Learning Engineering Virtual Training Systems with Learning Science, Data Standards and a Capabilities Maturity Model

Kevin Owens
Applied Research Laboratories: The University of Texas at Austin
Austin, TX
kowens@arlut.utexas.edu

Shelly Blake-Plock
Yet Analytics, Inc.
Baltimore, MD
shelly@yetanalytics.com

Jim Goodell
Quality Information Partners
Fairfax, VA
jimgoodell@qi-partners.com

ABSTRACT

The US Government Accounting Office (GAO) has recommended actions to the US Department of Defense (DoD) services to improve their management and oversight of DoD's virtual training programs (GAO, 2017):

1. Specify requirements for virtual training devices (VTD) to include:
    a. time available to train with the devices.
    b. intended usage rates to achieve proficiency standards.

2. Enable usage data to be collected and analyzed after VTD fielding to:
    a. determine the effective use of the device.
    b. systematically inform future virtual training programs.

These recommended actions suggest changes in VTD requirement statements, design, engineering, and testing for all future (even existing) DoD virtual training programs, especially those that will integrate with new learning systems such as the Army's Synthetic Training Environment (Stone A, 2017).

The GAO recommendations align with work of an Institute of Electrical and Electronics Engineers (IEEE) consortium[1] to establish Learning Engineering as a professional practice. Learning Engineering is a set of interdisciplinary team-based processes and practices that includes applying modern learning sciences, human-centered systems engineering, and data-informed decision making to the engineering of learning solutions and, with regard to future military VTDs, can result in better learning outcomes as part of a larger learning ecosystem.

An objective proposed by this paper is to integrate Learning Engineering with other DoD-sponsored initiatives such as the Total Learning Architecture (TLA), including a set of core data standards from the IEEE Learning Technology Standards Committee (LTSC)[2] portfolio. These standards apply directly to DoD military-service acquisition, management and maintenance of VTDs or any other type training system. The DoD TLA and related LTSC standards support learning engineering, recommended data collection and analysis requirements, as well as the data-informed decision-making of future VTD requirements.

This paper offers a framework for incorporating the processes and practices of learning engineering with data standards to inform VTD design requirements, selection, and specifications.

ABOUT THE AUTHORS

Kevin Owens is an Engineering Scientist at the Applied Research Laboratories: The University of Texas at Austin. After retiring from the US Navy, with years of experience as an instructor, curriculum designer and operational trainer, Kevin earned a BS in Workforce Education and Development from Southern Illinois University, and a MS in Instructional Design, Development and Evaluation from Syracuse University. Kevin has since spent over 20-years in industry and academia conducting DoD related learning engineering projects to improve education and training. He

[1] https://sagroups.ieee.org/icicle/
[2] https://sagroups.ieee.org/ltsc/

is currently working on Science and Technology projects related to the US Army's Synthetic Training Environment, researching a Competency-Based Experiential Learning model.

Shelly Blake-Plock is president and CEO of Yet Analytics and an officer of the IEEE Learning Technology Standards Committee (LTSC). He was principal investigator on the Data and Training Analytics Simulated Input Modeler (DATASIM) sponsored by the Advanced Distributed Learning Initiative and has provided expertise to the development and implementation of TLA capabilities within ADL, US Army, US Air Force, and US Space Force contexts as well as in commercial industry. He chairs the IEEE LTSC Technical Advisory Group on xAPI as well as the IEEE P9274.4.2 working group on xAPI Cybersecurity. He is vice-chair of the IEEE P2247.4 project on AI Ethics for Adaptive Instructional Systems.

Jim Goodell is editor of Learning Engineering Toolkit, co-author of Student-Centered Learning: Functional Requirements for Integrated Systems to Optimize Learning and a thought leader in the world of learning engineering and data standards. He is Director of Innovation at Quality Information Partners, where he helps lead development of the US Department of Education sponsored Common Education Data Standards. He is Chair of the IEEE Learning Technology Standards Committee, chairs the Adaptive Instructional Systems Interoperability Workgroup, and serves on the ICICLE Steering Committee. He co-facilitates the US Chamber of Commerce Foundation's T3 Innovation Network and co-led development of the Learning and Employment Record (LER) Wrapper Specification. Prior to QIP, he was Executive Vice President at the Center for Educational Leadership and Technology.

