Learning Engineering Competency-Based Experiential Learning within Military Institutional Training and Education

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ABSTRACT

Learning engineering is a modern discipline focused on applying learning science and technology to discover new methods, technologies and models for improving human learning. A challenge in modern institutional training and education environments is the low engagement and percentage of retention and transfer of taught material to the job site, creating low return on training and education investment. Today in both the civilian university setting, and in the Department of Defense, most institutional training courses still employ a traditional didactic instructional model that's been used for centuries. Meanwhile, modern learning science and practical research show that more active learning processes supported with technology can make institutional instruction more engaging, create longer retention of learning, and potentially can increase the transfer of instructed knowledge and skills to the job site.

This paper will discuss the starting phase of a learning engineering project that is experimenting with applying a learning model called Competency-Based Experiential Learning (CBEL) into a military institutional learning environment that currently incorporates a traditional instructional method. CBEL works within the US Army's Synthetic Training Environment Experiential Learning for Readiness (STEEL-R) framework, and applies modern learning science and neuroscience, uses simulation-based content, adaptive learning technology, and provides data-informed competency and learning feedback and criteria. We will provide a high-level description of the learning engineering process, the specific challenge we'll be engineering a solution for, and the CBEL model itself. We then describe the learning institution we partnered with to conduct this project, and the various outcomes of our initial investigation. We also discuss the major lessons learned to help inform others thinking of engineering solutions for similar challenges within other learning institutions.

ABOUT THE AUTHORS

Kevin Owens is an Engineering Scientist at the Applied Research Laboratories: The University of Texas at Austin. He has over 40-years practical experience in military, industry and academia engineering new learning systems and evaluating/improving military occupational competence. He has an MS in Instructional Systems Development and a BS in Workforce Education and Development. Kevin is currently working on engineering simulation-based experiential learning models, employing adaptive learning systems, and designing data strategies for improving warfighting competence.

Lisa Townsend is a Senior Research Psychologist at the US Army Combat Capabilities Development Command Soldier Center, Simulation & Training Technology Center. She has a M.S. in Industrial/Organizational Psychology and a BA in Psychology, from the University of Central Florida (UCF). She has worked on many diverse teams including those within Research and Development, Technology Transfer, Instructional Systems Design, and Human Systems Integration. Ms. Townsend's areas of expertise involve team training, Front End Analysis (FEAs), Training Systems Analyses (TSAs), Instructional Systems Design (ISD), Training Effectiveness Evaluations (TEEs), and the development of training and organization related metrics. Her efforts in these areas have spanned across Services and platforms.

Dr. Benjamin Goldberg is a Senior Research Scientist at the U.S. Army Combat Capability Development Command – Soldier Center. His research focuses on adaptive experiential learning with an emphasis on simulation-based environments and leveraging Artificial Intelligence to create personalized experiences. Dr. Goldberg holds a Ph.D. in Modeling & Simulation from the University of Central Florida and is well published across several high-impact journals and proceedings, including IEEE Transactions of Learning Technologies, the Journal of Artificial Intelligence in Education, and Computers in Human Behavior.

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INTRODUCTION

The hardest part of creating successful learning applications is the fact that we still don't know everything about how the human learns best. Therefore, we are still discovering for ourselves the best methods and technologies to facilitate learning tomorrow so that it improves how we learned yesterday. The developing field of learning engineering is the process of engineering new methods and technologies for improving human learning challenges based on the latest learning science and neuroscience, and by converging natural science, technology, learning practices and even learning philosophies. While several publications and other resources over the last few years have been written or recorded to provide the theoretical tools and processes required to conduct learning engineering (e.g., Goodell & Kolodner, 2023), in this paper we document an actual learning engineering effort "in the field" for testing and informing those existing theoretical processes. Our aim here is not to document the complete learning engineering process since that will be a multi-year venture. Instead, we capture our experiences and resulting information within our first phase of the learning engineering process, and document the sub-challenges, data, and methods we've collected, and discuss the lessons we've learned in the process. We will also share the premise of the learning model we intend to experiment incorporating, and the new technologies we're testing for other learning engineering projects in the future.

