Original Investigation

Improving Abnormality Detection on Chest Radiography Using Game-Like Reinforcement Mechanics

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Rationale and Objectives: Despite their increasing prevalence, online textbooks, question banks, and digital references focus primarily on explicit knowledge. Implicit skills such as abnormality detection require repeated practice on clinical service and have few digital substitutes. Using mechanics traditionally deployed in video games such as clearly defined goals, rapid-fire levels, and narrow time constraints may be an effective way to teach implicit skills.

Materials and Methods: We created a freely available, online module to evaluate the ability of individuals to differentiate between normal and abnormal chest radiographs by implementing mechanics, including instantaneous feedback, rapid-fire cases, and 15-second timers. Volunteer subjects completed the modules and were separated based on formal experience with chest radiography. Performance between training and testing sets were measured for each group, and a survey was administered after each session.

Results: The module contained 74 cases and took approximately 20 minutes to complete. Thirty-two cases were normal radiographs and 56 cases were abnormal. Of the 60 volunteers recruited, 25 were "never trained" and 35 were "previously trained." "Never trained" users scored 21.9 out of 37 during training and 24.0 out of 37 during testing (59.1% vs 64.9%, P value <.001). "Previously trained" users scored 28.0 out of 37 during training and 28.3 out of 37 during testing phases (75.6% vs 76.4%, P value = .56). Survey results showed that 87% of all subjects agreed the module is an efficient way of learning, and 83% agreed the rapid-fire module is valuable for medical students.

Conclusions: A gamified online module may improve the abnormality detection rates of novice interpreters of chest radiography, although experienced interpreters are less likely to derive similar benefits. Users reviewed the educational module favorably.

Key Words: Radiology education; gamification; rapid-fire; perception; chest radiography.

BACKGROUND

Reinforcement learning theory posits that the performance of a learner increases proportionally to the discrepancy between the learner's predicted outcome and the actual outcome as measured in reward or punishment (1,2). In radiology, teachers using the Socratic method during clinical service and traditional "hot-seat" style conferences are applying this reinforcement feedback mechanism to education.

The mechanism of reinforcement learning in humans is tied to dopamine D1 receptor and best examined in addiction disorders (3,4). These theories are an important part of software engineering, responsible for generating interest in otherwise mundane tasks such as stacking nondescript square quartets in endless layers (also known as Tetris), using Newtonian physics to destroy wooden structures occupied by porcine antagonists (Angry Birds), or in "first-person shooter" video games (5,6). Neuropsychology literature suggests that video games act on the reward pathway through striatal dopamine release, a phemenenon demonstrable on positron emission tomography (7). The patterns of goal-directed, reinforced behavior and dopamine release is similar to those seen in addiction and gambling (3,8,9). Reinforcement learning is also a salient form of information learning. The literature suggests that two primary modes of knowledge acquisition comprise the learning process: explicit vs implicit learning (10). In explicit knowledge acquisition, a trainee consciously studies a textbook or attends didactic lectures. In implicit learning, a trainee acquires skills without trying to learn but instead by processes of repetitive stimulus–response binding (10). For example, within radiology, listing the differential diagnosis of a solitary pulmonary nodule requires explicit knowledge, whereas identifying a solitary pulmonary nodule when reviewing a chest radiograph requires implicit skills.

Although the prevalence of technology-aided educational tools such as online textbooks, question banks, or reference tools is increasing, existing digital tools generally provide or

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test explicit knowledge (11). However, in diagnostic radiology, a paucity of opportunities exists outside of clinical service for active implicit reinforcement.

The inclusion of video game-like components in learning modules may help learners acquire implicit skill. Gamification refers of the "use of video game elements and mechanics in non-game contexts" (12). Video game elements that are most commonly translated to nongame context include points, badges, rewards, and leaderboards. However, elements central to video games and their appeal also include feedback, reinforcement, pattern recognition, and time pressure (12). Some well-studied benefits of including gamified elements include user engagement and behavioral modification (13).