Learning Engineering Virtual Training Systems with Learning Science, Data Standards and a Capabilities Maturity Model

Kevin Owens
Applied Research Laboratories: The University of Texas at Austin
Austin, TX
kowens@arlut.utexas.edu

Shelly Blake-Plock
Yet Analytics, Inc.
Baltimore, MD
shelly@yetanalytics.com

Jim Goodell
Quality Information Partners
Fairfax, VA
jimgoodell@qi-partners.com

INTRODUCTION

In 2017, the US Government Accountability Office (GAO) made recommendations to the Department of Defense (DoD) services that they "improve the management and oversight of their virtual training device (VTD) programs… to more efficiently and effectively acquire and integrate virtual devices into operational training…" (GAO, 2017). The recommended actions included: (1) documenting requirements that include the training tasks and objectives a future VTD will help service-members develop proficiency in; (2) develop capability to collect VTD usage data and analyzing it to determine the training time needed to be allocated, and usage rate expected to occur, to effectively build proficiency in the targeted tasks and objectives with a VTD; and (3) creating policies that define a consistent process on how to analyze and evaluate how effective a VTD is at training targeted task proficiency after its initial fielding - that can inform future VTD engineering improvements or selections.

A VTD is defined here-in as any technology that synthetically simulates or stimulates a person's or sensor's perceived information that would be used while performing an occupational task while conducting operational training. This includes large-scale platform or combat system virtual simulators/simulators, PC based virtual "games for training" type software, and cell-phone, head-worn or other forms of mixed-reality devices.

Many of the GAO recommendations being asked for are consistent with common systemic models of engineering training solutions and strategies. Today with the integration of adaptive learning systems, supported by modern learning science informed content, and the power of artificial intelligence (that requires continuous data to improve), as well as developing technologies to capture many forms of real-time learner cognitive, psychomotor and affective data, a new systemic model of defining VTD requirements and conducting its engineering design, testing and life-cycle management is needed. This new model should include more specific learning outcomes, iterative formative tests using learner-centered methods and practices, and a data-informed post-fielding life-cycle management process that systemically informs future VTD requirements and/or selection specifications.

DISCUSSION

The GAO recommended actions to reinforce a principle for any form of learning technology, whether for the military, government or industry: it is less about tools, devices, or specific content themselves, and more about the degree of learning and experience the technology produces. This is part of a Learner-Centered Design concept (Soloway, E., Guzdial, M., & Hay, K.E., 1994). No doubt it can be challenging to manage the technical engineering requirements of learning technology, while maintaining a clear focus on the priority objective of achieving needed learning outcomes. Therefore, it is important that a process of engineering VTD subsystems be integrated with the process of designing, and enabling the production of meaningful data produced by the VTD subsystems during a learning experience. In this way, a learning engineering-based team can work together to make decisions on the best technical trade-offs, while ensuring the final system designed features fully leverage the science of human learning and performance enhancement.

For example, as represented in Figure 1, engineers must understand that human learning is not an instantaneous transaction that creates learning because of a feature they design work alone but because it creates learning over time, within an experience (Kolb, 1984), and the context and focus the experience provides. At the same time, learning science tells us that all humans learn at a normalized rate; what makes the difference noted between people who seem to learn at different rates isn't because of system features, innate ability or disability but the number of learning opportunities or experiences one person can accumulate, and the quality of those experiences (e.g., fidelity matching, differences in contexts, difficulty matching, etc…), compared to others (Koedinger, K, et.al., 2023). At the same time, no technology can *rush* learning; it simply takes time and experience to elevate an individual or team to whatever standard of competence a branch of military service requires, for a given occupational task. This is especially true in the occupation of warfighting, which isn't learned well in controlled static environments. Context when learning also must be matched to the environment it will later be recalled and applied (transferred) in (Murnane K, et.al., 1999) – i.e., volatile, violent, complex and dynamic real warfighting environments. In addition, learning science has shown us long ago that human knowledge and skill naturally atrophies over time, thus requiring continuous "maintenance" through experiences, just like any other material system does (Ebbinghaus,1885). This is because human learning requires new proteins to be synthesized constantly in the brain by use and recall activities (Glasgow, S.D., et.al. 2023).

