Chapter 16
Intelligent Systems in Learning and Education

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After reading this chapter, you should know the answers to these questions:

- How has intelligent system-based medical education evolved from the days of Sir William Osler?
- What kinds of intelligent educational tools currently exist to support health professionals' education and training?
- What is the nature of mapping between learning with intelligent system tools and applying this learning in clinical practice?
- What are some of the challenges of using artificial intelligence tools for health professional education as we move to the future?

Introduction

Artificial Intelligence (AI) use is increasing rapidly in all fields, and it will have a significant impact on the way the doctors'practice medicine. However, the training that students and medical residents receive, about the importance of AI for their clinical practices, is woefully inadequate [1]. At the same time, the potential of using AI in the learning process has also not been completely realized in healthcare.

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AI-based systems, such as intelligent tutoring systems [ITS], can change mass education to personalized education, helping each learner to proceed at his/her own pace, with a curriculum that is dynamically sequenced to achieve the individual learning goals.

The amount of medical knowledge has long exceeded the organizing capability of the human brain. Yet the curricula remain information-based, prioritizing memorization over reasoning and managing information. The underlying assumption is that physicians should be the major source of medical information. However, this assumption is untenable given the vast, publicly available, online sources of medical information. For example, AI-based personalized medicine will require the new practicing physician to be able to understand the basis of this personalization and to explain this, along with the resulting treatment options, to their patients. Consequently, the skills taught to a new generation of physicians must move from remembering or acquiring information to collaborating with AI applications that gather data from multiple sensors, search vast quantities of information, generate diagnoses, suggest treatments, and offer confidence ratings for their suggestions [2, 3] (Chap. 19). These abilities must also be complemented by the development of physicians' higher-order judgment and decision-making skills to evaluate the quality of information generated to be useful in clinical practice. In this context, in the best of two worlds, physicians learn new ways to work in their practices, and AI systems gain from a better understanding of human context.

This chapter will examine how medical education systems have evolved over time, and their potential to incorporate AI-based systems for the learner, the teacher, and the education enterprise. The chapter will review the status of intelligent learning tools in medical education and examine to what extent and within what limits such learning systems map to real world practices. Finally, the chapter will take a longer view and will look at the future profiles of physicians' practices in 10 years, given the recent pandemic-driven trend to remote learning and telehealth. What knowledge and skills will be required for the practicing physicians in the next decade?

Historical Evolution of Medical Education: Philosophical Perspectives and Related Educational Strategies

Healthcare delivery has changed dramatically since Osler established the first modern residency training system at the Johns Hopkins Hospital in 1889 [4, 5]. He was the first to bring medical students out of the lecture hall for hands-on bedside clinical training, where he encouraged medical residents to learn through observing, talking, listening, and touching the patient. As medical and scientific knowledge was expanding at an unprecedented rate, Osler's philosophy continued to be recognized in the basic structure of medical education, with its mix of classroom-based teaching and experiential learning through activities such as bedside rounds and clinical services. As our healthcare system began to evolve further, our training of the next generation of physicians also changed. US medical schools began to use diverse education systems, resulting in more informal training with no specific standards. In 1910, a commissioned report by Abraham Flexner to evaluate medical education programs in the US had a huge impact and shaped modern medical education [6]. To provide a scientific basis to medical education and training, the medical curriculum was divided into basic science and an applied clinical component, separating science from practice. In response to the pure biomedical education and training model, alternative curricula began to spring up around North America.

Our medical education system is still evolving over 100 years after the Flexner report. Current programs reflect a more hybrid model, with Flexnerian-based scientifically grounded clinicians, who are clinically skilled at the bedside, as advocated by Osler. Although intelligent technology has revolutionized medical training [7]. Osler and Flexner's fundamental principles of science and medicine have not changed with similar issues confronting us today.

Acquisition of Clinical Competence

The primary goal of clinical education is the acquisition of competencies that are integral to the functioning of clinicians. Medical trainees must develop competence in several clinical skills (performance-oriented) and competence in understanding domain concepts necessary for supporting clinical problem solving and interpersonal skills. In addition, competence needs to be demonstrated in applying and transferring knowledge and skills from training situations to the "real-world" clinical environment. The use of intelligent systems introduces a layer of complexity, where training with these systems, in simulation contexts, mimics the challenges in transfer to real-world practice.

The assessment of clinical competence is typically based on Bloom's taxonomy of educational objectives. Although his original 1956 taxonomy [8] included the cognitive domain, these categories were ordered based on complexity and abstraction. The taxonomy was considered hierarchical in that a simpler category would need to be mastered before mastery of a more complex one. A revised Bloom's taxonomy [9, 10] moved from a one-dimensional (*Knowledge*) to a two-dimensional (*Knowledge* and *Cognitive Processes*) framework. Cognitive research uncovered aspects of learning that were not reflected in the original taxonomy. Studies have shown that in a complex domain such as medicine, people do not work in a linear fashion, but follow a non-linear pattern of activity, yet decision support systems, such as those embedded in electronic health records [EHRs] are designed and standardized for a linear workflow [11, 12]. Bloom's revised taxonomy suggests how more linear learning objectives can be supplemented with non-linear learning to reflect how people work and learn in complex environments. A digital taxonomy was created based on Bloom's taxonomy, which is restricted to the cognitive domain [13], containing cognitive elements, methods, and tools. The digital taxonomy is about the effective use of technology to facilitate learning.

Cognitive Approaches to Learning and Instruction

A National Research Council report [14] on advancing scientific research in education reports a lack of rigorous research in designing education programs, recommending the development of tools for education and training to consider a scientific foundation for learning and instruction. Theoretical and methodological advances in the cognitive and learning sciences have greatly influenced curriculum, instruction, and learning in biomedicine [15]. Empirical studies on the role of memory, knowledge organization, and reasoning as well as studies of problem-solving and decision-making in the medical domain led to a more informed curriculum about how people think and learn, and more specifically, how clinical expertise is developed [16].

There are two major cognitive learning theories: one focuses on individual structured learning (**ACT-R**, [17]; **Cognitive Load Theory**, [18, 19]), and the other on constructivist learning theories (Situative theory, [20]; Cognitive Flexibility Theory, [21]), which focus on complex learning within interacting systems. Although they often appear to be conflicting, researchers have argued [22, 24], both perspectives are essential in learning and instruction. Ultimately, both perspectives provide significant and valuable insights into how effective performance and learning occur (see Table 16.1). Research in both these programs has resulted in necessary knowledge about human learning that can inform the designs of effective learning environments and instructional methods.

