Precision Education for Personalized Learning

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Today's radiology trainee must sort through an enormous volume of web-based information and learning resources amid expanding volumes and complexity of clinical cases. Residencies and fellowships accept adult learners from a wide variety of prior experience, knowledge, and learning preferences. In addition, the complexity of the practicing radiologist's work now demands ready access to the most current and highest value information to guide image interpretation "in the moment" to support mastery-level practice. Perhaps it is time to evolve from the "information age" to the age of artificial intelligence (AI) [1].

The concept of personalized learning has only recently appeared in the medical literature, as computer systems show promise in supporting the nuanced learning needs of today's medical trainees. Personalized learning is defined as "a system [that] can adapt itself when providing learning support to different learners to defeat the weakness of one-size-fits-all approaches in technology-enabled learning systems" [2]. Radiology's apprenticeship model depends on a one-on-one personal interaction tailored to the needs of the trainee and could be considered the oldest form of personalized learning. However, with the emergence of big data systems and AI, it is now possible to develop large-scale computer-based adaptive learning systems to refine and personalize the learning experience. Akin to "precision medicine," we are now poised to refine medical education to support "precision education" for all radiology trainees.

The field of education has developed multiple terms to define a system that individualizes the learning experience [2]. Customized learning and individualized learning are typically reserved for early education, whereby individualized learning plans are created for students with learning differences [2]. Personalized learning and universal design of learning have extended to the graduate and postgraduate realms, in which the learning experience is built on a captured body of knowledge available in multiple formats to appeal to all learning preferences and individual needs [3]. Adaptive learning goes one step further in dynamically adjusting the delivery and content to provide "an individualised learning experience with technologies designed to determine a learner's strengths and weaknesses" [4]. This is the basis for precision education, whereby databases underwrite a knowledge engine that responds by providing the most relevant curricular material on the basis of learner performance, input, exposure, and changing educational needs. In this sense, no two learners will have the same experience, but all will achieve excellence by the end of training.

Precision education systems have been around since the 1970s with the emergence of computers in the workplace. All precision education systems have three key components: a knowledge repository, a user interface (UI), and a recommender algorithm (RA). The knowledge repository is housed in a learning management system (LMS), which is a highly indexed, cloud-based computer application supported by a searchable database that is responsive to the learner's actions. The UI may be the LMS itself, but more often it is the work environment, such as the PACS in radiology or the electronic medical record in a hospital. The RA is a computer program trained by machine learning to recommend the best knowledge elements from the LMS on the basis of case information and prompts from the UI. Over time, the RA gets "smarter" as it is trained by multiple users to select the most relevant material from the LMS. In the educational setting, this precision education model facilitates more efficient learning and teaching on the basis of delivered information that is of top quality and accuracy.

The concept of RAs is not new, with one of the first medical programs, MYCIN, developed in 1972 to help suggest the best treatment algorithms for infectious diseases [5]. Unfortunately, it was never used in clinical practice because of ethical

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concerns about using computers to practice medicine [5]. Google Brain, conceived in 2011, used a trained algorithm to identify images; the first success was with the use of computer learning to correctly identify a cat among 10 million images [6]. Google Translate (2016) uses natural language processing to achieve the best fit in translating text from multiple languages and is based on the Google Brain model [6]. Search engines such as Google and Internet Explorer use machine learning and RAs to return information with the best fit for one's search terms. As an everyday example, these search engines remember one's Internet shopping activity and preferences and will learn to send the shopper additional "teasers" to sell more products.

