A curriculum that effectively manages technostress enhances nurses' clinical and technical knowledge and skills, fosters collaboration between academic institutions and clinical practice, increases research capacity, and improves patient care outcomes (Wirth et al., 2024).

In recent years, concerns have been raised regarding newly licensed nurses who, lacking exposure to electronic documentation during their training, struggle to navigate complex digital health systems effectively. This deficiency in experience frequently results in inadequate documentation and increased patient care errors (Everett-Thomas et al., 2021, April). Research indicates that digital literacy significantly influences the effective utilization of EHRs; *however, many clinical training sites still neglect to provide students with access to their existing EHR systems during clinical education* (Ellis et al., 2020, October 20). To address this gap, it is proposed that students engage actively with academic EHR (aEHR) during training, using a simulated EHR containing information about simulated patients. Working in an actual EHR can provide clinical decision, dosing and other integrated support and surface the actual complexity of patient encounters. However, an aEHR allows instructor manipulation of patient data to match curricular objectives and easier retrieval of information about student performance. The aEHR approach can enhance learner confidence and digital literacy while minimizing the opportunity for documentation errors in actual patient records (Everett-Thomas et al., 2021, April; Kleib et al., 2021, April 27). This essential integration of clinical technology into simulation enhances the fidelity of each scenario, which is crucial for effectively preparing future nurses for the modern healthcare work environment. Such preparation may also mitigate technostress experienced by newly licensed nurses and ultimately contribute to reduced turnover rates and improved patient safety (Tietze et al., 2024, January 19).

Improving technological fluency

The goal of improving technological fluency through innovations in simulation is being embraced by healthcare industry partners. Many vendors are contributing to curriculum redesigns occurring in educational teams, such as by supplying barcode-labeled practice medications that can be scanned directly into multiple commercial aEHR systems. Collaborations among industry suppliers, digital platforms, and learning management systems are emerging daily. The affordability and scalability of these platforms are becoming critical to supporting essential curricular changes that enhance simulation fidelity and competency-based education.

Integrating the aEHR into simulations at all levels of a nursing program ensures that students cultivate essential technological fluency through hands-on experience in digital documentation, data management, and data-informed clinical decision-making (Tietze & Thomas, 2024). Such integration serves as a mechanism for programs to bridge the divide between theoretical knowledge and practical application. Moreover, this may improve the confidence and well-being of new graduate nurses by reducing technostress, which is a significant factor contributing to high attrition rates among nurses during the first year following graduation (McBride et al., 2020; Tietze & Thomas, 2024).

Ultimately, the expense of integrating this technology into educational programs is justified by the potential for reducing errors in clinical settings, fostering a deeper understanding of how technology supports patient care, and making graduates more competitive (Wyman et al., 2024). An authentic aEHR that facilitates education and is comparable to those used by nurses and other healthcare workers at inpatient facilities, rather than limited function substitutions, must be incorporated into the educational preparation of future nurses to ensure the demonstration of critical informatics competencies upon graduation and entry into the workforce. Nursing programs have an **obligation** to provide the necessary resources and digital tools to deliver high-fidelity simulations that accurately reflect the current work environment, thereby ensuring that future nurses are prepared to exhibit clinical competency in high-risk activities such as medication administration.

Integrating aEHR and BCMA technology into training programs provides nursing students with essential hands-on experience in digital health tools, enhancing their familiarity with accurate medication administration processes. While BCMA technology is particularly relevant for nursing education, the benefit and importance of integrating the aEHR – and other modern clinical technologies - into trainee education extends to physicians, pharmacists, and other allied healthcare professionals. Ongoing structured opportunities to learn about the capabilities, limitations and applications of new and emerging technologies also benefit experienced clinicians.

Building on these foundational technologies, clinical decision support (CDS) systems can offer advanced resources to further improve clinical decision-making and patient safety.