Our learning engineering project is focused on the investigation, creation and implementation of a US Army sponsored science and technology learning model referred to as Competency Based Experiential Learning (CBEL). This model is intended to improve upon traditional institutional learning by converging learning science and other simulation research, as well as data science, with another recent US Army science and technology framework. Aside from improving learning in institutional classrooms, this effort will be focused on informing the US Army's developing Synthetic Training Environment (STE), as well as integrating its latest simulation capabilities. The CBEL project is sponsored by the U.S. Army Combat Capabilities Development Command - Soldier Center's Simulation and Training Technology Center (STTC), and is being planned and executed in close collaboration with the Department of Military Instruction (DMI) at the US Military Academy (USMA).

BACKGROUND

Learning Engineering

Learning engineering is a process that employs advancements in science, technologies, and best practices related to human learning for advancing the fundamental ability to survive and thrive in the modern world. While often compared to other more learning-product centered processes like *learning experience design* and the legacy *instructional systems design* or the more generalized *performance improvement* processes, learning engineering is less about just creating learning products than the discovery of methods, values, technologies, and practices learners, instructors and evaluators can use to improve human learning outcomes. Using the latest data science, practices, and empirical and inspectable data, the learning engineering process guides research and discovery of ways to improve learning or mitigate causes of restricting learning or competence sustainment. To do this, learning engineering requires teams of practitioners from multiple disciplines that not only include learning experience designers or instructional designers but other science, technology, engineering, art and math specialists who play a critical role in examining data, discovering results, and building solutions, as well as creating new learning environments or architectures, all focused on improving human learning. Learning engineering is a forward-looking process that requires thinking beyond an existing learning model, product or practice.

As illustrated in Figure 1, learning engineering consists of a three-phase, systematic and cyclic-process that can be started at any phase. The learning engineering model also works systemically, since some phases consist of "nested" intra-cycles that perform the same three-phase cycle, thus allowing for more agile formative development within a given phase of engineering (Totino & Kessler, 2023).

