Applying Learning Experience Design to Real-Time Simulator-Based Adaptive Training

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ABSTRACT

The value of developing and deploying a training simulator that assesses a student's strengths and weaknesses and that adapts scenarios automatically in real time is clear. The question is how? First, a machine learning based approach to providing adaptive simulation-based training must be imagined. Then, a measurement scheme must be formulated that assesses trainee performance within a scenario thereby enabling appropriate feedback to be provided by the adaptive system. The final planning piece, before building a prototype, is applying evidence-informed learning experience design (LXD) to ensure beneficial training, minimize negative training, and maximize training transfer to the performance environment. The first two steps have been described previously (Cooley, 2021: Oswalt, 2019); this paper focuses on the third. That is, the design of a learning system and the employment of the best possible instructional methods for real-time adaptive training that meets learning objectives. For example, the adaptive simulation system will present the trainee with more scenarios where they lack proficiency, and less in areas where they are proficient. Scenarios must be spaced over time and iteratively delivered for the student to learn how to perform tasks and not just manipulate the simulator. Because there are many ways to implement real-time simulator-based adaptive training, LXD assessment is required – e.g., does decreasing training time by focusing on adapting the delivery of required skills to areas of less proficiency translate into learning retention in a real context? The authors focus on how to apply LXD to produce required performance results.

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Dr. Tim Cooley is the President and Founder of DynamX Consulting, a veteran owned consulting firm. Dr. Cooley spent 17 years on the U. S. Air Force Academy faculty, both in uniform and as a civilian, holding numerous positions including the DMSO Modeling and Simulation Chair, Deputy Department Head, and Senior Researcher. As the principal investigator, he completed many innovative mathematical and cost analyses for the USMC, USAF, and OSD and has performed counter-terrorism research for Joint Staff. He has significant experience using Machine Learning and Neural Networks for pattern recognition/classification in the medical community.

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INTRODUCTION

We have been studying how our brains work for many years. Regarding learning, we moved through several learning theories, from behaviorism, cognitivism, constructivism, and socio-cultural. In 1956 two main events happened; the Dartmouth Summer Research Project on Artificial Intelligence, where the term artificial intelligence was coined, and the Symposium on Information Theory which gave rise to cognitive science. The work and research of those participants at the Dartmouth Summer Research Project influenced the development of cognitive science; and further influenced the sub-discipline cognitivism or often referred to as information-processing psychology (Doroudi, 2021). AI researchers look at how people think and solve problems, cognitivism focuses on how people learn. (Doroudi, 2021). Cognitivism influenced the design of educational technologies. In the early years of Computer Based Training (CBT) and Web-Based Training (WBT), Instructional System Designers (ISDs) adapted well researched instructional design guidelines to these environments to provide more adaptive instruction to a larger number of learners in many different content domain areas (Iding et al., 2002). Simulations offered even more robust capabilities to improve the fidelity of the environments to map the learning experience to the real world as much as possible. For years, the focus has been on the technology, building interoperable standards, collecting and transferring data, constructing the infrastructure of adaptive learning environments, yet often times failing to use the results of learning science to shape the learning experience for the trainee (Dahlmann, 2021*)*.

Figure 1 shows the progressions of steps the authors have previously taken, the current effort, and the future efforts envisioned to shape this environment using AI and ML in simulation-based training systems to improve the learning experience and meet the learning outcomes set forth by organizations.