Radiology's foray into AI, most notably deep learning, has focused on lesion detection, image quality, workflow, and NLP, among others [7]. We identified the potential for a lesser known use of AI using machine learning to develop personalized education to augment image interpretation and radiology training. Our laboratory developed RADIAL (Radiology's Intelligent Adaptive Learning), a comprehensive LMS connected to the PACS [8]. A second "plug-in," the Intelligent Tutor, uses DICOM data to select and display contextual educational resources from RADIAL in a discrete popup window. Over time, Intelligent Tutor learns each user's preferences and patterns and stratifies the available choices. Expert radiologists' preferences are recommended back to individual learners to inform a personalized profile for each user. Logs of preferences and case exposure—including metadata tags such as study type, modality, disease, body system, age, and gender—are recorded and fed into heat maps to display strengths over time. As people tend to gravitate to areas of strength and avoid weaknesses, the system displays both users' strengths and gaps in exposure, with the ability to recommend missing content to bolster their educational experience. This personalized educational program—the PACS–Intelligent Tutor–RADIAL interface—is the first of its kind in radiology education (Fig. 1). Figure 2 shows how use will depend on user preferences and prior knowledge. A mixed-methods analysis is under way to determine effects on cognitive load, the efficiency of image interpretation, and the quality of radiology reports.

The next challenge for such a personalized education system is to maintain its relevance and quality. The foundational elements of the radiology curriculum have remained constant over time; only a minor piece of the curriculum will change with new discoveries and technology. We have built into Intelligent Tutor a simple drag-and-drop "ideas box" whereby suggestions are reviewed regularly by subject-matter experts to suggest updates. Through further training of the model, individual heat maps will become increasingly granular to further personalize the learning experience.

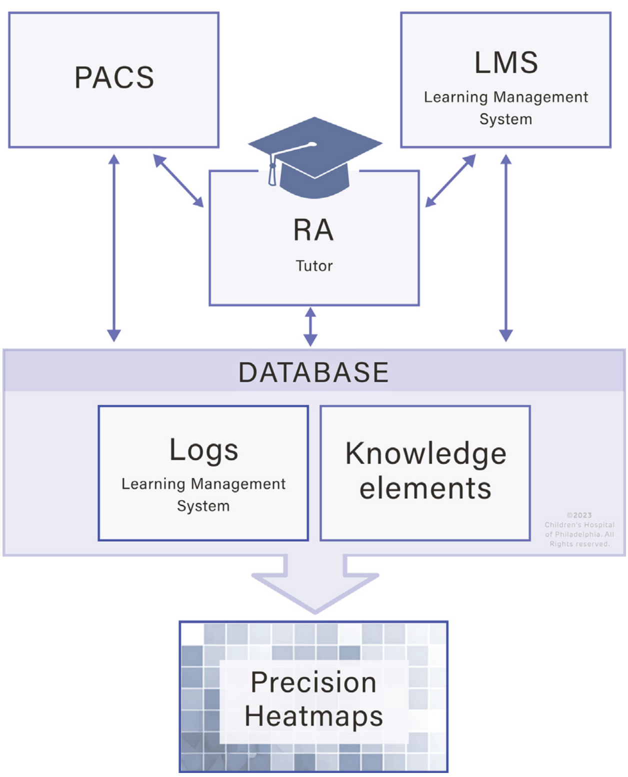

Fig. 1. Schematic for the PACS–Intelligent Tutor–RADIAL personalized education program. The PACS loads a study and sends the examination code and other DICOM data to the recommender algorithm (RA), also known as Intelligent Tutor (IT), which selects relevant knowledge elements from the learning management system (LMS), also known as RADIAL (Radiology's Intelligent Adaptive Learning), which are displayed in the RA's popup window. Over time the database (DB) collects logs of cases viewed and knowledge elements presented, opened, studied and assembles them into heat maps that show strengths (viewed, opened, and studied) versus gaps (no exposure to case type, age, sex, modality, diagnosis, or relevant knowledge elements). These gaps feed back to the RA to send suggestions for further exposure and study.