Table 16.1 Cognitive theories of learning relevant to medical education and training, showing basic concepts, conceptual differences, and diverse emphases (Published with permission from [23])

Theory	Basic concepts	Most applicable	Example
Adaptive Character of Thought-Rational (ACT-R)	Declarative and procedural knowledge, production rules	Well-structured domains, formal knowledge acquisition	Learning of anatomy, basic biochemistry using cognitive tutors
Cognitive Load Theory (CLT	Cognitive load, working memory, memory limitations	Well-structured domains and somewhat ill-structured domains; formal knowledge	Learning of basic clinical medicine in classroom situations; design of instructional materials
Situativity Theory	Situation, context, activity system, social interaction, collaboration	Ill-structured domains, apprenticeship	Learning in residency training involving interactions with clinical teams; acquisition of tacit knowledge
Cognitive Flexibility Theory (CFT)	Advanced learning, conceptual understanding involving abstract concepts	Formal learning of complex concepts, conceptual structures	Learning of advanced physiology, genetics, and clinical medicine during specialization

The situative theorists propose that cognition does not always involve the manipulation of symbols, but rather that agents in activity are involved in many cognitive processes by directly using aspects of the world around them without the mediation of symbols. The learning of surgery, for instance, is an example of **situated learning** in that the surgery apprentice learns to perform different tasks without having to represent symbolically the procedures involved in such tasks. Much of clinical performance, especially in routine situations, involves non-deliberative aspects, where **deliberation** would result in considerable inefficiency in performance. For example, in the diagnostic tasks in perceptual domains, such as dermatology and radiology, a significant degree of skilled performance relies on pattern recognition rather than deliberative reasoning. Furthermore, numerous clinical problems require rapid responses, such as in emergencies, where **deliberative reasoning** is not possible. In such cases, the situated approach can be used to characterize cognition as a process of directly using resources in the environment, rather than using **reflective thinking** to arrive at conclusions [20, 25]. The notion of a direct connection with one's environment is prominent in cognitive engineering [26], and human-computer interaction research [27]. Here, well-designed artifacts can be closely adapted to human needs and capabilities through the appropriate use of invariant features (e.g., panels on a screen display) [28]. Well-designed technologies provide "**affordances**" that are perceptually obvious to the user, making human interactions with objects virtually effortless [29]. Affordances refer to attributes of objects that enable individuals to know how to use them (e.g., a door handle affords turning or pushing downward to open a door).

One situated approach emerged from the investigation and development of intelligent systems that support performance in complex "dynamic real-world environment." Severe time constraints characterize such systems and continuously changing conditions in emergency departments, surgical operating rooms, or intensive care units [30].

The well-documented problem of implementing intelligent systems in training mirrors the gap between theories of learning and their application to medical practice. The notion of learning in context is one of the most important messages for education and even more critical with more sophisticated and intelligent systems. Well-designed, theory-based education and training programs are needed for the future healthcare workforce, where the development of these systems needs to be more user-centered, augmenting human intelligence. This argument begs for a careful evaluation of AI education systems before they are disseminated widely for use in education and training programs (Chap. 17). This allows us to reexamine and redefine the current technology design by considering these intelligent systems' different roles for various functions.

In summary, how does history enlighten us about the current education system in the digital age? Earlier, the medical education curriculum reflected the philosophy of William Osler, who famously stated, "Listen to your patient, he is telling you the diagnosis". Reconsidered from a complexity stance, Osler's suggestion hints at the insights clinicians may gain by viewing the patient as an embodiment of embedded complex systems (through biological and disease mechanisms), and as an individual whose health and the embeddedness of other complex systems shapes healthcare.

Flexner's report, which followed, had a distinctive feature of the thoroughness with which theoretical and scientific knowledge were combined with what experience teaches in the practical responsibility of taking care of a patient. The revision of Bloom's Taxonomy reorganized the learning taxonomy into a higher-order cognitive hierarchy. Connecting Bloom's Revised Taxonomy characteristics was necessary for creating online learning activities according to students' needs. Bloom's **Digital Taxonomy** guides us to navigate various digital tools to match learning experiences for specific groups of students. Selecting the most appropriate digital activity depends on the level of difficulty associated with the cognitive levels stated within Bloom's Revised Taxonomy.

Approaches to Artificial Intelligence in Education and Training

AI has applications in learning, teaching and education management. However, much of today's technology in education is a one-way transmission of information, often using engaging methods of graphics, animation, and interaction. Feedback, if provided, is not personalized to the learner's level of knowledge or progress. A learning system is considered to be intelligent if it customizes its content and delivery, in real-time, based on learner performance, errors, misconceptions, needs and affect, and based on principles of cognitive and learning sciences. Underlying intelligent systems are a panoply of AI tools and methods, as well as a range of methods to represent data so that they can be operated on by AI tools, to move a learner along a path to an end-state of knowledge, skills and behavior competence (Fig. 16.1).

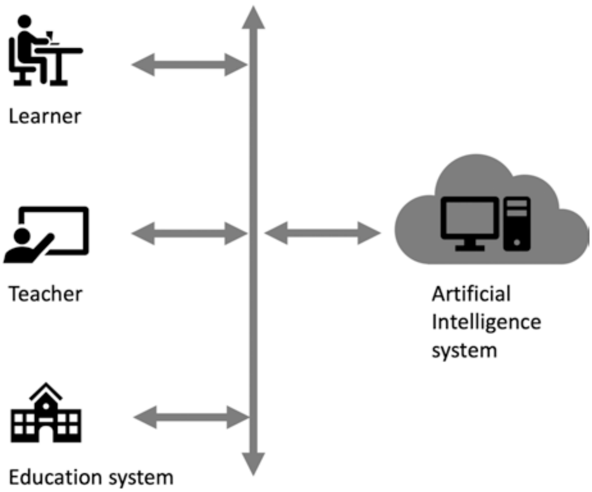

Fig. 16.1 The education system and AI. AI systems can support the entire education enterprise, including the learners, the teachers, and the educational system

AI tools can be applied to the individual learner, the teacher, as well as to the education enterprise. For the individual learner, the greatest promise is in personalizing learning and learning materials. AI systems can adapt pedagogic practices to individual learners and can allow learners to learn at their own pace. Such systems have been most successful in well-defined knowledge areas, such as school-level mathematics [31]. AI-based instructional systems are not yet widely available in healthcare, nor is continuous AI-augmented evaluation of learner or education program performance.