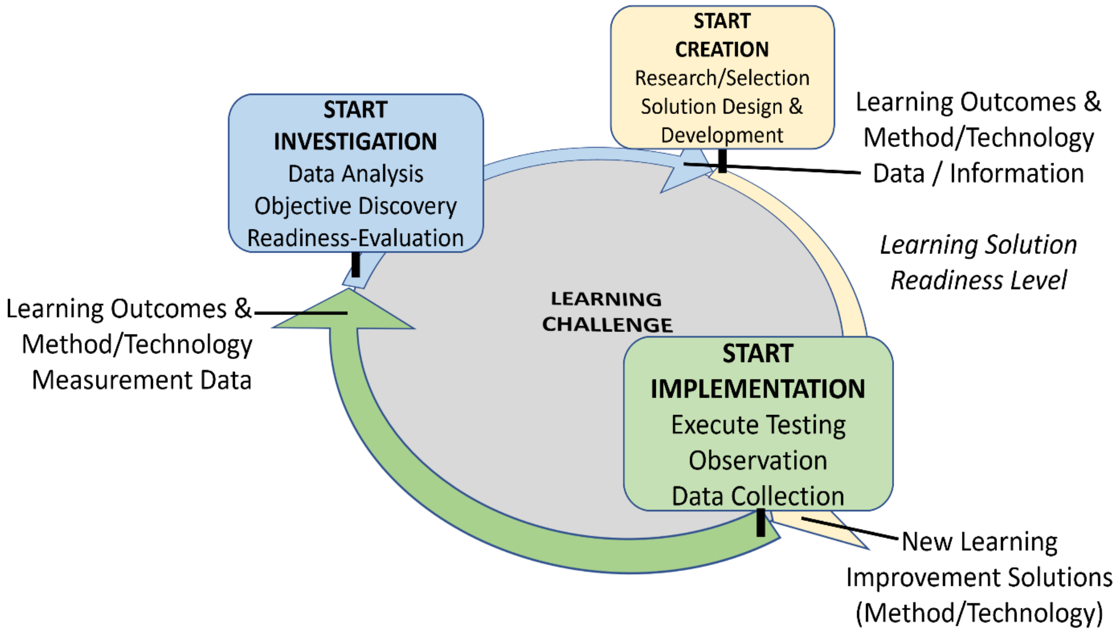

Figure 1. The Learning Engineering Model

The learning engineering *Investigation* phase starts when data related to the engineered learning challenge or solution has been measured and is available. This phase also consists of researching the latest learning science, neuroscience and best practices for the learning environment(s) being investigated. This phase consists of collecting, reducing and cleaning, analyzing, and evaluating data, and discovering or making decisions on the learning solution readiness result that form the insights or requirements for the follow-on *Creation* phase. The creation phase begins when designers and developers of various disciplines and skills use the discoveries, decisions, insights or information from the investigation phase as guidelines to create working iterative solutions to address the learning challenge. These creations can be, for example, experiments with instructional media, modalities, biometrics, and different learning experience support or automation technology for learner stimulus, assessment, data collection or student monitoring tools. Creations can also be instructor, learner or evaluator techniques or procedures that support or enhance a form of technology that is hypothesized to improve the learning challenge being researched. The third phase is the *Implementation* of the creation, which begins when a created solution has gone through its own iterative learner-centered design and development process, and is ready to be tested with real learners or learner surrogates. In this phase, learning solution activity and outcome data is collected from biometrics, psychometrics or other sources of cognitive or psycho-motor data from the learner's response to whatever stimulus they're given. All phases should occur not only during the initial solution engineering development but even after implementation of a product, and throughout the life-cycle of fielding in an education or training environment. Key is the need to continue collecting data samples of learning processes and outcomes to provide the evidence that a solution is systemically impacting the challenge over the long-term.

Our Challenge

Over the last decade the traditional methods of instruction have been tied to student disengagement (Chipchase, 2017). At the same time, research on the effectiveness of classroom active learning methods over traditional instructional models show a significant improvement on retention, engagement and success rate (Freeman et al., 2014). In addition, military sponsored training research has shown that there is a problem with transfer of institutional learning to the job site with traditional institutional training methods (Bickley et al., 2010). Like in K-12, and the secondary education setting, most military institutional learning environments rely on the traditional model of instruction where students must listen to a series of lectures by a subject matter expert, usually accompanied by media of some sort. These classroom experiences usually require very little cognitive effort or activity by students other than listening, writing notes and/or viewing images and reading along with an instructor's content on a screen. In short, they require little active thinking.

Therefore, our challenge is to produce a learning environment that maximizes the active cognitive activity taking place in a classroom, while increasing student retention, engagement and learning success. We hypothesize the time spent in a classroom can be more productive and effective using a more active experiential learning model, where instead of receiving context-less preliminary lectures, students will learn more by being immersed in episodic experiences, followed by data-informed feedback, resulting in more reflection and better and longer retention (Herbert & Buck, 2004). We also believe that by employing modern simulation systems for stimulus and adaptive learning technology for data collection, assessment and feedback, we can make classroom instruction more efficient, and impactful.

The CBEL Model

CBEL offers an alternative model to traditional institutional instruction, based on classic and modern learning science and neuroscience. CBEL employs a cyclic systemic process that employs natural human experiential learning activities that scientists have found align with how the brain processes (and learns) information (Kolb & Kolb, 2017; Zull, 2002). The idea is that simulated content exists, that immerses learners in real-life experiences, and in a real occupation environment for a given domain, role, task or topic to be learned. Based on this idea, an example of the overall CBEL model is shown in Figure 2 below.