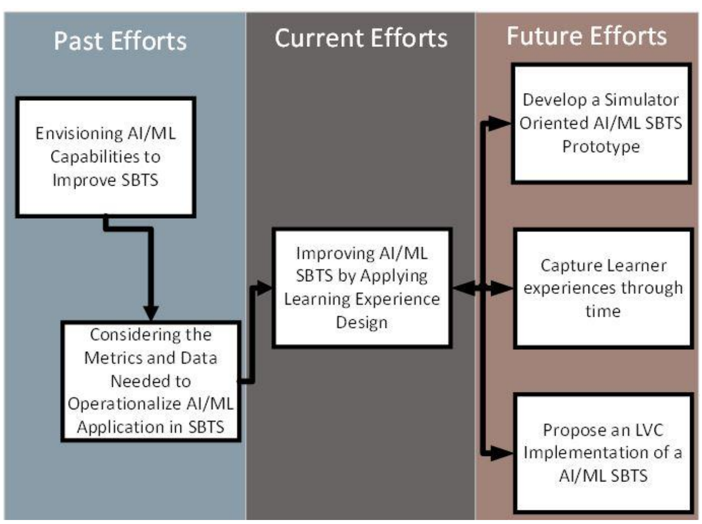

Figure 1 - Incorporating AI/ML in Simulation-based Training Systems (SBTS) Evolution of Implementation

METHODOLOGY

Based on past efforts that explored the use of AI and ML in simulation-based training and postulated sample metrics required for determining mastery of skills, it is now required to investigate how to design the learning experience for these types of environments.

Figure 2 describes the workflow the authors considered as a design framework for creating a learning experience using adaptive learning strategies in a simulation-based training environment. First, the authors researched the best strategies for designing a learning experience in an adaptive learning environment that increases the role of AI and ML in a simulation-based training system. Then they reviewed the existing frameworks that can be used to architect that experience. Finally, they assessed how these changes impact the role of a trainer or facilitator. The authors of this paper focus on key components in learning science and how they are mapped or not mapped to AI and ML to date, informed by existing adaptive technology frameworks, and how the trainers' role shifts when moving to an adaptive learning environment.

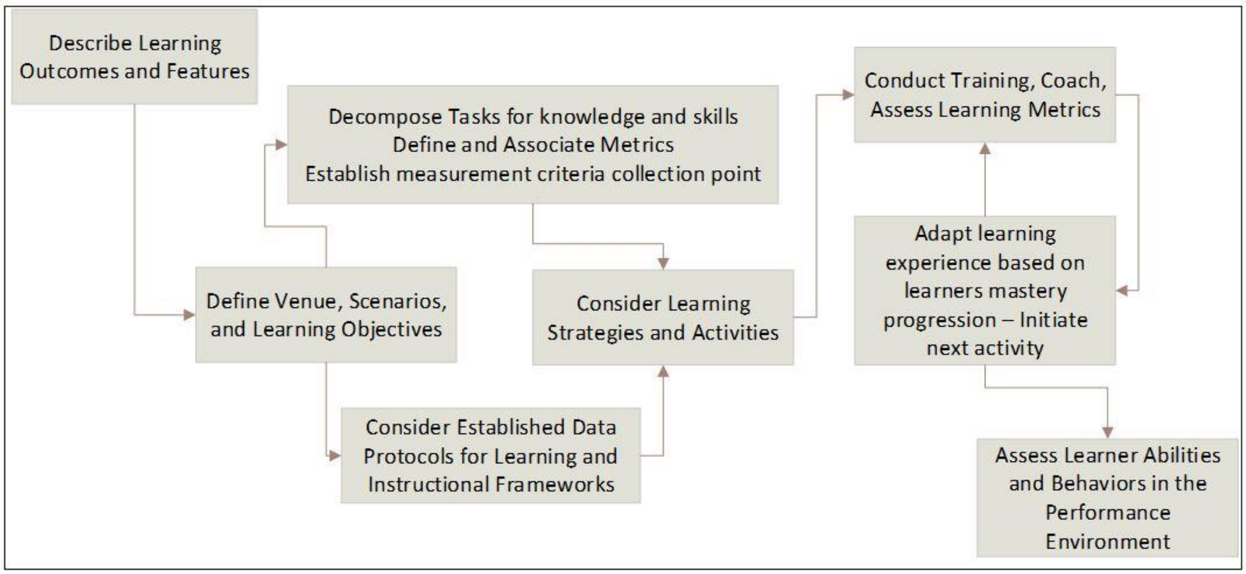

Figure 1 - The Process for Designing a Learning Experience in Simulation-Based Training using AI/ML