The next section will describe technology and studies on intelligent systems for educating the individual learner, followed by a description of the possible uses of AI methods in analyzing and improving the education enterprise.

Artificial Intelligence Systems and the Individual Learner

AI has the potential to curate and deliver knowledge at the point of need. At the same time, it is essential for the practitioner to understand the AI technology underlying new healthcare services such as imaging diagnostics, identification of biomarkers, and population health recommendations. Introductory courses are being designed to address the understanding of AI technology in healthcare practice [32]. However, AI-based learning systems, to support optimal knowledge delivery, are not in wide use yet.

The next section will examine the various components of AI systems for use in individual learning in medical education.

Computable Representations

For an AI system to function, it requires a formal, **computable representation** of the knowledge (content), skills (tasks, actions, or behaviors) and strategies (reasoning and decision-making underlying the use of specific knowledge or skills) that an expert may be expected to know. It may also contain the misconceptions, incorrect skills, and mistaken strategies that may be common when learning this domain. The data structure must be a formal, computable representation, so that learning objectives can be defined, such as a state in feature space, and a learner's progress can be assessed by movement towards a desired state. Inevitably, a domain model represents a subset of the actual domain. It may simplify the actual content, may leave out non-essential components, or may be unable to represent ill-defined areas. Further, any representation of a domain may be implementable in different data structures, for example as a graph, an ontology, or a feature vector space.

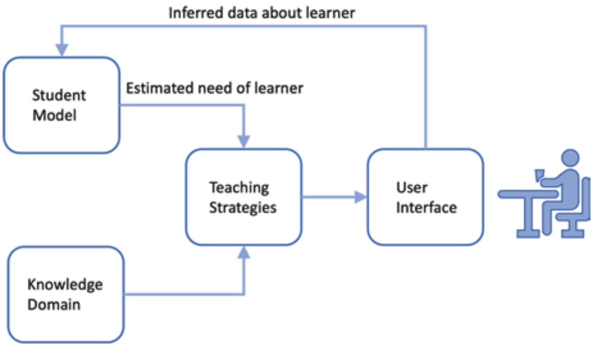

Fig. 16.2 The components in an Intelligent Tutoring System

Intelligent Tutoring Systems

An Intelligent Tutoring System (ITS) models the learning process so as to provide personalized instruction or feedback to learners, without requiring intervention from a human teacher. It usually has the following four components: The Domain model, the Learner model, the Pedagogy model, and the Interface model (Fig. 16.2).

The **domain model** contains a formal, computable representation of the knowledge, skills and strategies, as described above. It also includes misconceptions, incorrect skills, and mistaken strategies. The learning objectives are defined as states in domain space, and a learner's progress is assessed by movement towards a desired state.

The **learner model** represents the learner's current state in the domain space, and is updated in real-time as the learner progresses through the learning exercises. For example, the learner model can be a record of the knowledge states that have been mastered within a domain model with a much larger set of possible knowledge states. The learner model and the domain model are compared, using tools such as Bayesian statistics, to select the next problem which will correct a misconception or fill in a deficit. The learner model may also include the affective and motivational state of the learner as a guide to the tutoring process.

The **pedagogical model** represents and selects effective approaches to teaching. These approaches include typical human pedagogic approaches such as providing new knowledge, assessing the student's knowledge to give hints, guidance or feedback, and allowing the student to explore and make mistakes (productive failure) before guiding them back to the correct path. The pedagogic model uses the domain and student models as input to select the instructional strategy to move the learner's state closer to a desired state in the domain model. Because there must be a correspondence between computational methods in the pedagogy model and representations in the learner model, they must be designed in tandem. For example, ITSs that teach using conversational dialog will use computational techniques that match words, phrases, and sentences in the learner's answer to recommended sentence-based preferred answers in the domain model, by using content matching, latent sematic analysis or other statistical methods based on features present in conversation. The pedagogical model moves learning forward by generating the next instructional step but can also respond to learner questions or requests for help.

The **interface model** enables the dialog between the ITS and the learner. While the interface model is not directly a component of pedagogy, its structure is important in how information is exchanged between the learner and the ITS. The learner receives information from the ITS through text and multimedia on the screen, through audio and, increasingly, through viewing simulations in immersive three-dimensional (3D) virtual worlds. The learner then responds through available devices such as keyboard, text, voice, and gestural or haptic devices. For ITS systems that include detection and use of affective states, the interface may include sensors for eye-tracking, facial expression detection, or neural state tracking.

Kulik and Fletcher [33] reviewed the effectiveness of ITSs, based on published studies, and found that students who received intelligent tutoring outperformed control students on posttests in 46 (or 92%) of the 50 studies included in the meta-analysis. Successes were particularly evident in systems where the domain knowledge could be formally represented and where the assessment method was based on the same representation as the digital content. Examples are the DARPA Digital Tutor for teaching information technology systems to Navy personnel [34], the Geometry Tutor for high school geometry [35], and iTutor for engineering mechanics [36]. Similarly, Ma et al. [37] showed that the only learning environment which out-performed the use of ITS was the small group learning environment.

Dialog Systems and Natural Language Processing

Bickmore and Wallace (Chap. 7) have provided an in-depth review of issues underlying current dialog systems. While there are many healthcare simulations and games that include or require dialog between the learner and a character in the simulation, only a few use AI to generate any part of the conversation. Commercial technologies such as Amazon's Alexa, Apple's Siri, or Google Home, or customized software from Recourse Medical or SimConverse, can generate conversation between a virtual patient and a learner. However, they do not apply the principles of Intelligent Tutoring to guide and coach the learner. AutoTutor is an example of a dialog or tri-alog based ITS.