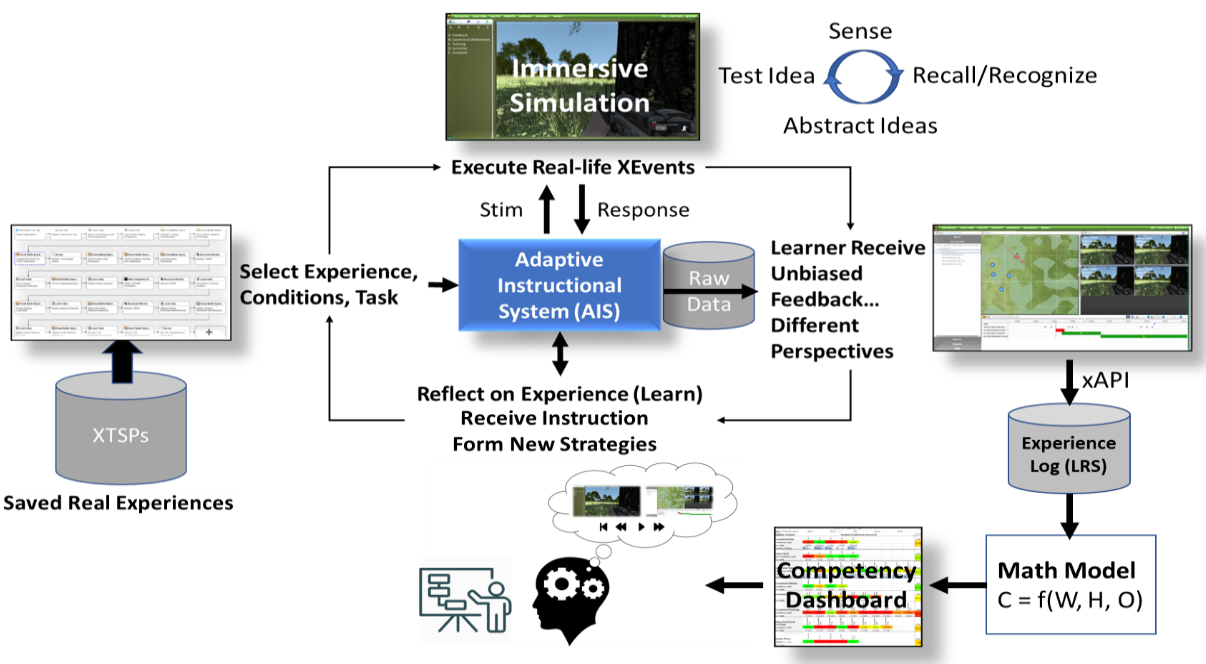

Figure 2. The CBEL Model

The CBEL learning cycle employs a systemic process of immersive simulation capabilities and modern adaptive instructional technology that stems from the STTC STE Experiential Learning for Readiness (STEEL-R) science and technology framework (Goldberg et al., 2021; Owens et al., 2022). While STEEL-R was originally designed to support the US Army's individual or team-based occupational training programs, CBEL intends to employ the STEEL-R framework into an institutional classroom-based training program (Owens et al., 2024). As shown in Figure 2, with CBEL, "lessons" would be replaced by multiple rapid synthetic experiences, which incorporate multiple real-task events reconstructed from real work-site environments and conditions. When an experience is selected, an adaptive instructional system (AIS) automatically sets up the simulation for each student to interact with, as well as sets up real-time data collection, stimulus strategies, and performance assessment algorithms that the instructor can monitor and/or control remotely in real-time. From these synthetic experiences, students will be stimulated to employ the natural cognitive activities of recalling, retrieving and recognizing patterns, forming abstract ideas in response, then actively testing those ideas to complete tasks within the simulated environment. Each student's performance is logged and automatically compared to data-mined baseline expectations that result in their performance being classified as *at*, *above* or *below* expectations. After the experience is completed, the AIS then provides an interface that shows each student a data-informed objective view of their performance from data sources within the simulation. The viewing of data-informed results may also be accompanied by feedback from different perspectives such as by learning-peers. After this feedback, the students are given time to reflect on their experience, gather any needed instruction, and to view their long-term competence state which drives their next experience selection and configuration. Needed instruction can be instructor-led or self-directed, and only focused on subject-matter based on what the data shows the instructor and learner. Key is that this entire experience is now fully active, and altogether, produces longer-term episodic memories that students can now "connect" any given instruction to instead of having to rotely memorize instruction in working memory for future applications or testing.