Clinical Decision Support Promotes Patient Safety

Clinical decision support (CDS) systems have emerged as essential tools in healthcare, aiming to enhance clinical decision-making and patient care through the integration of evidence-based guidelines and patient-specific data. This exploration addresses the current state of CDS, including examples and applications in clinical practice and education, the technologies driving its advancement, the challenges faced, and the future trajectory of CDS, focusing on improving patient safety and quality of care.

CDS encompasses a variety of tools and interventions, computerized as well as non-computerized. Non-computerized tools include clinical guidelines and digital CDS resources (e.g., apps), which can be easily integrated into simulations (Wasylewicz & Scheepers-Hoeks, 2019).

Another category of CDS systems, sometimes referred to as basic or simple CDS systems, includes tools to help focus attention, such as laboratory information systems (LISs) highlighting critical care values or pharmacy information systems (PISs) presenting an alert about drug-drug interactions or dosing limits (Wasylewicz & Scheepers-Hoeks, 2019).

In recent decades, most attention has been directed towards advanced CDS systems which provide patient-specific recommendations (Wasylewicz & Scheepers-Hoeks, 2019). Advanced CDS provides clinicians, staff, patients or other individuals with knowledge and person-specific information, intelligently filtered or presented at appropriate times, to enhance health and health care (HealthIT.gov, 2024; Wasylewicz & Scheepers-Hoeks, 2019). Each CDS system requires computable biomedical knowledge, person-specific data, and a reasoning or inferencing mechanism to combine knowledge and data to generate and present helpful information to clinicians as care is being delivered.

Current Technologies Driving Advanced CDS

Modern CDS tools leverage enormous datasets, the EHR, and advanced analytics to support clinical decisions. For example, algorithms designed to identify patients at risk for sepsis have shown promise in reducing morbidity and mortality (Seymour et al., 2017, June 8)

Additional examples of advanced CDS systems include:

- checks for drug disease interactions,
- individualized dosing support during renal impairment,
- recommendations on laboratory testing during drug use,
- computerized alerts and reminders for care providers and patients,
- condition-specific guidelines and order sets,
- focused patient data reports and summaries,
- diagnostic support, image recognition and analysis,
- clinical trial matching,
- emergency department triage tools,
- radiation dose monitoring,
- contextually relevant reference information,
- predictive analytics, and resource allocation and management (HealthIT.gov, 2024; Kawamoto et al., 2005, March 14; Wasylewicz & Scheepers-Hoeks, 2019).

Many hospitals and clinics have adopted CDS to improve efficiency, reduce medical errors, and ensure adherence to clinical guidelines (Friedman, 2024, January 10). Studies have demonstrated that effective application of CDS tools can improve health outcomes and reduce healthcare costs (Bates et al., 1999).

Support for CDS Development and Adoption

The Assistant Secretary for Technology Policy/ Office of the National Coordinator for Health Information Technology (ASTP) supports efforts to develop, adopt, implement, and evaluate the use of CDS to improve health care decision making (HealthIT.gov). These efforts aim to promote the consistent implementation of CDS tools, which can drive improvements in clinical practice, optimize resource utilization, and support evidence-based care delivery.

Current State of CDS in Clinical Practice

Different types of CDS may be ideal for distinct processes of care in different settings (Bates et al., 1999; HealthIT.gov, 2024). Health information technologies designed to improve clinical decision making are particularly attractive for their ability to address the growing information overload faced by clinicians, while providing a platform to integrate evidence-based knowledge into care delivery. For example, clinical alerts regarding medication interactions or allergy warnings are commonly implemented in EHRs to improve patient safety (Bates et al., 1999). The majority of CDS applications operate as components of comprehensive EHR systems, although stand-alone CDS systems are also used (Bates et al., 1999; HealthIT.gov, 2024).