AutoTutor is an ITS augmented with Natural Language Processing (NLP) that has been applied in numerous subject areas [38]. It simulates the conversation patterns of human tutors, based on analysis of human-to-human tutoring sessions and theoretically-grounded tutoring strategies based on cognitive learning principles [39]. AutoTutor's dialogues are system-driven and are organized around difficult questions and problems that require reasoning and explanations in the answers. The

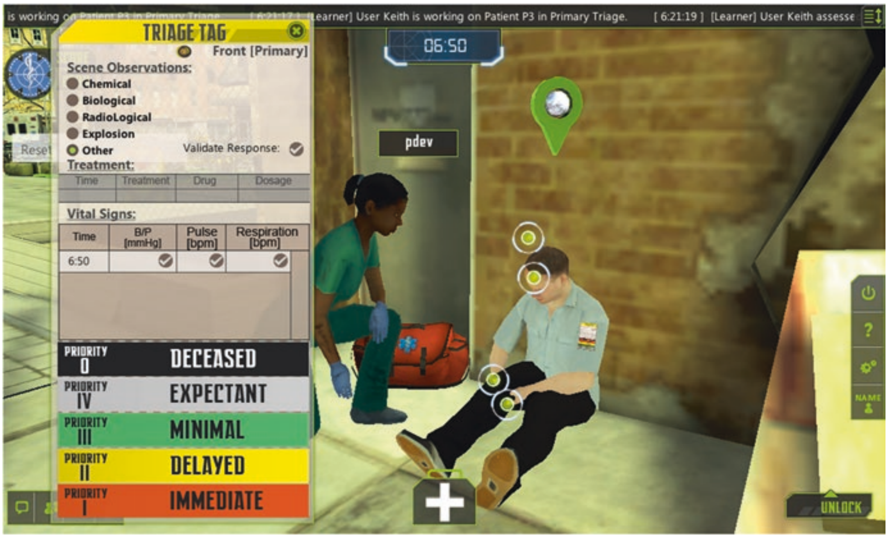

Fig. 16.3 The Virtual Civilian Aeromedical Evacuation Sustainment Training Program (V-CAEST) teaches triage processes for mass casualty

major components of AutoTutor include an animated conversational agent who initiates the dialog, dialogue management, speech act classification, a curriculum script, semantic evaluation of student contributions, and digital resources, such as a textbook or a procedure manual.

A medically relevant example is the Virtual Civilian Aeromedical Evacuation Sustainment Training program (V-CAEST), a learning simulation for teaching mass-casualty triage and aero-evacuation during an emergency [40, 41], that uses a web-based version of AutoTutor, AutoTutor Lite (Fig. 16.3). In V-CAEST, a team of learners enter the virtual environment, an earthquake disaster site, and search for injured casualties in the debris-covered streets. The learning task is to triage these victims correctly, assessing their need for medical intervention and air evacuation. The intelligent tutoring system intervenes if errors are made, and a digital tutor character walks the learner through the triage process, asking questions focused on the errors.

AutoTutor Lite uses natural language processing to analyze the learner's typed answers and matches the concepts against stored concepts of the ideal answer using **Latent Semantic Analysis**. With each answer, it updates its model of the learner's knowledge of that topic. Through hints and additional questions, the tutor prompts the learner to articulate a well-elaborated, detailed answer. When its model of the learner's knowledge is sufficiently like the stored model of that topic, the tutor lets the learner return to the simulation to continue triaging the victim or to search for another victim (Fig. 16.4) [42].

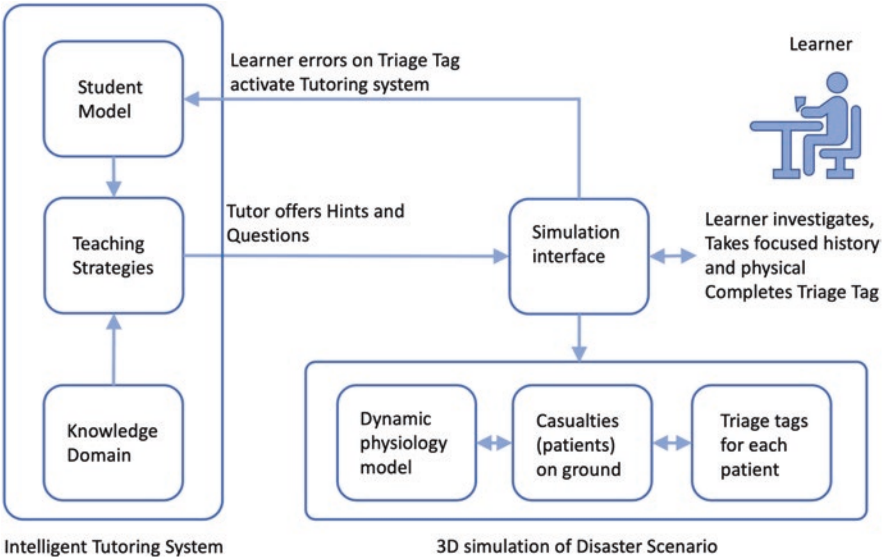

Fig. 16.4 The components of an Intelligent Tutoring System as applied to the V-CAEST program

Question Generation

Question answering is a common form of learner's mental assessment. Understanding assessment depends on understanding the process by which the learner generates the responses to the questions. However, generation of good questions with least amount of ambiguity, is time-consuming and prone to errors. Multiple choice questions (MCQ), in particular, are widely used as learning tools, for evaluating learner knowledge, and to assess efficacy of the instructional activity. Automatic MCQ generation from medical text has been shown to produce questions that are, for the most part, equivalent to traditionally developed items from the perspective of expert medical reviewers [43]. Leo and colleagues [44] present a system for generating case scenario-based questions using knowledge in a medical ontology system, Elsevier Merged Medical Taxonomy (EMMeT). They selected four MCQ question formats that are representative of scenario questions in texts for preparation for medical board examinations. Using these formats as question templates, and EMMeT as a content resource, they generated over three million questions of which a sample was evaluated by experts for appropriateness and difficulty. An important result in this evaluation was that review of generated MCQ questions was far faster than the process of generating each question by a human.

Dynamic Assessment, Feedback, and Guidance

AI has multiple applications within educational assessment, ranging from support of the learning process, to assessing whether learning was achieved [45]. The embedding of data collection within digital education products, paired with computational techniques, makes automated education data analytics feasible and useful. The most common use of analytics is for summative feedback and grading, including AI-based scoring of assignments. While this automation of a manual process is very helpful, an interesting approach is the application of AI-based assessment to support the learning process itself.