METHOD

Project Plan and Team

From the beginning we needed to determine what phase to begin our learning engineering project at. In our specific case we decided to begin at the Investigation phase (Figure 3) since we would have to get familiar with the learning institution, access any existing learning data, and determine a subject to focus on before deciding on how we would implement our model into the institution's curriculum. We expected any planning would need to be agile to adapt to the many new challenges and findings our initial investigation would reveal. We also assumed our team's membership would morph with the ebb and flow of the challenges we face, and the phases of the process we engage in. At a minimum we would need team competencies in learning systems and cognitive psychology to ensure we were using principles and practices of learning science. We also knew we would need skills in simulation design since we would be incorporating synthetic content. Human-systems integration would be needed to ensure our simulated content, messages and systems were optimized to support the CBEL model, and to minimize any additional technology learning requirements. We also needed experience and skills in instructor practices so we were sensitive to the duties and responsibilities of the expert who would guide the CBEL learning processes. We needed data science skills and tools to help us reduce, label, and analyze the data we'd be collecting, and software engineering skills because the model we were testing involved software technology we would need to adapt to the institutional learning environment. Most importantly, we'd need members of the target learning environment, whom our model was being created to support, and whose insights and feedback would inform the learning engineering process over time.

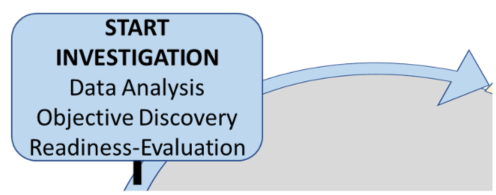

Figure 3. Our Starting Point

The Learning Institution

An opportunity to conduct this learning engineering effort was provided by the US Army's USMA DMI. The DMI teaches military science (MS) across three-courses over a four-year program (see Table 1). This currently uses a combination of traditional classroom instruction, simulation based training, and live training sessions. This combination of instructional modalities provides our learning engineering project a number of alternative options the CBEL model could be applied to. The DMI already integrates its curriculum program with a well-equipped, state-of-the-art, Simulation Center providing an opportunity for data collection and a potential testbed. In addition, the USMA program provides chances to capture data from culminating live training events towards the end of its Cadets' tenure; data that can be used to evaluate the long-term impacts of the CBEL model.

Table 1. USMA DMI Program

Cadet Standing	Summer	Academic Year
4th Class (Plebe)	Basic Training - 6 weeks	Military Science 100 Introduction to Warfighting
3rd Class (Yearling)	Field Training - 4 weeks	Military Science 200 Small Unit Operations
2nd Class (Cow)	West Point Leader Detail - 4-6 weeks	Military Science 300 Platoon Operations
1st Class (Firstie)	Troop Leader Training - 2-3 weeks Leader Development Training - 4 weeks	MX 400 Officership Capstone
2nd Lieutenant	First Active Duty Assignment	

On average, DMI teaches approximately 550 Cadets in each of its three courses each semester. This creates a large statistical sample of research participants who will not only provide a wide diversity of learner data, but a diverse sample of learner backgrounds, contributing to increased confidence in the results of data. Another benefit in partnering with the USMA is that it enables future officers of the US Army to not only help in shaping the concept and practice of CBEL but have opportunities to be involved in the testing and informing of its learning technologies. This input could then influence the STE program which Cadets will have to use to train and sustain the competence of their Soldiers and themselves in the future .

While it is a military institution, DMI faces many of the same challenges that other academic institutions face when using traditional instruction, such as the fixed instructional periods, inability to monitor and directly support each Cadet as they receive a lesson's instruction; having to determine the level of Cadet understanding of instruction so they can modify the material presented; having to create, administer and grade multiple written assessments that contain mostly graphical answers or open-ended type responses that may be hard to read, comprehend within a limited response area, and having to translate to generalized rubrics that greatly increase the cognitive workload of the instructor. Finally, not having the means to record, auto-reduce and analyze data points from each Cadet's individual activities (e.g., during presentations, tests, assessments, or evaluations), in a format easy to analyze, can impact the type and amount of feedback and coaching that can be presented to Cadets.