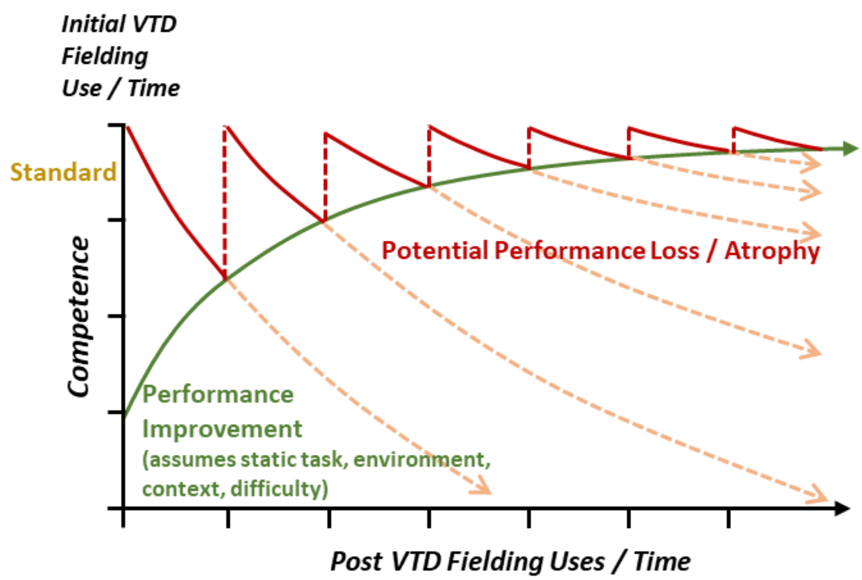

Figure 1. Typical Human Learning Loss / Retention and Competence Development

Because humans learn in these ways, the requirements, the engineering, the testing and the use of a VTDs after initial fielding, as recommended by the GAO, should adopt these human learning principles in order to maximize return-on-investment, while managing a VTDs ability to integrate and "keep up" with changing ecosystem capabilities, doctrine, new operational environments, and today's evolving near-peer competitors. In short, the methods used for VTD learning must continuously evolve with the learning science it employs, the needs of the learner, and the information, tools, procedures and environments learners must ultimately perform within.

METHODS

We suggest a new systemic engineering model is needed to address the GAO recommended actions noted above, and the integration of VTDs into new virtual training and data management technologies. Two key enterprises are suggested to incorporate these changes of existing DoD VTD training programs:

1. IEEE sponsored and multi-disciplinary informed Learning Engineering processes and practices, and
2. Data standards, architectures, levels, and reporting standards initiated and specified by the DoD.

IEEE Learning Engineering

Learning Engineering provides a system-of-systems approach to the design and data-driven iterative optimization of learning and training solutions, and provides a super-positional perspective during the component development of any learning experience. As such it increases the methodological rigor of learning experience design by holistically integrating human-centered design, data instrumentation, engineering mindsets and concepts, and the learning sciences to support the planning, execution and evaluation of the primary goal of any training device program: achieving specifically-targeted human performance objectives (Goodell, J., Kessler, A., & Schatz, S., 2023). This includes working with and helping to inform multiple other occupational disciplines required to develop VTDs within the advanced and complex modern learning ecosystems, such as currently being developed in the U.S. Army's synthetic learning environment (STE) program (Stone A, 2021).

Learning Engineering is a concept that was first suggested in the 1950's (Charters, 1951) and again in the 1960's (Simon, 1967), and has evolved into a burgeoning area of technical and methodological expertise supported through open practices of professional community building, and the development of professional competencies. This venture is being orchestrated through the IEEE Industry Consortium (IC) on Learning Engineering (ICICLE), a consortium sponsored by the IEEE Learning Technology Standards Committee. The processes and practices being investigated and developed by ICICLE stakeholders address findings, best practices, and data-driven advances developed across multiple disciplines over the past decade (IEEE, 2023). These Learning Engineering methods are leveraged and practiced within and across various industry and academic organizations – including recently in the research and development of the US Army's Synthetic Training Environment Experiential Learning for Readiness (STEEL-R) Science and Technology project (Blake-Plock, S, Owens, K., Goodell, J, 2023; Goldberg, B., Owens, K., Gupton, K., et.al, 2021).

Learning Engineering is "a process and interdisciplinary practice that applies the learning sciences using human-centered engineering design methodologies and data-informed decision making to support learners and their development" (Goodell, J., Kolodner, J., 2023). In practice, this includes the systematic application of evidence-based principles and methods from multiple discipline areas including educational technology engineering, the latest neuroscience and learning science, and includes practices from data-science, computer-science and even creative arts to create engaging and effective learning strategies and experiences to overcome difficulties and challenges of learners as they learn, as well as using data-informed analysis to better understand teams and learners, and their needs for learning and improving performance, as well as making engineering decisions on features and capabilities. The overall systemic model is shown in Figure 2.