AI-based analytics can support dynamic assessment for continuous feedback and guidance for each individual learner. The role of assessment then shifts from one of assigning a final grade to that of being a coach, guiding the learner by supportive and corrective feedback. By shifting the emphasis from summative assessment to coaching for mastery learning, the educational system moves from assessment of learning to assessment for learning [46]. Realistically, this mode of assessment is possible only though the use of big data, that is, data obtained by digital observation of each step of the learner's progress through the instructional material. As described above, in the section on "Computable Representations", this approach requires that the representation of the knowledge to be learnt is in a computable format, to support algorithms that can identify the steps to guide the learner from a current state to the destination of goal state of knowledge.

Very few such AI-based dynamic, personalized assessment systems exist in medical education, except as experimental products. A particularly interesting one, albeit in computer science education, was deployed in a course on computer programming. This massive on-line course, taken by 12,000 students around the world, used an AI feedback system to detect and critique errors in code for individual students [47]. Over 16,000 such critiques were offered and, in 97.9% of the cases, the students agreed with the AI system's assessment. Guidance systems such as this are still in an early development stage, but could be applied in many areas, including medical diagnosis and patient treatment.

Machine Learning and Neural Networks

Machine learning has been applied extensively in using data from learning management systems to make the education delivery process more efficient [48]. For the individual learner, machine learning has the potential to be used to guide optimal learning based on the performance of a cohort of similar learners.

An early study [49] used neural nets to identify information gathering behavior of medical students as they worked through a clinical immunology case. Students with successful solutions demonstrated successful acquisition of the results of relevant diagnostic tests and clinical data. Unsuccessful solutions showed two patterns of performance. One showed extensive searching using a range of tests, demonstrating lack of recognition of relevant data. Another unsuccessful approach showed data collection biased towards solving an unrelated problem, that is, the students had the correct solution but to the wrong problem.

Some examples of the use of big data and analytics are discussed in the section on "Artificial Intelligence Systems and the Education Enterprise".

Affect and Emotion Aware ITS

Emotions are closely related to cognition and are an essential component of learning. Yet, the generation and measurement of emotion is not usually included in the development of technology-rich learning systems [50].

Pekrun [51] postulated a **control-value theory** of achievement emotions. He considered that activity-related emotions such as enjoyment, boredom and frustration, as well as outcome-related emotions such as pride, hopelessness, and danger, related to success or failure, needed to be considered when evaluating education systems. In a systematic meta-analysis of studies on technology-based educational systems, Loderer et al. [52] found that the emotion-level evoked differed across systems, but the relationship between emotions evoked and learning correlated with Pekrun's control-value theory.

Virtual and Augmented Reality

3D graphics and interaction add a dimension of realism that immerses the learner in the learning environment. **Virtual Reality** (VR) moves the 3D experience from the computer or tablet screen into a 3D environment that surrounds the learner. The experience can feel so real that moving through the visual environment, using gestures, while staying physically in one location, can induce motion sickness. **Augmented Reality** (AR) differs from virtual reality in that the real 3D environment remains visible but is overlaid with labels, pointers, or even a semi-transparent 3D virtual environment. Multi-user environments add collaboration capability by bringing others into the environment seen by the user, whether it is in VR, AR, or the computer screen. The use of AI tools and technology can be added to any aspect of 3D interactive simulations, VR or AR. This application of AI is not yet in wide use, so examples of possible new uses are presented.

Interaction within a VR or AR environment, while moving one's head, requires deep understanding of this environment. The incoming camera imagery is transformed into a 3D representation so that the controller in the user's hand (or the representation of the hand itself) recognizes the object's distance and touches it accurately. This capability is present in many 3D games. However, the interaction

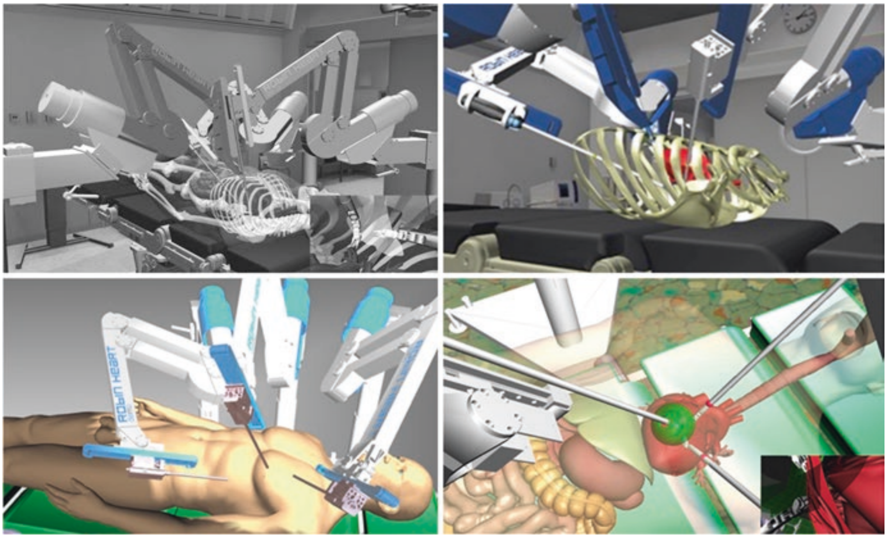

Fig. 16.5 This simulation (Virtual Reality operating room) is used for planning operations using Robin Heart robots (examples are for heart surgery) and for testing robots (in the conceptual phase), and training surgeons. The program was tested for use: (1) on a computer stand; (2) in the Robin Heart Shell 2 robot control console; (3) VR goggles (Oculus). The images are examples of how to visualize simulated operations. The last image outlines the green workspace available for the tool chosen by the surgeon. (Published with permission from [53])

between the hand and the object can be increasingly sophisticated, based on intelligent information about the object and the hand. Sculpting in 3D is an early example of sophisticated interaction between virtual hands and a virtual mass.

Extending this example into surgery, advanced advisory systems can be developed that bring together knowledge about surgical tools and the target tissue. Nawrat [53] demonstrates a prototype VR system for robotic surgery on the heart where the space available for tool movement is visualized relative to the heart and its surrounding anatomy. Aside from the geometric information available in the imagery, intelligence that can be embedded in the advice includes data about typical hand movements, resilience or fragility of the tissue, and common decision and movement errors (Fig. 16.5).