To advise our research, help us navigate the DMI official procedures, and even help execute our experiments, we were able to add a DMI staff researcher to our learning engineering team whom we found to be a critical component of our project and effort and, and who made our planning and preparation much more effective and successful.

Project Preparation

There were two-steps needed to prepare before the investigation phase could begin. One was the need to brief DMI leadership in order to obtain awareness, permissions, and agreements to conduct our experiment, and then we needed to brief other approval boards to obtain and to be able to share needed information and data. To this end, a Memorandum of Agreement (MOA) was created. This step highlighted the importance of having our DMI staff team member to help obtain permission to conduct the experiment and to collect the data we needed to start our initial investigation.

Investigation Phase

To make a precise evaluation on whether our CBEL learning model would be more or less effective in a short period of time we needed to understand several factors that will affect a Cadet's learning experience: (1) the content and tasks to be learned (2) the spacing of knowledge or practice retrieval (a curriculum design trait). (3) conditions of retrieval (a learning environment trait). (4) the degree of student original knowledge, skill or experience. (5) the instructional strategies used to stimulate and promote learning, and (6) student individual traits and agency differences. As such, we were required to begin our learning engineering process by first investigating each of these with our DMI partners.

Our investigation started by learning the DMI MS course structure and the eight main phases every Cadet must complete to earn sufficient points to graduate and become active-duty officers (See Table 1). In addition, thanks to our DMI staff team members, we were able to get access to the DMI MS curriculum content and tests. From this information we created a program learning "map" that enabled us to plot how the time, modules and learning objectives were executed through different methods of instruction, assessments and to determine where experiential learning and simulation-based learning elements were already being employed in the three-courses.

A key objective of our investigation phase was identifying a topic area to focus our CBEL project on over several years. A requirement for this topic was that it would need to be a task-based knowledge and skill that a Cadet would need to employ (and measure) across and throughout a Cadet's academic career at USMA; this way, we could track learning impact not only laterally across different Cadet "sections" (classes) but longitudinally over their various MS courses and summer activities. Another requirement was selecting an initial topic that could easily be integrated with simulation as an initial experiment but could still be supported by the legacy content as needed.

Our next form of data collection was observing a sample classroom instruction session and evaluation session so that we could determine what traits the instructors provided that were critical in the traditional learning process, as well as how the content was being used by both the instructor and the learners. After observing portions of each of the three courses, we then arranged interviews with Instructors for each course. From this we noted that each instructor provided their own "style" of instruction as well as their own methods of assessing their student's learning. This information revealed more insight into how the curriculum is executed, its limitations, and some opportunities. We also worked closely with the DMI curriculum manager who advised us on parts of the curriculum he was working on improving. From this investigation, we found multiple task-based topic candidates where we could center our CBEL experiment. We also noted opportunities where our CBEL technology could aid the DMI in pulling more objective and labeled data to provide instructors with better insight into Cadet learning progress or curriculum managers with data evidence on curriculum area effectiveness.

Another revelation from our investigation was that by providing the CBEL technology, we could likely address noted limitations at DMI, especially the fact that instructors at DMI had many other duties other than instruction, thus needing a process that would reduce their workload. Aside from the natural challenges instructors have with managing 10-20 Cadets learning progress during a instructional period, we also noted from our curriculum review and observations that although some use of a learning management system was being employed for quizzing, the more weighted test data was being collected manually using traditional paper-based forms because the test-items required more open answers and practical application responses. This offered an opportunity we felt would be a perfect application of simulation-based content, in that testing data could be collected and evaluated automatically during the synthetic experience. This approach would not only support Cadets and instructors in generating and further assessing test responses but would help categorize and track the response data more effectively. This data could then inform instructional decision-making, identify Cadets struggling at an earlier stage, and make the grading process more objective.