Current State of CDS in Healthcare Education

While our traditional sense of medical simulation involves scenarios, manikins, resuscitation exercises, and procedural training, we must now expand this vision to incorporate modern technologies (Pappada & Papadimos, 2017). For example, in radiology education, simulation cases with computer-generated CDS feedback may improve the educational value of interpreting imaging studies at a workstation without adding additional time. This ability may be particularly relevant in this era of increasing remote work and asynchronous attending review (Shah et al., 2022).

More broadly, integrating CDS in healthcare education is critical to ensure that future healthcare providers understand data science and artificial intelligence (AI) principles(Kafke et al., 2023, August 11; Seth et al., 2023). More programs are now teaching trainees how to use CDS tools effectively, highlighting the need for critical thinking and clinical judgment alongside these automated systems. By exposing students to real-world scenarios and data-driven decision-making, healthcare education can better prepare them for clinical practice. As the field evolves, regular updates to data science and faculty development programs are essential for effective implementation (Seth et al., 2023).

Technologies Driving the Evolution of CDS

Several innovative technologies are driving the evolution of CDS, including:

1. AI and Machine Learning (ML), which are used to analyze vast datasets, identify patterns, and generate predictive insights (Topol, 2019).

2. Natural Language Processing (NLP), which enables CDS systems to interpret unorganized data from clinical notes and medical records, improving the relevance of recommendations provided to clinicians (Ahmed et al., 2023).

3. Wearable Devices: Integration of data from wearable health devices into CDS systems can provide real-time monitoring, and data capture, as well as alerts based on patients' data.

Challenges and potential solutions for CDS

Several challenges impede the effectiveness of CDS systems, including variability in the effectiveness of CDS implementations. While some systems yield substantial benefits, others are underutilized, inadequately customized, poorly integrated into clinical workflows, or unhelpful, leading to issues such as alert fatigue and resistance to acceptance among providers (Fallon et al., 2024, January; Teufel & Binder, 2021; Wasylewicz & Scheepers-Hoeks, 2019; Yoo et al., 2022). In addition to developing CDS that provides valuable, relevant, and needed information, collaborative technology teams can design more user-friendly interfaces. This would allow customization of alerts based on clinical context and implementation of targeted education and training programs to enhance clinician engagement with CDS tools. Additionally, the effectiveness of CDS tools is heavily reliant on high-quality, interoperable data. Poor data quality can lead to incorrect recommendations (Teufel & Binder, 2021; Yoo et al., 2022) However, advances in interoperability may raise concerns about data privacy (Yoo et al. 2022).

Future Directions for CDS: the Next 5 Years

The next generation of CDS tools will harness AI and patient-specific data to offer customized recommendations, including modeling and prediction of individual patient outcomes and trajectories of care, which can lead to more accurate decision-making (Pappada & Papadimos, 2017).

As standard data formats are more widely adopted, leveraging the large data sets generated by EHRs, and integrating CDS across various platforms will become easier and more user-friendly, supporting advanced algorithms, analytics and machine learning approaches (Pappada & Papadimos, 2017).

Finally, future CDS systems will empower patient engagement in their care by giving them actionable insights based on CDS recommendations.

Digital Twins

Healthcare Digital Twins (DTs) are a group of technologies that leverage models and simulation to more comprehensively create interactive virtual representations of patients, healthcare equipment, and clinical systems, with the intention of imparting in-depth understanding and valuable predictive data.

A DT is a set of virtual information constructs that mimics the structure, context, and behavior of a natural, engineered, or social system, or system-of-systems. The bidirectional interaction between the virtual and the physical is a key characteristic of a DT. Information from the physical counterpart is acquired with sensors and observation; this information is fused and assimilated to inform the virtual representation. The virtual representation is dynamically updated with data from its physical twin; the virtual representation then uses modeling and simulation, AI, and other methods of analysis to make predictions and inform decisions. There is ongoing interaction between the physical counterpart and the virtual representation, and there should be “human-in-the-loop” participation in decision-making. The digital twin should operate within a framework of verification, validation, and quantification of uncertainty, as well as considerations of ethics and security (National Academies of Science, Engineering and Medicine, 2024).