Simulations and Serious Games

Simulations and Serious Games have been shown to increase engagement in the learning process. The use of a Virtual Patient (VP), a simulated patient presented on the computer screen or in VR approximates the real-world experience of patient care, engages the learner, and focuses the learner's attention on the subject being presented [54, 55]. Screen-based virtual patients, with scripted reaction and

Fig. 16.6 The numerous ways in which AI could augment the use of Virtual Patients in medical learning. The figure shows a virtual patient undergoing ventilation. AI could improve the user interface (natural language input, haptic sensation), augment the physiology model, make the simulated equipment and instruments aware of their interaction with the simulated patient, and track all interaction to provide guidance to the user in the learning process

feedback, are in wide use in medical and nursing curricula today (Fig. 16.6). However, the potential for introduction of AI technology is immense.

SimSTAT Anesthesia [56] is an example of a simulation that uses a rule-based AI model of patient physiology, for Maintenance of Certification by the American Society of Anesthesiologists. The simulation is viewed by the learner on a computer screen while the learner plays the role of the anesthesiologist. The learner guides the on-screen anesthesiologist to care for the unconscious patient by clicking on desired interactions, such as the equipment in the room or the icons at the bottom of the screen. Through these interactions, the learner can control the level of sedation, give medications, fluids, and gases, and monitor the patient's physiologic status in dynamic stability. The branching scenario, or story, makes the case appear different from learner to learner, based on their actions, and allows multiple passes through the case to experience the many possible outcomes for the patient. The learner's actions are recorded, and the simulation provides detailed summative feedback at the end of the case. The feedback evaluates whether key clinical actions were taken on time, and whether the ongoing status of the patient was held in a safe zone or allowed to deteriorate too dangerously, even if the patient finally was brought safely through the surgery.

Artificial Intelligence Systems and the Education Enterprise

Learning Analytics

Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, in order to understand and optimize learning. Ellaway et al. [57] point out that if health professional education is to be accountable for how its programs run and are developed, then health professional educators will need to be ready to deal with analytics and 'big data'. Analytic methodologies include descriptive analytics which examines past data to analyze all stages of the student life cycle, and to detect trends; diagnostic analytics, which focuses on the question "why did it happen"; and prescriptive analytics, for recommendations and advice on possible outcomes.[1]

As **Competency-Based Medical Education** (CBME) is introduced in graduate medical education, the volume of assessment data imposes a significant burden on faculty and supervisors. Learning analytics has the potential to process this data and provide insight that will support the assessment process. Chan et al. [58] review learning analytic techniques, with potential application for use by Clinical Competency Committees. In subsequent work, they present design-based research to investigate what issues may arise as faculty consider the use of learning analytics, as well as the importance of user input to the design of 'dashboard' or visualization methods that condense and present this data, when analyzing data on the progress of emergency medicine residents towards completion of Entrustable Professional Activities. Their research identified three sets of issues: challenges in implementation of data collection, such as changing international practices regarding data gathering; challenges in the processing of data, such as data security, analysis, access and governance; and challenges in the presentation of the analytics results, such as efficacy and ethical requirements. They also found that residents and faculty required significantly different visualizations in order to derive utility from the learning analytics 'dashboard' [59]. As design prototypes, these studies utilized a significant amount of manual data processing. However, they show the need for, and provide guidance on future research for more automated, AI approaches to medical education data analytics while retaining the role of the human instructor.

Continuous quality improvement of the medical education system. Boulet and Durning [60] point out that electronic medical records, unique provider identifiers and access to patient records, make it easier to conduct studies that link learning analytics data from medical schools and residency programs to quality of care by individual physicians (assuming appropriate care for the privacy of both patients and the physician). It is possible, therefore, to identify opportunities and flaws in medical education systems. Tsugawa et al. [61] combined graduation data, from medical school records, with clinical performance data from Doximity, the professional network for physicians, to study one possible relationship, in this case, the relationship between country of graduation and practice outcomes. They found that, on their measures of 30-day mortality and re-admission rates, there was no difference between US and foreign graduates, thus allowing them to address concerns that admitting foreign medical graduates to train and practice in the US might worsen US medical care.

Going further, Triola et al. [62] suggest continuous improvement of the educational process itself by linking curriculum and curriculum delivery data to clinical

[1] https://www.solaresearch.org/about/what-is-learning-analytics/ (accessed August19, 2022).

outcomes data. This can be very effective in the early clinical years, identifying gaps in the curriculum that result in poor clinical performance and clinical outcome. Once such analysis is incorporated into a continuous quality improvement process, it could become routine for education systems to have intelligently responsive curricula that teach students to be as well-prepared as possible for the real world of medical practice.

As Chan et al. [58] point out, development and application of learning analytics will be complex and expensive. Therefore, it is important that this should have a significant impact on the efficiency of the learning process, the quality of learning achieved, and the safety and quality of patient outcomes.

Ethics and Regulation

AI technology depends on the use of large datasets, statistical techniques, machine learning and deep learning. The neural networks that implement the resulting algorithms can be inherently complex or, even unknowable because of the process of machine learning. The resulting situation is the creation of "black box medicine" [63].

The algorithms underlying black box medicine can improve the process of care, deliver medical recommendations tailored to the individual, and increase hospital efficiency. However, these algorithms are only as good as the data on which they were trained. Much of this data is derived from the electronic health record (EHR) and related databases, data that was often entered with no regard to the potential of introduction of bias. Currently, the care provider uses the EHR as a replacement to capturing the information on paper, without understanding the long-term potential impact on the use of this data [64]. Algorithms generated with data that can reflect existing racial or gender health disparities, if unexamined, can contribute to perpetuating bias and existing inequalities in healthcare. Therefore, education on how to input unbiased data into the EHR is essential.

The above is an example of the need for understanding the ethical implications of AI systems (Chap. 18). Because many of these systems have been designed by non-medical personnel, who may not have deep understanding of the sources that created the data they use, it is essential for physicians and other health professionals to develop an understanding both of medical AI technology and how to create the content that will populate the databases used by this technology. Meanwhile, AI-based devices are being regulated and authorized for use by the United States Food and Drug Administration [65, 66] even while there is considerable variation in the quality of data used by manufacturers to test their AI software. The physicians of the future must have the underlying knowledge of both the power and the limitations of AI, so that they are prepared to deal with the potential need to bypass the recommendations from the AI products they use.