LEARNING SCIENCE

Learning science is simply the scientific study of learning (Quinn, 2021). More specifically, it focuses on how humans learn, what strategies best support learning, and how we apply this to creating meaningful learning experiences that meet the intended outcomes. Learning science is an interdisciplinary field of study and applying it to the creation of a learning experiences takes special skills and competencies. No matter the delivery platform; resident, virtual, or adaptive learning systems, the need for applying evidence informed practices is necessary for ensuring we create effective, efficient, and engaging learning experiences. The area of adaptive learning is not new, however, the art and science of designing a responsive experience that incorporates the elements of AI and ML within a simulation based training environment is an area of innovation that warrants significant investigation and analysis.

Table 1 outlines some key evidence-informed learning strategies mapped to cognitive activities. While these practices need to be considered for any learning design, they also need to be investigated relative to how they relate to AI and ML.

Table 1 - Learning Strategies to Cognitive Activities Matrix

Evidence Informed Learning Strategies	Cognitive Activities
Desired Difficulties and Scaffolding	**Encoding and Retrieval, Schema Development**
Cognitive Load, Chunking & Context	**Encoding and Retrieval, Schema Development**
Interleaved Practice and Feedback	**Encoding and Retrieval, Schema Development**
Spaced Learning	**Reconsolidating Memory**
Reflection	**Retrieval, Generation**, **Elaboration**
Metacognitive Strategies (Planning, Monitoring, Evaluating)	**Unconscious decisions** (Automatic responses) and **Conscious decisions** (controlled responses)

Encoding and Retrieval

The psychological process of learning starts with sensory memory, moves to working memory, then finishes in long-term memory. It seems so easy, but there are several cognitive activities happening. In order for information in working memory to move into long-term memory it must be encoded (Gagne, 1970). We must encode before we can retrieve. Retrieval is often triggered by cues, either externally or internally, a search occurs, then recognition, then a piece of information you encoded is moved back into working memory, also known as short-term memory (Gagne, 1970). This happens to perform some type of task, or it happens to prepare for new encodings or information. When we construct learning experiences, we must find ways to support learners in the process of encoding and retrieving both old and new information.

Schema Development/Mental Models

When we encode information, we create a schema or mental models (Piaget, 1964). Basically, these are the filing cabinets in your brain filled with drawers, files, and papers of everything you've been exposed to that you encoded into long-term memory (Brown, et al., 2014). There are several strategies that support encoding and retrieval, as well as schema development.

Desired Difficulties and Scaffolding

Scaffolding is a strategy used to support the learning process (Brown, et al, 2014). If you think of a scaffold around a building that supports the construction process; the key to this strategy is eventually removing the scaffold. We support learners when learning new knowledge and skills by providing some desired difficulties that are intentionally presented at specific times within the learning experience. Lee Vygotsky referred to this as the Zone of Proximal Development (ZPD) (Doroudi, 2021). Desired difficulties help the encoding and retrieval by slowing down the learning and eliciting more effort (Brown, et al, 2014). These scaffolds need to be intentionally designed to occur at the right time and to support the learner in mastery of a skill. They cannot be added haphazardly.

Cognitive Load, Chunking, and Context

Cognitive load is the mental effort we need to process new information (Sweller, 2010). If working memory is overloaded with too much information or contains too much distraction and noise, the ability to learn is severely impaired (Shank, 2017). We need to activate our long-term memory and have it work with working memory to make sense of information. To support the cognitive load, we use practices such as chunking and ensuring content and experiences are put into context or made meaningful to what we are learning.

Interleaved Practice and Feedback

Practice is extremely important in any learning experience; we must ensure the decisions learners make and the tasks they practice as close as possible to those they need to perform on the job. Interleaving practice; which is the mixing of two or more related concepts and skills together in one study session, rather than studying one concept or skill at a time (Brown, et al, 2014). When we design this strategy throughout a course, it activates the retrieval process, so that each time a person practices, they strengthen the memory trace of those actions. Feedback on practice or assessments must be specific to be effective, especially if we are looking for some type of change in behavior. There are several different types of feedback that can be provided to a learner, the most effective is epistemic feedback (Neelan, et al., 2020). Showing where the mistakes were made and fixing any misconceptions a learner has is imperative to achieving mastery.

