Leveraging Cognitive Science and Artificial Intelligence to Save Lives

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Abstract. Medical error is the third-leading cause of death in the United States, just behind heart disease and cancer. We describe a software platform used to train healthcare workers to prevent their errors. The platform (Amplifire) harnesses artificial intelligence and principles of cognitive psychology. Amplifire's AI continuously decides whether and when to require additional learning events, provide corrective and metacognitive feedback, and/or deliver self-regulatory guidance for the learner (e.g., "slow down"). Amplifire was deployed to several thousand nurses at a large healthcare system in attempts to reduce the rate of two types of hospital-acquired infections. The result was a 48% reduction in central-line-associated bloodstream infections (CLABSI) and a 32% reduction in catheter-associated urinary-tract infections (CAUTI). These findings demonstrate the effectiveness of using cognitive science along with AI in an e-learning platform.

Keywords: Artificial intelligence · CAUTI · CLABSI · Cognitive science · Confidence · Feedback · Healthcare · Metacognition · Training

1 Introduction

Artificial intelligence (AI) is widely used in education because it can substantially enhance learning. Successful intelligent tutoring systems (ITSs) incorporate AI at various stages of the learning process in order to promote all facets of the Learner-Instructor-Knowledge triangle [1]. For example, the Andes Tutor leverages Bayesian-network solution maps to provide customized feedback as the student solves physics problems, while consequently improving the instruction provided by updating the probabilities of the Bayesian networks [2]. Other systems (e.g., ALEKS) determine a student's knowledge state and progress only to concepts for which the student has sufficient prerequisite knowledge [3]. Guru uses an animated tutor that integrates tutorials, collaborative dialogue, and direct instruction into a life-like user interface [4].

Although AI has permeated education, largely through ITSs, findings from cognitive psychology and other learning sciences have gained less traction in ITS research and the classroom. One reason may be that some cognitive phenomena are counter-intuitive; how learners, teachers, and even researchers think learning should work is not always how it actually works [5]. For example, the testing effect is the finding that retrieving information from memory is much more powerful than being re-exposed to

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the information (e.g., by re-reading; [6]). But classrooms in 2019 still rely heavily on watching videos, sitting through lectures, and reading chapters. Even ITSs often use testing exclusively for assessment purposes (although there are exceptions, e.g., [7]).

We describe an e-learning platform—Amplifire—that uses AI and incorporates findings from cognitive science to optimize learning. Amplifire is designed to be content-agnostic. It has helped typical and non-traditional students perform better on exams, trained call-center employees to provide better customer service, and helped helicopter pilots earn recertification. Below, we review how Amplifire shapes the learner experience with AI and cognitive science, and we report on the reductions in CAUTI and CLABSI after nurses at a large healthcare system were trained in Amplifire.

2 AI-Directed Cognitive Science

Amplifire begins by asking questions in a variety of formats (multiple-choice, select-all, matching, interactive). This approach is beneficial even if the learner couldn't possibly provide the correct response to the question [8, 9]. Attempting to answer questions is perhaps the most powerful way to gain knowledge and skills [6], even if the generated answers are incorrect [10].

When responding to questions in Amplifire, learners indicate their confidence in their responses, making them consider the question more carefully [11] and improving their memory for the material [12]. This cognitive benefit only obtains when answers and confidence are considered simultaneously [13], a process Amplifire has patented. Learners in Amplifire click an answer once to indicate partial confidence or twice to indicate certainty. They can also click "I don't know yet."

After submitting a response, learners receive immediate feedback on whether their response was correct. Metacognitive feedback guides learners to understand whether they have been under- or overconfident [14]. Amplifire's AI also determines whether and when to provide *self-regulatory feedback*, which is focused on correcting learner behavior in the platform. For example, a learner might be told to "make sure to read the question carefully" if they answer in less time than it would take to read the question.

Corrective feedback for a given item is provided after a delay, which enhances learning [15]. Amplifire's AI optimizes this delay by considering information collected about the learner (e.g., their estimated ability), the content being learned (e.g., the item's estimated difficulty), and the learner's response to that particular item (e.g., how long the learner spent reading the prompt). The corrective feedback takes the form of elaborative explanation [16] and, when appropriate, worked examples [17]. The rationale behind the correct response is provided and the error the learner made is explained (e.g., miscalculation, buggy knowledge, etc.).

Amplifire does not provide corrective feedback after full-confidence correct responses because doing so does not improve retention [18]. Learners' time is therefore better spent on more productive activities [19]. Corrective feedback is, however, provided after partial-confidence correct responses [20], and is especially powerful in cases of confidently held misinformation [21].

For problems or conceptual questions on which learners were not both fully confident and correct, Amplifire repeatedly tests the learner until its AI has determined that they have reached a mastery state. These repeated attempts profoundly improve the learner's long-term retention of the material [22]. Amplifire's AI considers learner, content, and response data in order to determine the optimal delay between successive attempts on a concept. This delay harnesses the spacing effect, which is the finding that distributing learning over time is more effective than massing it together [23]. Amplifire targets the point in the learner's forgetting curve where a retrieval attempt is difficult but not impossible [24, 25].