Technology Acceptance and Implementation

Implementation of technology systems, and learner or faculty acceptance of these systems after they are installed for use, have proven to be very difficult. In a review of AI applications in medical education, Chan and Zary [67] analyze the many reasons that make implementation difficult. The major difficulty in implementation was found to be difficulty in assessing effectiveness. Other factors included the difficulty in creating the domain model, the need for content specialists who understood the AI authoring process, the knowledge gap between the physicians and the engineers creating the system, and the difficulty in scaling the system because of the narrow domain of application of each intelligent system. They conclude that, to implement AI in medical education, two challenges need to be overcome—how best to assess the effectiveness of AI in learning and in curriculum design, and how to manage the technical difficulties associated with development of an effective AI system.

The expense of software development is being approached through the open-source movement. The US Army Research Laboratory provides the open-source design framework and authoring system, Generalized Intelligent Framework for Tutoring (GIFT) [68]. Other sources include AutoTutor and AutoTutor Lite (http://ace.autotutor.org/IISAutotutor/index.html). Another expense is the high cost of knowledge content representation, with estimates of 200 or more hours of development for one hour of instruction. Therefore, intelligent tutoring systems are cost-efficient only when deployed over a very large number of learners.

Artificial Intelligence Systems in the Future Workplace

Given that AI-augmented systems will be increasingly available for health care, the education of students, residents and professionals about AI will be essential for acceptance and safe use of these systems. In fact, insufficient knowledge of AI has been found to be key in current resistance to AI acceptance [69], in addition to the system's inability to explain its decisions (see Chap. 8). Aside from lack of understanding of AI methods and explainability, a further barrier to acceptance is the perceived assault on the clinician's professional identity. Education about the optimal use of AI systems, and their role in the support of clinicians, will be an essential step in acceptance and use of AI. Clinicians with an understanding of the foundations and methods of AI will be in a good position to influence the development of the next generation of AI tools, as well as to evaluate these tools and prevent unfounded reliance on exciting but unproven technology [70]. At the same time, the AI systems should be developed with the nature of the user and the workplace environment in mind, as described earlier in this chapter.

Image-based medical disciplines, such as radiology [1], ophthalmology [71–73] and dermatology [74], will be the earliest to experience the use of AI-augmented diagnostic equipment (Chap. 12). In step with this need, an introductory curriculum about AI methods, named AI-RADS, has been piloted for education of radiology residents [32]. A monthly lecture on an AI method was followed by a journal club discussion of an article that required some knowledge of the topic of the lecture. Assessment was conducted using pre-and post-intervention surveys. The residents demonstrated increased confidence in their ability to read AI-related articles in radiology journals, and in their ability to explain key concepts. More such courses and curricula will be needed, across medical disciplines, to familiarize physicians with significant changes expected in the near future.

Some examples of artificial intelligence technologies that the learner can expect to encounter in the clinical workplace include:

- Medical diagnosis, with underlying AI technologies such as pattern detection, knowledge representation, ontologies and reasoning (see Chap. 5); [75]
- Natural language interaction for patient-facing applications based on speech recognition, sentiment understanding, speech synthesis, and chatbots (see Chap. 7); [76]
- Virtual and augmented reality for diagnosis, interventional procedures, and team communication (see Chap. 9);
- Robotic sensing and manipulation, based on object recognition, and path planning and avoidance, for surgery as well as for hospital logistics and materials movement, and
- Predictive analytics for hospital process optimization and for public health, based on large data sets, machine and deep learning, and neural nets (see Chaps. 11, 13, and 15.

Besides learning about AI, these technologies can increase the impact of what physicians learn. Continuing medical education is considered essential for practicing physicians. Their choice of courses usually depends on credentialling requirements or on keeping abreast of the latest medical knowledge in their field. Correction of knowledge or skill deficits is desirable. However, individual practitioners are not always aware of their deficits or may choose to ignore these deficits, to the detriment of their patients. AI methods that are used in ITS are appropriate for evaluating a practitioner's current knowledge and generating a recommended syllabus, both as a remedial course and as a guide toward their new learning goals.

The Road Ahead: Opportunities and Challenges for Intelligent Systems in Training, Learning and Practice

Education today is taking big leaps towards embracing intelligent systems and its applications in the teaching and learning methodologies. As Coiera [77] points out AI-driven tools will define the way medicine will be practiced in twenty-first century. What might the medical practice in the future look like? The hypothetical scenario below, *A typical day in a future physician's life*, says well that intelligent systems will be a critical part of our daily lives in future healthcare. This will require doctors to be knowledgeable about and skillful at using these intelligent systems, creating opportunities for education and training programs for the new age. However, there are also challenges. In the hypothetical future scenario, there is not much room for doctors to use human judgment, when caring for patients. There is a critical need to develop systems and training programs that complement and extend human intellect to foster human-AI collaboration. Future physicians and patients are sometimes challenged to build trust with machines since AI systems are often viewed as competing against human intelligence, as reflected in various Games (*humans vs. machines*).

A Typical Day in a Physician's Practice of the Future

As Dr. X prepares in the morning, her Smart Glass shows her the day's case load. The hospital's Smart Support System (SSS) has reviewed the schedule for the day. It has prepared a simulated Digital Twin of each patient for Dr. X to review before each appointment. The Digital Twin includes an annotated three-dimensional view of anatomy and pathology to the level of detail that Dr. X wishes to explore, including genetic analysis if needed. For those areas where SSS has uncertainty about the data or the inferences, it indicates this with a cloud, and is able to explain its reasoning that leads to its uncertainty. The medical team begins the morning with a huddle to review each Digital Twin and raise issues that SSS can investigate before the actual patient meeting. A nurse queries the ethics of a difficult decision and SSS presents a few prior examples, how they were handled, and the medico-social outcomes of each decision.

Meanwhile, Dr. X notices that one case involves an unusual genetic mutation and she requests SSS to prepare a micro-course for her to study before the appointment. SSS is aware of Dr. X's knowledge status, and uses its ITS to collect the necessary content to fill in the gaps in her knowledge. The micro-course includes subtle problems and choices to assess whether Dr. X has correctly understood the complex new information.

During the course of the day, SSS observes under which situations, Dr. X had to request additional information or get additional consults. It uses this to prepare a refresher summary and course for the close of the day. SSS may also send information back to the medical schools, indicating where there are gaps in the training and education.