Brief description of DT technology

Computer simulation involves creating a computer-based model or virtual representation of a system or process to study and analyze its behavior. As an extension to traditional computer simulation, DT is a virtual representation of real-world entities and processes synchronized at a specified frequency and fidelity. DTs transform business by accelerating holistic understanding, optimal decision-making, and effective action. DTs use real-time and historical data to represent the past and present and simulate predicted futures (Grieves & Vickers, 2017).

Healthcare DTs offer value by enhancing operational efficiency, improving patient care, and accelerating research and development. Models of healthcare facilities and individual patients can help leaders to optimize resource allocation, reduce costs, and design more precise/effective personalized treatment plans. DTs can accelerate drug discovery by enabling virtual clinical trials, accelerating time to market. DTs allow caregivers to try different solutions virtually, hastening healing. As healthcare shifts towards data-driven practices, DTs will become a vital strategy for maximizing clinical and financial performance.

Current DT use in healthcare care

DTs are typically created via mechanistic or data-driven models. Mechanistic models are based on our understanding of the underlying biological processes that contribute to a disease or condition. These models are typically created using mathematical equations that represent the interactions between different cells, molecules, and pathways (Baker et al., 2018; Laubenbacher et al., 2024, March 7; Sakata et al., 2024).

Data-driven models are created using EHRs, genomic data, and imaging data. These models use machine learning algorithms to identify patterns and relationships in the data that can be used to predict disease progression and response to treatment (Baker et al., 2018; Laubenbacher et al., 2024, March 7; Sakata et al., 2024)

Hybrid models combine elements of both mechanistic and data-driven models. These models leverage the strengths of both approaches to create more accurate and robust digital twins (Baker et al., 2018; Laubenbacher et al., 2024, March 7; Sakata et al., 2024).

DTs can be used to study a wide range of diseases. By simulating the progression of a disease in a DT, researchers can gain insights into the underlying mechanisms of the disease and identify potential targets for treatment (Baker et al., 2018; Laubenbacher et al., 2024, March 7; Sakata et al., 2024).

System DTs support workflow redesign and configuration for hospital operations. To create opportunities to improve services and ultimately improve patient care, DTs can:

- simulate hospital processes,
- forecast demand for hospital services and inform future needs
- optimize the allocation of resources
- simulate emergency situations (Zhong et al., 2022)

Future state of DTs

Effective DTs require data, system models, and a framework for model interoperability. Physics-based, data-driven, multi-scale, and hybrid models are needed to represent human physiological systems and the body as a whole. While many system models have been built, most of these models are monolithic and not interoperable. Future work includes the creation of malleable, interoperable, learning models. Future work will also include the creation of data collection and validity standards to support trust. Finally, a system-of-systems interoperability standard is required.

In the future, DTs will be used to create high fidelity models of both general and specific patient populations. These models will support education, patient care, and research and development. Educational use will include the ability to “load” any type of patient or population necessary to support case-based learning. Models of patient populations will support activities such as drug development and testing as well as inform population health policies. Representation of individual patients via their DT will support both analysis of current and prediction of future health based upon various potential interventions.

Physiological systems can be massively complex. As our understanding of complex human systems increases, model and data complexity will follow suit. Complex models require complex, complete, and accurate data. Healthcare data collection will increase exponentially, requiring new technical and regulatory mechanisms and processes. Among the challenges to DTs is the requirement that the underlying data be sufficiently comprehensive, accurate, precise, relevant, and correctly representative (e.g., unbiased) to support DTs which are both trustworthy and trusted.