Reconsolidating Memory

During this process there's a reconsolidation or reconstructing of the components of the skill or knowledge, this helps to strengthen the learning path or memory trace, the cues associated with the information/skill, and reinforce the meaning (Brown, et al., 2014). Designing spaced learning requires short sessions of chunked knowledge or skills and then revisiting them often, just before the learner may forget. This strategy forces them to retrieve and reconsolidate each time.

Generation and Elaboration

Generation is the act of trying to answer a question or solve something without being given the information or solution. In other words, the answer is being generated by the learner and not recalled (Brown et al., 2014). Elaboration is the process of finding additional meaning in new material (Brown et al., 2014). It's the process of adding onto the existing knowledge or schema. Generating an analogy helps to map the new information to existing information and improve that mental model or attach to a new mental model. Both of these cognitive activities help to improve existing schema and to create new schema. Recalling information takes effort. Reflection is an important learning strategy that does not get enough attention and must be intentionally designed into any learning experience. This is the opportunity to help learners fix misconceptions by asking them to summarize what they are learning into their own words either through elaboration or generation.

Unconscious and Conscious Decisions

In the book *Thinking Fast and Slow*, Daniel Kahneman (2013) discusses two analytic systems, system 1 being the unconscious or automatic which draws on intuition, memory, and the senses. System 2 is the conscious or controlled system where there is more analysis and reasoning to make choices and decisions, and to manage ourselves. Metacognition is simply defined as "thinking about our thinking" or what psychologist refer to as monitoring our own thinking, is related to System 2. When we do this poorly, we tend to delude ourselves into an illusion of knowing. This is where our judgments of how much we know or do can lead us astray. There are perceptual illusions, cognitive biases, and memory distortion that can affect our learning processes (Brown, et al., 2014). We need to help learners improve their metacognitive skills, as these skills translate not only to the training environment, but also to other areas of their lives. In the training environment for example, the learner will need to plan how they will participate in a learning experience, monitoring how they are doing, and evaluating how well they've met the learning goals.

Enabling effective learning via the creation of schema and mental models using AI/ML augmented simulation-based training systems is facilitated by applying relevant frameworks and is informed by current activities and results.

ADAPTIVE LEARNING FRAMEWORKS

There are several adaptive learning frameworks and data standards developed to date for intelligent tutoring systems and other platforms that can support evidence informed learning strategies. In the area of frameworks, xAPI is at the top of the list. The Experience Application Programming Interface (xAPI) is an e-learning software standard that makes it possible to store and retrieve records about trainees and share them between systems via a learning record store (LRS). This store can host analytic tools and can also export the data for use within other applications, which may include the ML algorithms needed to create adaptation training solutions (Chambers, 2021; Sett, 2022). The Methodology for Annotated Skill Trees (MAST) is a framework that facilitates the creation of descriptive and rule-based content and was used in the Virtual Intelligent Tutor for the Andragogy of Military Medicine INtegrated Skills (VITAMMINS) (Federal Reporter, 2016; Charles River Analytics, 2021). VITAMMINS combined MAST with a Bayesian approach to assess student performance and provide cognitive feedback to focus students on critical clues. There have also been previous efforts to develop adaptive learning architectures for simulation training systems. One that is particularly relevant here presents "a theoretical framework that focuses on providing an adaptive learning experience whereby a user can progress or regress to appropriate skill levels in the simulation based on his response or non-response to well-crafted stimuli" (Sestokas, et al., 2009, p. 3).

RECENT RELEVANT DEVELOPMENTS

There are several areas of innovation within the field of learning sciences that are applicable to the design and development of real-time simulator-based adaptive training. The first includes Human-In-The-Loop and Active Learning which train the predictive algorithm via a process that integrates human knowledge and experience, either initially or continuously, to improve model accuracy (Wu, et al., 2021; Minieri, 2020). This could be used in a simulator-based adaptive training system to reduce the training time and improve the accuracy of the ML algorithm to be employed.