In order to foster an AI-human collaborative education program, it is necessary to know the strengths of AI systems, and those of human beings. AI systems' strengths in changing a physician's practice and patient outcomes are already known. So, what are the physicians' strengths? In a 2019 NEJM Catalyst conversation hour, Nirav R. Shah, described the four Cs, which he considered physicians' strengths in dealing with patients: critical thinking, communication, collaboration, and creativity [78]. These four Cs, which are patient-centered, were identied by Shah as the most essential human skills that will need to be augmented in the age of AI. It is necessary to make sure that intelligent systems for training and education are developed with human-centered design strategies in mind to empower us to collaborate in teams, develop understanding, innovate, and solve new problems creatively.

As this chapter highlights, advances in intelligent systems have brought technology-supported education in healthcare to a new era, changing the nature of work towards creating a more efficient, effective, and safe practice environment. By incorporating human intelligence, a machine could serve as an intelligent tutor, tool, and facilitator of clinical decision-making in educational and clinical settings. Using intelligent systems in medical and health education has created new opportunities for designing productive clinical learning activities and developing better technology-enhanced learning applications and environments. The healthcare team is more likely to be multidisciplinary in the future. However, the interdisciplinary nature of AI-based education involving researchers and practitioners from different disciplines raises the unique challenge of building trust. These also include collaborations among computer scientists, engineers, cognitive and social scientists, and health care practitioners. Thus, understanding team-based collaborations will be essential and challenging for developing intelligent collaborative systems for training and education.

Healthcare systems are complex, requiring different ways of implementing ideas and assessing the AI systems as compared to the established approaches [79]. Challenges in a complex environment with uncertainty is seen as embracing the opportunities to adapt, stimulating innovative solutions, and leveraging the sociocultural system to enable ideas to emerge and spread. Training in such an ill-structured environment will be necessary, using instructional materials that do not oversimplify the content or the structure to reflect the reality of complex clinical practice.

Finally, with technological advancements the role of intelligent systems or AI in medical education will increase. Medical schools need to consider curricular reforms, including content related to AI as part of their curriculum and emphasize empathy and integrity. There will be many obstacles in implementing AI in medical education, including insufficient time in curricular hours and difficulties in developing AI applications that are usable, clinically relevant, and safe. At the same time, the potential for a collaborative, even symbiotic, relationship among learner, teacher, education enterprise, and AI system is immense, and points to new, efficient, and enjoyable future learning methods.

Questions for Discussion

- What would Osler say about today's intelligence-based education?
- How can learning with intelligence-based tools augment cognitive limitations of human abilities?
- What user-centered design issues need to be considered before implementing intelligence-based tools for health professionals' education?

- Evaluate the scenario of *a day in a life of a future physician* presented in the chapter. What are some missing aspects of clinical practice?
- Describe some of the challenges and possible solutions of using AI-tools for learning and instruction as we move to the future?
- Design a curriculum for medical education which you believe we will need 10 years in the future.

Further Reading

Patel VL, Yoskowitz NA, Arocha JF, Shortliffe EH. Cognitive and learning sciences in biomedical and health instructional design: a review with lessons for biomedical informatics education. J Biomed Inform. 2009;42(1):176–97.

- This review illustrates how formal methods and theories from cognitive and learning sciences would prove useful in development of assessment criteria and design of instructional tools that match the competencies to be acquired by the trainees. The methodologies and theories discussed are oriented toward understanding and characterizing the cognitive, and to some extent the social impact of technology, on learning and instruction.

Silverman ME, Murray TJ, Bryan CS. The quotable Osler. Philadelphia, PA: American College of Physicians; 2008.

- This book is a collection of quotations compiled from Sir William Osler's various publications by three American editors. The book is divided into themes such as personal qualities, the art and practice of medicine, diagnosis and science and truth. The selected quotes portray Osler as a deeply moral, committed and enthusiastic doctor who believed 'that the practice of medicine is an art, not a trade; a calling, not a business; a calling in which your heart will be exercised equally with your head'.

Rosenberg L. Metaverse 101: defining the key components. n.d. https://venturebeat.com/2022/02/05/metaverse-101-defining-the-key-components/. Accessed August 19, 2022.

- This is short article which puts together some of the useful definitions of concepts related to metaverse. It defines metaverse as a persistent and immersive simulated world (Virtual Reality and Augmented Reality) that is experienced in the first person by large groups of simultaneous users who share a strong sense of mutual presence.

Patel VL, Groen GJ, Norman GR. Reasoning and instruction in medical curricula. Cogn Instr. 1993;10(4):335–78.

- This original research paper examines the knowledge and explanatory processes of students in two medical schools with different modes of instruction. The results presented show the impact of instructional methods on the trainees' organization of knowledge, development of specific reasoning strategies, and generation of coherent explanations for diagnostic hypotheses. The paper presents the importance of process-based assessment of learning and instruction.

Cohen T, Blatter B, Patel VL. Simulating expert clinical comprehension: adapting latent semantic analysis to accurately extract clinical concepts from psychiatric narrative. J Biomed Inform. 2008;41(6):1070–87.

- This manuscript presents cognitively motivated methodology for the simulation of expert ability to organize relevant findings supporting intermediate diagnostic hypotheses, an important psychological construct. Latent Semantic Analysis (LSA) is shown to be a powerful tool for automatic extraction and classification of relevant text segments that is evaluated against expert annotation.

Yu KH, Beam AL, Kohane IS. Artificial intelligence in healthcare. Nat Biomed Eng. 2018;2(10):719–31.

- This review outlines recent breakthroughs in AI technologies and their biomedical applications, identifies the challenges for further progress in medical AI systems, and summarizes the economic, legal and social implications of AI in healthcare.

Dev P, Schleyer T. Digital technology in health sciences education, Chapter 25. In: Shortliffe EH, Cimino J, editors. Biomedical informatics. 5th ed. New York, NY: Springer; 2021.

- This chapter reviews learning theory and digital technology approaches in health sciences education, including classroom technologies, intelligent tutors, simulations, augmented/virtual reality, and collaboration tools.

McGrath JL, Taekman JM, Dev P, Danforth DR, Mohan D, Kman N, Crichlow A, Bond WF. Using virtual reality simulation environments to assess competence for emergency medicine learners. Acad Emerg Med. 2018;25(2):186–95. https://doi.org/10.1111/acem.13308. PMID: 28888070.

- This paper examines the current uses of virtual simulation (VS) in training and assessment, including limitations and challenges in implementing VS into medical education curricula. It also provides insights into the needs for determination of areas of focus for VS training and assessment, development and exploration of virtual platforms, automated feedback within such platforms, and evaluation of effectiveness and validity of VS education.

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