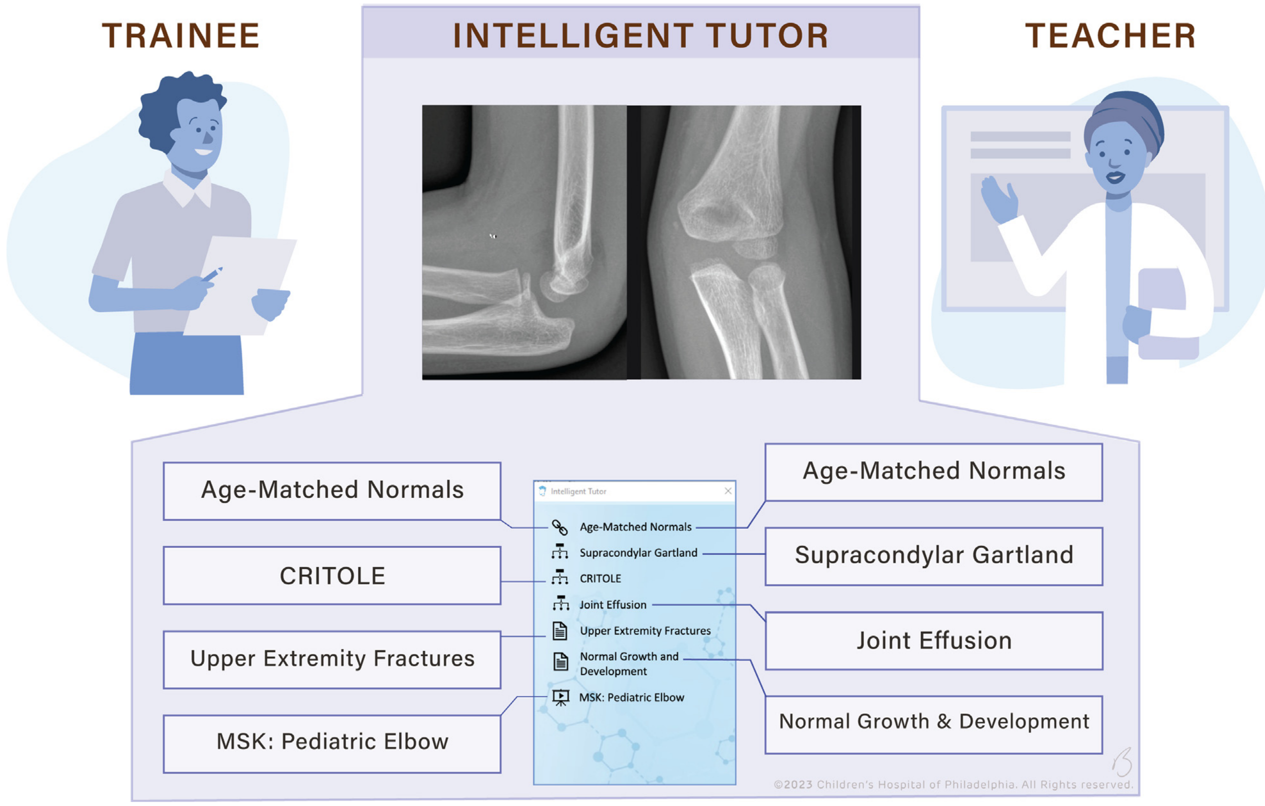

Fig. 2. Difference in the use of Intelligent Tutor between trainees (medical students, residents, and fellows) and teachers (attending radiologists). The novice trainee interpreting this 5-year-old's elbow radiograph will want to know what normal anatomy looks like. The novice might want to read about typical fracture patterns or watch a recorded lecture and take a quiz in preparation for the rotation. The attending radiologist might open the age-matched normal studies to teach normal anatomy and show examples of effusions from the teaching cases. The attending radiologist will likely suggest relevant articles to read during the rotation.

Radiology training remains an apprenticeship that can no longer depend on knowledge available from traditional sources and cannot rely on unfiltered information on the Internet [1]. The presence of voluminous digital information and learning resources is overwhelming for many trainees who seek guidance on what to study and where to efficiently find information. Beyond passing the qualifying examinations, we hope our trainees who are our future colleagues develop comprehensive knowledge and a trajectory toward mastery. The solution is to produce a personalized curated high-quality system that delivers a curriculum that is up to date and improves the educational experience. As Wartman and Combs [1] aptly stated, "Systematic curricular attention must focus on the organization of professional effort among health professionals, the use of intelligence tools involving large data sets, and machine learning and robots, all the while assuring the mastery of compassionate care."

Given our expanding digital environment, it is time for precision education for personalized learning in radiology. We have the potential to do this and do it well.

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