The second, Adaptive Learning 3.0, uses AI to strive to replicate one-on-one training.

> "AI-powered adaptive solutions leverage network knowledge maps to create knowledge and behavioral nodes, forming deeper relationships between content, learning objectives, and persona types, to name a few. This powers a more efficient, effective learning experience and enables:
>
> - Complex, real-time adaptations based on learner performance and behavior
> - Data-driven, personalized hints, feedback, remediation, and knowledge reinforcement
> - Predictive, forgetting curves and insights into future knowledge application
> - Comprehensive application-level mastery of skills and knowledge
> - Reduction in learning times

It is not just the learning experience that is amplified. The platforms that are fully embracing AI and machine learning are also able to provide dramatic efficiencies to learning development and content creation" (Weir, 2019).

Next, there is the use of reinforcement learning to teach simulated humans (robots) how to perform a task (see figure 3). Deep Reinforcement Learning algorithms normally require an extremely large number of training samples. While recent work has focused on addressing this issue by implementing distributed training, this investigation concentrates on distributed simulation, via the examination of a set of tasks. In one, a simulated human must learn to run and change directions on a terrain filled with obstacles. The reinforcement function rewards speed toward the desired target and penalizes excessive torque applied to the joints. The result is an ability to train the simulated humans (robots) to run gracefully in less than twenty minutes (Liang, et al., 2018; Alarcon, 2018).

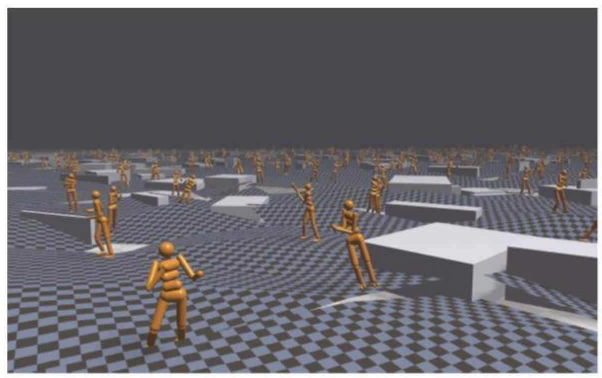

Figure 3 - Deep Learning Trained Robots

Finally, an assessment is underway on the effectiveness of an artificial intelligent tutoring system's application to simulation-based training which used an AI algorithm, the Virtual Operative Assistant, to analyze data derived from the NeuroVR (CAE Healthcare) simulator platform which "provides individualized audiovisual feedback to improve learner performance during simulated brain tumor resections" (National Institutes of Health, 2021). These developments and results have significant potential to improve the design and use of adaptive simulation-based training systems.

TRAINING MANAGEMENT PARADIGM SHIFTS

The role of the trainer in a simulation-based training system augmented with AI was briefly mentioned in a previous paper (Cooley, Oswalt, 2021). Indeed, it should be no surprise that when the method of training delivery changes, the instructor must adapt. We have previously experienced this in more formal academic settings, notably at the U. S. Air Force Academy (USAFA) when the Department of Mathematical Sciences integrated technology into the classroom and moved from a traditional lecture-based format to a student-centered model (Cooley, 2003). In this endeavor, the classroom instructor went from the "Sage on the Stage" to the "Guide on the Side". This involved taking on the role of a coach, being prepared for a wider range of questions than just that day's material, understanding how the technology functioned and, most importantly, how to interpret results from the technology. The delivery format also changed from a prepared, well scripted presentation to a more interactive, student engaged session with hands-on learning. These sessions varied considerably class to class as different students asked different questions and needed clarification on different topics. The linear, scripted presentation was no more.