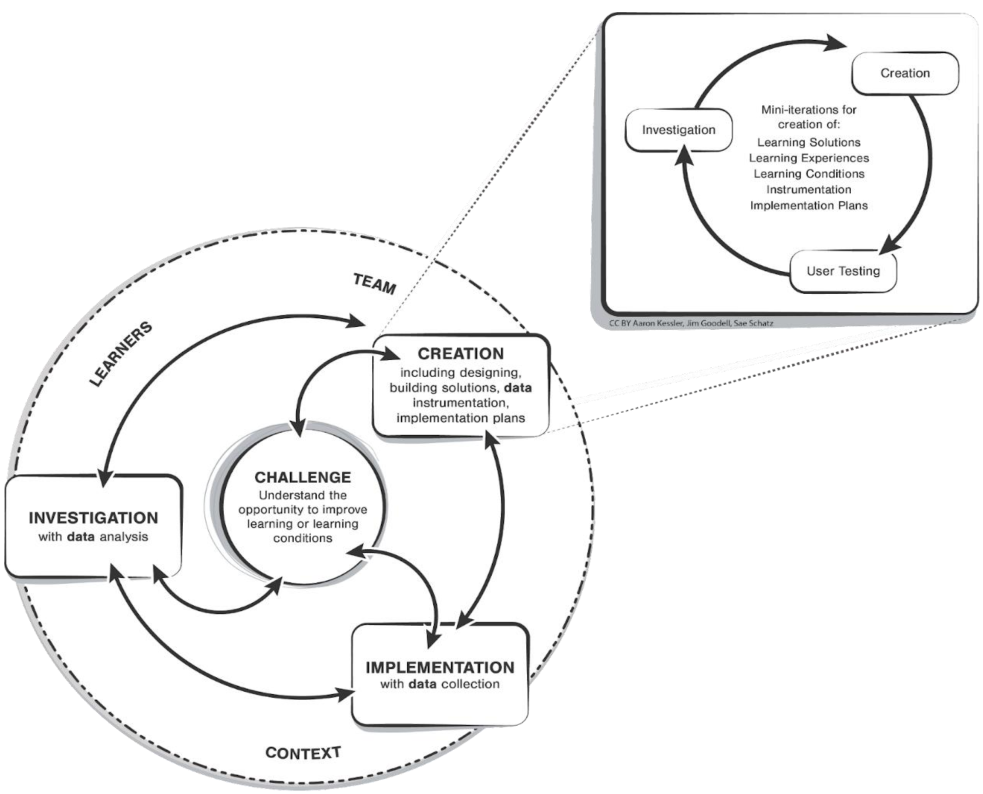

Figure 2. The learning engineering process adapted from iFEST poster
(Goodell, J., Kessler, A., & Schatz, S., 2022) and (Schatz, S., & Goodell, J., 2022).

Learning Engineering strategies are varied and can be applied to take on challenges such as that of the GAO recommendations. As applied to the improvement of task objectives and learning outcomes as relate to VTD, these strategies can include:

- **Applying learning sciences.** Design and test VTDs based on the scientific principles of how people learn (Goodell, J., Kolodner, J., & Kessler, A., 2023). For example, some studies have shown that more costly and higher production value learning modalities can be less effective than lower cost options (Saxberg, B., 2018). Test unknowns using iterative experimentation and data-informed decision-making.
- **Using human-centered design.** Engage learners early and often in the process to test assumptions related to GAO recommendations such as time available to train with the devices and viability of estimated usage rates and durations to achieve proficiency standards. Human-centered design typically involves understanding learner variability, developing personas to refer back to during design, making ideas concrete with prototypes, and testing ideas iteratively with representatives of the learner population. (Thai, K. P., Craig, S. D., Goodell, J., et.al, 2022).
- **Applying engineering principles and methodologies.** Employ a system-of-systems perspective during VTD component development. Consider factors other than the device. Consider how other subsystems and supersystem factors such as learner schedules will impact outcomes such as times required to achieve proficiency. Use early VTD fielding experiments for collection and analysis of data to understand weaknesses in the current approach, detect boundaries of effective use of the device (Barr, A., Dargue, B., Goodell, J., et.al, 2023). This supports the GAO recommendations to inform future virtual training programs, device maintenance, and future device improvements.
- **Employing data instrumentation and analytics at all stages of the learning engineering process.** Design and develop data pipelines while developing the VTD and use those data for adaptive feedback to learners, to inform the training command, and to inform the learning engineering team for iterative improvement of the VTD (Czerwinski, E., Goodell, J., Ritter, S., et.al, 2023). Analyze data from rapid-cycle A/B testing to inform design decisions (Barrett, M., Czerwinski, E., Goodell, J., et.al, 2023).
- **Learning engineering strategies may have broader implications** as to how VTDs are procured and developed (Hernandez, M., Blake-Plock, S., Owens, K., et.al; Blake-Plock, S., Owens, K., Goodell, J., 2023). For example, the learning engineering process calls for a rapid-cycle iterative, data-driven approach. The GAO recommendations also suggest a more iterative and data-informed approach to R&D in which one iteration of a VTD or program can systematically inform future virtual training programs. Rather than a single long-term project budgeted for a single release of a VTD, a learning engineering approach would budget and plan for a gated sequence of releases, beginning with low technology prototypes tested with end-users and leading to iterative releases that field test the device with increasingly added proficiency standards coverage and tuning.