Data Collection Technology

Without getting too deep in the details of the STEEL-R technology being used in CBEL, for brevity, it can be best described as a data strategy that employs a generalized adaptive instructional architecture that includes technologies from the Department of Defense sponsored Advanced Distributed Learning program (Hernandez et al., 2022). While learning institutions by their nature incur various time-based restrictions and limitations to learning, our belief is that CBEL can at least make those limited learning periods more effective and efficient by mitigating current learning workloads, and improving the collection and use of empirical learner data to improve everyday learning decisions. In addition, we believe this data could provide sufficient evidence that perhaps over time, will influence institutions to incorporate more learning science-based practices. Aside from the psychometric data, other types of data the adaptive learning technology can collect could consist of biometric data, as well as video and audio data. This data could not only provide a much more detailed measure of the Cadet learning states in real-time but could influence their affective states through feedback and induced reflection. An example of the type of data CBEL will collect and provide for assessment and feedback is shown in Figure 4.

	realEngTime	engActTime	realActTime	engAction	actor	target	result	shotProj	hitLat	hitLon	hitDir	hitElev	hitRelDir	hitZone	hitDmg	totalDmg	sho
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6	2/19/2024 15:16	38.67500305	15:17:26	TgtHit		opfor_Team1Tgt2								wheel_1_2_damper	0.021390291	0.021390291	
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21	2/19/2024 15:16	38.84500122	15:17:26	TgtHit		opfor_Team1Tgt2								hull	0.082860306	0.142312527	
22	2/19/2024 15:16	38.84500122	15:17:26	ShotHit	blufor1Team1Gunner	opfor_Team1Tgt2	hit	tracer_red.p3d	31.18882	-97.657	72.3654281	2.704538766	314.0359089				
23	2/19/2024 15:16	38.84500122	15:17:26	TgtHit		opfor_Team1Tgt2								wheel_1_2_damper	0.073055357	0.094445646	

Figure 4. Example of Data Collected Automatically With CBEL

Process Mining

Our investigation also looked into technology we could use to make the more complex experiential performance more measurable. Because CBEL can automate the capture, reduction and labeling of Cadet activities in simulated scenarios, we needed a data-science tool that could rapidly process, discover and identify patterns of student performance from this data that we can then use to inform the criterion of performance as being *above*, *at* or *below* a normed expectation of performance.

The data-science technology we investigated is called process mining, which can rapidly cull through lots of experience-base, time-stamped, labeled data (like Figure 4). Van der Aalst (2016) links process mining to methods for modeling and improving business activities. Instead of manually recording and plotting a business process model by hand, process mining uses algorithms to learn a model based on recorded event-log data.

These models are represented in a form of flow-chart referred to as business process model notation (BPMN). Figure 5 represents a BPMN process model for an example Army task of conducting an artillery mission at a Fire Direction Center (FDC) that could be used for documenting and assessing Field Artillery Gunnery training.

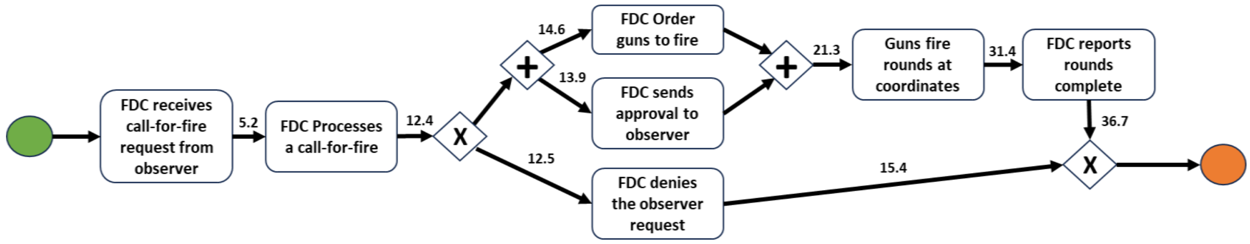

Figure 5. An Example Process Model for an Army Artillery Fire Mission.