Moving from the current simulation-based DoD training paradigm to one with a simulation-based AI augmented training system is very similar to the situation described above. First, the trainer must be well versed on each of the training tasks for that system. Similar to the previous style of classroom instruction, current training typically involves working through a scenario in a simulator. That scenario will have the same tasks in the same order every time it is exercised. In that situation a trainer is able only to be knowledgeable on those tasks for that exercise as that scenario will never change. Contrast that with adaptive training using an AI-infused system. In this situation, no two scenarios are necessarily alike and while the overall set of tasks are known, any one of those tasks could be included or not depending upon the skill of the trainee. Now it becomes necessary in each training session for the trainer to be skilled at all of the tasks the system trains and not just a subset for a scenario.

Along with this, the trainer will need to understand the system's technology to best assist the trainee. They must be able to explain the system's feedback, clarify any issue on the after-action report and provide coaching on how to better accomplish the task(s). Because of the metrics necessary for the system to adapt (Cooley, Oswalt 2021), the AI infused training system will provide increased granularity in the feedback. Scores, or at least a pass/fail rating, will be given for each task and not just the entire scenario (which currently is often just a pass/fail score). The trainer will then need to understand the nuances of each task and the more detailed feedback the AI system provides to best coach the trainee. Finally, because each training session will be unique depending upon the skill of the trainee, the idea of a set lesson plan with set tasks is much less workable. Much like the USAFA situation discussed above, the trainer must be flexible and adapt with the training system acting more like a coach and much less like a trainer to be successful. These changes are all possible, but will require a shift in the mindset and paradigm of training.

CREATING A LEARNING DESIGN MODEL FOR ADAPTIVE LEARNING ENVIRONMENTS

In the mid 90's, M. David Merrill wrote about his Instructional Transaction Theory (ITT) and included a description of it as a chapter in A New Paradigm of Instructional Theory book. He wrote about Instructional Design 2 (ID2) as a means to bring about a design model to support knowledge representation in a technology environment (Merrill, 1996). We propose a model titled A.D.A.P.T. This model helps those responsible for creating learning environments using adaptive technologies, while incorporating evidence informed learning strategies and leverages existing technology frameworks. Instructional design models like Gagne's Nine Events of Instruction, Dave Merrill's First principles, and Kolb's Experiential Learning support learners in organizing the flow of their content and activities, generally for each lesson in a course (Gagne, 1970; Merrill, 1996; Kolb 1974). The A.D.A.P.T. model, as summarized in figure 4, is similar to those, however, it's specific to adaptive learning environments. These models are different than Instructional Systems Design models, like Analyze, Design, Develop, Implement, and Evaluate (ADDIE), which is focused on the whole system:

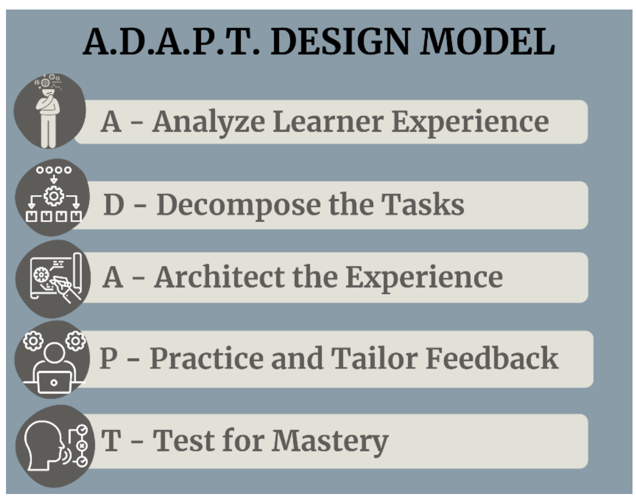

Figure 4 - A.D.A.P.T. Design Model

1. **A - Analyze the Learner's Experience**. Using existing data standards like xAPI and Learning Record Stores (LRS) is critical to designing an adaptive experience. Design decisions are dependent on what the learner may or may not have accomplished in the past and when they need to reach mastery.
2. **D - Decompose the Tasks**. When a task analysis is conducted, it requires that the steps be placed in a logical sequence and that necessitates the capturing of the knowledge and skills that will be taught to master the steps and the tasks. It's at the most granular level. There are existing frameworks, as mentioned above, that

can support how we label, capture, and deliver knowledge and skills at the most basic level to support the primary content domain, but also secondary content domains. Determine the type of knowledge and skills that must be taught, such as, rules, concepts, facts, processes, or procedures and then how AI and ML can be used to augment the training environment being employed.