Data Standards

As the military services and the general public are experiencing the many real episodes of combat from the war in Ukraine on a daily basis from the ubiquitous sources of raw data available in the battlefield, it provides a perfect example of how modern data collection capabilities can not only inform the general public in near real-time of the state of war but produce evidence to engineers, tacticians and performers of the effectiveness of systems, tactics, techniques and features previously designed. In short, data can be considered the "new ammunition" of warfare, and is as valuable as the material capabilities a new VTD provides in operational training. Today the practice of capturing, saving and analyzing longitudinal learner data is not well established in doctrine or practiced in the military services. However, programs like STE, and projects like STEEL-R, are requiring new doctrine and data strategies that future VTDs will need to integrate with and adopt. However, what will be needed are standards so that all data provided from built-in VTD learner sensors, learning tracking methods, and formats can be stored, shared, analyzed and used for the various insights it can provide VTD management such as usage rate and time, as well as to define what specific tasks and performance standards the VTD best supports from its measures.

The maturation of Learning Engineering within the IEEE has matched parallel developments in the maturation of the Total Learning Architecture (TLA) within the DoD and the maturation of the IEEE Learning Technology Standards Committee (LTSC) data standards that support the TLA. This threefold alignment of methodology, architecture, and technology standards is at the core of the new paradigm available to VTD. The core standards activities within the

LTSC – covering metadata, activity, competencies, and summative records – are at the center of an ecosystem of interconnected software technologies that include the:

- Enterprise Course Catalog (ECC) – which in a modern extended learning environment can be thought of as a repository and index of available learning experiences.
- Experience Index (XI) – a learning experience metadata repository governed by IEEE P2881.
- Experience Design Tool (XDT) – a learning experience scenario builder that shares data within the experience application program interface (xAPI) modality.
- Learning Record Providers (LRP) – data sources that emit event-based activity data in the xAPI format and which can leverage xAPI Profiles as models.
- Noisy LRS – a Learning Record Store nearest to a data source where the primary function is to validate the data as conformant to IEEE 9274.1.1.
- LRSPipe – which is a data forwarder-filter governed by xAPI Profiles as defined by IEEE P9274.2.
- Transactional LRS – which validates filtered xAPI data and ensures that it is made available to downstream TLA business systems.
- Competency Assertion – which aligns to the shareable competency definitions concepts represented by IEEE 1484.20.3.
- Reporting – which can take the form of native xAPI Learning Record Consumers or commercial off-the-shelf (COTS) business intelligence platforms fed data from the TLA databases.
- Learner API – which is currently in development as the communication capability sitting between the transactional layer of the TLA and the summative layer: whereas LRSPipe exclusively sends data between LRSs to manage the data flow and business-readiness of event-based activity data (on the right side of the chart below), the Learner API (on the left side of the chart) communicates with systems both within and without the TLA to update the state of the learner in the summative sense of records, competency levels, and credentials.
- Enterprise Learner Record Repository (ELRR) – which is defined by the data model of IEEE P2997 and which stores the roll up of enterprise data about the learner both as derived from the learning activity generated within the TLA and by human capital and other systems integrated with the Learner Profile database.
- Business Systems – that use the data flow of the TLA in part or whole to accomplish a variety of tasks ranging from readiness assessment to workforce and mission human resource planning.

This triad of methodology, architecture, and technology standards should be central to the modernization of VTD and the assurance of alignment between data-instrumented technical capability and data-driven learning outcomes. Table 1 below presents the STEEL-R use case to illustrate how material requirements and corresponding learning experience requirements can be supported through this standards-based data architecture and can therefore support key phases of the VTD lifecycle process.