Altogether, Amplifire leverages AI and cognitive science to optimize the learner's time spent mastering the material, promote long-term retention and transfer to related tasks, and maintain learner engagement.

3 Application and Efficacy in Healthcare

Amplifire has partnered with career-focused online universities, GED providers, and other educational institutions that support non-traditional and underserved student populations. More recently, Amplifire has expanded into healthcare training. Medical errors are responsible for more than 250,000 fatalities in the United States annually, making them the third-leading cause of death [26]. More than half of all medical errors are attributed to the "cognitive failures" of healthcare professionals [27]. Amplifire was used at a large healthcare system to combat the cognitive failures that contribute to two hospital-acquired infections: CLABSI and CAUTI. The healthcare system made no other changes to policies, training, or available resources during this period; all effects were attributed to Amplifire.

3.1 Central-Line-Associated Bloodstream Infections (CLABSI)

A central line is a thin tube (catheter) placed into a large vein. Central lines are used to administer nutrition or medication (e.g., drugs for chemotherapy), and to monitor central blood pressure during acute care. When a healthcare provider inadvertently contaminates the equipment or the insertion site, the patient can develop a central-line-associated bloodstream infection (CLABSI). The incidence of CLABSI is expressed in terms of the number of infections caused for every 1,000 days that patients had central lines ("CLABSI per 1,000 line-days").

All central-line-attending nurses at a large healthcare system (N = 3,712) were trained in Amplifire. The results are displayed in the left panel of Fig. 1. In the 28 months before training, there were 1.09 CLABSI per 1,000 line-days. In the seven months after training, there were 0.56 CLABSI per 1,000 line-days—a reduction of 48%. An exact Poisson test indicated a statistically significant reduction in the CLABSI rate after training: $p = .00014$. Given CLABSI's mortality rate of 25%, this reduction should save approximately 13 lives per year at this health system [28].

3.2 Catheter-Associated Urinary-Tract Infections (CAUTI)

A urinary catheter is a thin tube inserted into the bladder via the urethra. An indwelling catheter remains in the urethra and bladder for continuous drainage of urine and monitoring of urine output during acute care. As with central lines, healthcare workers' mistakes can contaminate the catheter and cause a catheter-associated urinary tract infection (CAUTI). Similar to CLABSI, the incidence of CAUTI is expressed in terms of the number of infections caused for every 1,000 days that patients were catheterized ("CAUTI per 1,000 catheter-days").

Urinary-catheter-attending nurses (N = 4,512) at the same healthcare system were trained in Amplifire. The results are displayed in the right panel of Fig. 1. In the 28 months before training, there were 1.29 CAUTI per 1,000 catheter-days. In the seven months after training, there were 0.88 CAUTI per 1,000 catheter-days—a reduction of 32%. An exact Poisson test indicated a statistically significant reduction in the CAUTI rate after training: $p = .01363$.

Although both CLABSI and CAUTI were reliably reduced, the smaller magnitude of the CAUTI reduction may be attributable to two factors. First, only nurses interact with central lines, but both nurses and technicians interact with urinary catheters; part of the caregiver population was not trained on CAUTI. Second, the CAUTI course did not employ any multimedia [29]. A revised and improved CAUTI course will be distributed to both nurses and technicians in the coming months.

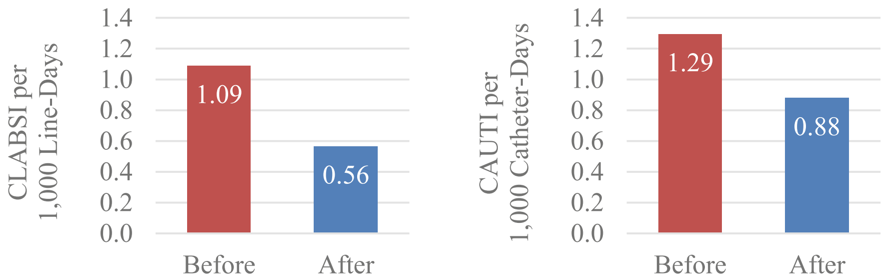

Fig. 1. Rates of CLABSI (left) and CAUTI (right) before and after Amplifire training.

4 Conclusion

Amplifire is an online learning platform that relies on principles of cognitive science. By allowing AI to determine how best to leverage many of those principles in real time, Amplifire delivers individually optimized learning in a wide variety of domains. Its test-focused approach improves learners' ability to retrieve information from memory. Its emphasis on confidence creates an additional dimension of learner introspection and understanding. Its multiple types of scaffolded feedback ensure that difficulty, engagement, and remediation are managed effectively, while also supporting metacognition and self-regulation. Amplifire's ability to substantially reduce medical error demonstrates the power of cognitive science working hand in hand with AI.

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