3. **A - Architect the Experience**. Thinking through the evidence-informed learning strategies and current technical frameworks, it is then important to determine how can these be incorporated into the experience in a meaningful way to support the learner's journey and map to how they learn. How do you adapt the experience based on how well or poor the learner is moving through the learning activities? How does AI and ML enhance or improve the training system to provide the content to the learner? And finally, how will we collect and sort the data that results?
4. **P - Practice and Tailor the Feedback**. It is critical to determine at what intervals does a learner need to practice and how and from whom will they receive feedback to correct any mistakes, misconceptions, or reinforce correct decisions - in real-time, during pauses in training, or after individual scenarios are completed.
5. **T - Test for Mastery**. This fifth and final step concentrates on the metrics that need to be captured, how they will be captured, and what will mastery look like when the learner completes tasks in a satisfactory or exemplary manner. Other considerations incorporated here include, how do we measure how proficiency transfers from the synthetic or simulated environment to the actual performance environment?

FINDINGS AND NEXT STEPS

The goal of any simulation-based training is to bring a trainee to proficiency in all tasks and skills in a system in such a way that they will retain that proficiency in a live environment (training transfer). Innovative ability to adapt to a trainee's performance to provide more training on less proficient tasks and less training where the trainee is competent provides the next level in training efficiency. However, without a solid learning experience design that is incorporated into the framework and architecture of the system, that next level could be more harmful than beneficial. Even tasks that the trainee has shown proficiency need to be presented at varying times in a curriculum to cement that proficiency in their mind (National Research Council, 2002, p. 137). Failure to exercise proficient tasks may lead to skill degradation. Tasks and skills that the trainee struggles with also must be scattered throughout the curriculum to promote long-term memory retention (National Research Council, 2002, p.137). In this paper the authors have presented the ADAPT model to use as a guide in designing an adaptive simulation-based training system infused with AI and ML. Using this framework along with the techniques presented in this paper will aide in designing an adaptive system that reduces overall training time but also increases the simulation's training transfer capability. Additionally, the coach/trainer is crucial to the success of the training and the value of the system. The trainer must be experienced with the system and its feedback as well as being almost a subject matter expert (SME) on the tasks and skills being trained.

This is the third in a sequence of papers that examine how AI and ML can be incorporated into training simulations and articulating some of the associated advantages. Next steps include:

- Designing the technical architecture of the system, the AI modules, and the real-time modification techniques and locations using the ADAPT model to design the architecture with careful implementation of solid learning experience design.
- Determining the necessary elements for actual implementation. This would include methods to gather and to store data for each trainee - necessary to determine the proficient and non-proficient tasks for each trainee.
- Characterizing the feedback mechanisms from the system and the data necessary in the after-action reports so that the trainee and coach can understand how to correct any deficiencies.
- Investigating the development of a prototype that would simulate certain parts/modules of a training system in order to flesh out any issues with the other system modules - decomposing the system and designing in very manageable pieces.

Simulation has developed and improved substantially since the first Link Trainer was constructed and employed within the aviation training community in the 1930s (Naval Air Station Fort Lauderdale Museum, 2010). Recent innovations include augmented and virtual reality, distributed and federated delivery, increasingly higher levels of fidelity, with an ability to run in real-time based on massive improvements in software, compilers, chips, and networks. However, at the center of every training simulation is the trainee. AI and ML augmented real-time simulator-based training, delivered using evidence-informed learning experience design, now makes it possible to provide a more persistent training environment that supports minimizing the forgetting curve, maximizing task mastery, and improving overall performance while decreasing training time and increasing the training transfer.

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