In figure 5, the text boxes represent the labeled activities from the event log while the diamonds represent logical path-points that define the variance in activities found in the data. The "x" diamond symbol represents an Exclusive OR point, meaning that only one input condition can be true, or in other words it's a conditional decisional point. The "+" diamond symbol represents a point where parallel task activities have been detected in the data. Also note the times between the activities and decision point which can also inform expectations for specific task performance criteria.

A process model like this can be used to find distinct task performance and completion paths by a population of performers performing in a specific role and/or across a team. These models can also be a combination of human and some other AI-based entity performing together in a teaming capacity. Process models can also help identify bottlenecks in task performance, as well as optimum paths of performance. Process models can then help analysts answer questions about a task process, such as whether the steps of a task were necessary or which steps take longer in different experience conditions (e.g., day vs. night). Educational process mining has already been applied to identify learning patterns, and to discriminate between high- and low-success learning paths. Educational process mining has shown it can model the learning path through a given lesson as the task (Bogarin et al., 2014; Cerezo et al., 2019) or to model granular tasks such as performing a medical procedure (Rabbi et al., 2024).

Process mining is a tool we hypothesize can be used to not only produce complex models for assessment but finding and updating normed expectations of performance within different task conditions. Not only does this provide a more accurate measure of performance but a more detailed and comprehensive level of feedback; making it easier for learners to build mental models of their own or others' performance to reflect upon.

By applying process mining in our CBEL engineering project, we hope to document, model and digitize the expected activities of a given task experience. Today learning objective test criteria is determined through standard task analysis by manually observing a few task performances that are often simple single path stable procedures that don't change much; however, this method isn't practical in cases where complex task activities are required. With this new technology, we hope to be able to create, update or modify complex process models as simulation conditions and parameters change or as Cadets perform in different learning environments.

CONCLUSION

While there are many more phases and cycles of learning engineering we will need to complete before we can ascertain that CBEL is a viable model for institutional learning, we feel we have learned enough through the *investigation phase* of the process to share with others who may have similar interests in engineering new learning methods for institutional learning environments to at least help them in their preliminary planning process.

Lessons Learned

When forming your learning engineering team, ensure you include team members from the target learning institution's instructor staff who are in a position to convey the proposed model to management and who will coordinate the collection and sharing of information and data generated from the engineering process. You should also find out about any data sharing policies and needed agreements before deciding on working with the institution since it will be data that will determine if the new model is working or not. Immerse your team into the institutional learning environment in order to get a good understanding of the culture and philosophies and subject-matter the new model will need to be integrated into. Interview instructors who should be more than willing to share details of the challenges they consistently encounter in the classroom environment, that cannot be learned from just reviewing the content. In addition, you might find, as we did, that there are instructors who are enthusiastic about learning more of your model, and willing to test out your methods.

Another lesson that is only just beginning to form is the need to emphasize change management into any learning engineering planning. The methods and technologies used today in institutional learning have been around a long time, and many have careers not only based on the results of those existing learning methods and technologies but the ideas about how learning occurs that existed when they either received their education or provided education to others. The attitude that “it worked for me”, while maybe not supported by more recent data learning science has revealed, is still a real factor that needs to be convincing as a value to the military training and education process. For the military, this means there is a real need to incorporate lessons on what the latest learning science, neuroscience and best practices are to junior and senior officers, and civilian decision makers, from both military and civilian education sectors. Not only does this make the effort to engineer, implement and test future learning science and technology more collaborative in the many environments and contexts military learning occurs in but it produces ideas in those who must create education and training policy, and make decisions on how to train and educate the next generation of warfighters.

Next Phase

With the DMI we have selected a topic area to integrate CBEL into. Now we will begin the iterative Creation phase using what we refer to as a *learning readiness* assessment. Here we will take our investigation of the latest learning science and neuroscience, and best practices in classroom learning and technology, and integrate them into notional storyboards as well as create profiles of our intended learners. We will then begin to prototype our learning process model and technology in a laboratory, and begin testing with our supporting DMI instructors, and collecting data from real learner volunteers using our prototype to help us learn and refine our model before we actually begin the Implementation phase of testing the model in a live classroom session.

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