Therefore, delivering immediate, unambiguous, repetitive feedback under simulated time pressure using mechanics traditionally seen in video games may be an effective mechanism for teaching implicit skills in radiology. In this work, we created an open-source online teaching system using clearly defined goals, rapid-fire cases, and constrained time limits. Using this software, we present the effect of a one learning session on a trainee's ability to detect basic abnormalities in chest radiography.

MATERIALS AND METHODS

Study Population

We recruited 60 subjects, including medical students, first-year residents before any formal training (eg, first day of residency), senior residents, fellows, and attending radiologists. Each subject was presented with the software interface, which obtained informed consent from the respondents and provided an opportunity to opt out of the module's research component.

Software Creation

We created a freely available, open-source application named Centaur. The web-based graphical user interface (GUI) is coded in PHP, HTML5, JavaScript with JQuery (http://www.jquery.com). The back-end software is based on a MySQL database. An XML parser is implemented in PHP, and individual modules are defined using XML. Although Centaur is designed to be used on a desktop or notebook computer, it is also fully compatible with mobile devices running Apple iOS, Google Android, or Microsoft Windows Phone.

The user interface displays a static image such as a radiograph or a single frame of a cross-sectional examination. The module creator may choose to display the answer choices alongside or underneath the image. The software supports up to two questions for each case. For instance, a case-writer may ask the user to select a diagnosis in one question and to gauge its severity in a second question.

A case timer may be set to a predetermined length. The system scores the case as incorrect if no response is received before the prescribed time elapses. Extra time is not rolled over to the next case.

Selecting one of the responses elicits the immediate feedback mechanism consisting of three elements: (A) color-coded feedback for correct (green) and incorrect (red) responses, (B) an animation displaying the point earned, and (C) an annotated explanation (Fig 1). The software offers the user a moment to review the correct solution; after reviewing the case, the user presses the Next button to continue the module.

At the end of the module, participants receive their tabulated score combining the testing and training phases, showing both the total points and performance subdivided by each finding (Fig 2).

The source code is licensed under GNU Public License and hosted on a GitHub repository (http://github.com/). An implementation of the code and its working modules, including the chest radiography module used for this study, is freely available at http://bit.ly/rapidfirerad.

Implementation of the Chest Radiography Module

To demonstrate the effect of rapid, immediate, and unambiguous feedback on learning, we used the software system to create a high-tension scenario in which the review of 74 chest radiograph cases was compressed into a 20-minute experience. Each case consisted of either a normal chest radiograph (32 cases, 43.2%) or one of the following findings: a focal consolidation (17 cases 23.0%), a pneumothorax (8 cases with 1 tutorial case, 12.2%), or a solitary pulmonary nodule (16 cases, 21.6%). We chose these findings because the findings require relatively little explicit knowledge, and detection primarily relies on implicit skill and experience. Additionally, we limited the case selection to commonly seen findings because the intended group of users for this training system included medical students and nonradiology physicians, for whom the detection of these findings was felt to be more relevant. The included number of cases for each diagnostic category was based on case availability and the necessity to include both obvious and subtle cases. Additionally, more cases of solitary pulmonary nodule and focal consolidation were included relative to pneumothorax because they were felt to have a higher variety of appearances with respect to location and shape with respect to the surrounding mediastinal and osseous structures. Examinations were extracted from our institutional picture archiving and communication system (PACS; General Electric Healthcare, Little Chalfont, UK), and reviewed and annotated by two American Board of Radiology-certified radiologists with 5 and 7 years of experience, respectively. The two radiologists' professional consensus provided the ground truth.

Before starting the module, users were instructed to optimize their viewing condition by using a desktop or laptop computer. Mobile devices were supported, but at least a 10-inch screen was recommended for optimal viewing condition. However, as the module was made freely available over the