Why DTs might matter

Healthcare practitioners become experts because they '"train through repeated exercises" within day-to-day clinical activity' (Fogarty & Mauksch, 2014, December). This starts in undergraduate education and continues through graduate education and practice. Successful healthcare education efficiently creates proficient practitioners with comprehensive expertise. DTs have the potential to support education by lessening the need for physical access to patients to learn. DTs can increase learning fidelity, enabling expertise by enabling a deeper representation of both general and specific physiological systems. DTs can help learners accurately consider how our physiological systems interact with both other physiological systems and external systems. DTs have the potential to represent a subject's health at any phase of their lifetime based upon critical components such as diet, exercise, or predisposed condition. The ability to rapidly represent individual future health based upon critical factors will improve the systems thinking approach required to treat patients comprehensively.

Summary of DT potential

The future of DTs in healthcare is promising, driven by the availability of complex patient data, an aging population with complex healthcare needs, a shortage of clinical staff, and advances in artificial intelligence (AI). DTs have the potential to enable precise, real-time modeling of patient conditions, allowing for personalized interventions. As the aging population grows, DTs can support management of chronic conditions and prediction of disease progression, optimizing care and resource use. Assuming ongoing staff shortages, DTs, combined with AI, have the potential to automate routine care, provide real-time insights, and support clinical decision-making, allowing healthcare workers to focus on more complex problems. AI integration with DTs will enable massive data analysis and continually improving learning models. Together, these innovations have the potential to improve patient outcomes, streamline healthcare delivery, alleviate the strain on healthcare systems, and allow safe and cheaper care.

Keeping up with advances in simulation technology

There are challenges and opportunities encompassed in the technologies addressed in this chapter, as with the other chapters in this series. Technology-enhanced simulation may be used in a simulation laboratory or center to standardize and control content and variables for educational or research purposes. When a controlled environment is desirable, how can simulation centers have access to equipment and software that adequately replicates the resources available in actual patient care environments? Is there a way to support the inclusion of "extras" of equipment or licenses being used in real patient care settings? Is the previous, but now replaced, version of equipment or software available at a discounted cost? Will it be good enough? Should real equipment be rotated through the simulation center as a matter of course? Would it be useful for the simulation center to maintain standards sufficient to allow it to serve as a backup resource for patient surges during natural disasters or mass casualty events?

For technology-enhanced simulation used in actual patient care settings, whether for education or for research, are there cybersecurity hazards that should be addressed? Metrics and events for analysis are collected by healthcare delivery organizations based on the care of individual patients, or in response to credentialing, certification, or ranking criteria. To facilitate in situ simulations to test healthcare delivery, should simulated patients be integrated into the operating room schedule? How might simulations conducted in situ adversely impact metrics collected by healthcare delivery organizations? And how might simulations conducted in situ easily contribute to, and benefit, the data collection that the organization desires?

To support ongoing improvement of technology-enhanced simulators and simulations, what feedback mechanisms would be useful and effective to provide information and suggestions about accuracy, functionality, innovative applications or other insights developed during use of the simulators and simulations?

This chapter, as a contribution to the larger future of technology in simulation project, has scratched the surface on ways that the combination of different types of simulation and a variety of technologies can be used to advance healthcare provider education and improve the systems that support and optimize healthcare delivery. Additional technologies that can be leveraged with the goal of improving healthcare delivery include motion tracking and eye tracking; other technologies are no doubt on the horizon.

Summary

The integration of evolving technological innovations in healthcare simulation offers students experiential learning in limited-risk environments, improves critical thinking, supports patient safety, and increases learner engagement students (Gause et al., 2022). This form of experiential learning improves learner outcomes and preparedness for real-world challenges (Bienstock & Heuer, 2022, June 24; Oyekunle et al., 2024).

Similarly, technological innovations will increase the convenience and augment the effectiveness of simulation for the assessment of performance and the conduct of research aimed at improving the capabilities of individuals, teams, and healthcare systems coping with real-world challenges.

Considering the rapid emergence of scientific developments, technology-enhanced simulation will continue to be a powerful tool in the service of optimizing healthcare delivery.

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