Table 1. Connections between material and learning experience requirements in US Army STEEL-R project.

Requirement Type	Design Methodology	Platform	Capabilities	Standards
Material / Technical	TRL 5-6 GOTS R&D + COTS; Agile methodology	AWS cloud architecture w/ XDT, LRS, LRSPipe, CaSS, Data Vis	General technical approach: Standards-based scenario design, data capture, business filtering, competency assertion, and reporting	IEEE 1278.2 DIS, IEEE 1516 HLA, IEEE 1484.20.3
Learning Experience (LX)	Competency-based Experiential Learning	STEEL-R learning science and capability set	Specific LX-required approach: Data flow governed by xAPI Profiles with standardized metadata to provide standardized evidence to the competency assertion system	IEEE 9274.1.1 xAPI, IEEE P9274.2, IEEE P2881 LOM/XI, IEEE 1484.20.2

RECOMMENDATIONS

Requirement writers and managers of the military service's VTD programs can neither manage nor monitor their programs sufficiently if they don't have the right systemic processes, and teams of people with the right mix of competencies. In addition, VTD programs need data-informed performance criteria to defend design decisions and specifications regarding learning-related features. The requirement writers and device engineers of VTD programs need the right tools and techniques in order to evaluate their designs and to collect continuous empirical data during the device's life-cycle. Finally, without such data, it is extremely challenging to inform the user with doctrine on how to best employ a VTD because without data, they simply cannot understand how often and how long they need to employ the VTD to achieve the learning objectives and performance standards they're designed to help achieve.

To provide a decision-aid to DoD programs or proponent-offices on what processes of Learning Engineering and data standards to incorporate into VTD engineering, management and oversight, Table 1 below provides a matrix of key Learning Engineering process areas and degrees of incorporation from a non-learning engineering process to one that is fully incorporating the learning engineering process. Note that not all these processes-areas and levels need to be adopted holistically or uniformly but, in any combination; they are intended to work systemically together. Once a working VTD is developed and tested or fielded, data must then be collected and analyzed to determine if the engineered VTD supports the learning and proficiency standards required by the service, and its usage specifications to achieve those standards.

Table 2. Learning Engineering Capability Maturity Model

Process Area	Level-0	Level-1	Level-2	Level-3
Team				
Teams are formed into primary and alternate roles, with regular scrums and meetings, and a common understanding of what min performance and learning solution outcome is required.	Teams are formed ad-hoc within a outside organization without given specific roles and no regular collaboration scrums to work with each other's capabilities and solutions. No common vision of what minimum performance or final learning solution outcomes need to be.	Teams are formed from initial challenge data collection and analysis. Are assigned and fall into specific roles. Still don't collaborate and scrum regularly or as much as they should. May or may not have a common vision of minimum performance or learning solution outcome.	Teams are formed and mature into consistent roles based on best talents. Always have a consistent vision of min performance and learning solution outcome with data support. Meet regularly (scrum) to look at test data, see progress of others, and iterate with work by other team-roles' effort/solutions.	Teams are formed and are smaller because each member can perform more than one role. Always have a consistent vision of min performance and learning solution outcome with data support. Meet regularly (scrum) to look at test data, see progress, iterate with work by other team-roles' effort/solutions.
Team members take initiative as needed, communicate regularly, and are cross-trained for shared understanding and collaboration.	Team members have limited or no knowledge of the other team roles' domains of knowledge, vocabularies and skill-sets. Don't take initiative. Little to no collaboration or cross-support.	Team members have some awareness of what other team roles bring to the learning engineering process. Take some initiative to support but don't collaborate, share information.	Team members have received some training in other roles' knowledge, skills and attitudes. Take initiative. Endeavor to directly support other roles and communicate/.	All team members are competent in each learning engineering team-role and can anticipate or support other team roles' directly or indirectly. Take initiative to ask other roles if support is needed, share information, and communicate regularly.
Process				
The learning engineering process is used	A waterfall and non-iterative process is used.	Another process is used that lacks some elements of the learning engineering process, e.g., challenge-centric, iteration, human-centered, data instrumentation, data analytics.	The learning engineering process is used without full fidelity or limited by constraints of the enterprise policy structure.	The learning engineering process is used with full fidelity and is fully supported by the enterprise policy, e.g., budgets for maintenance and continuous improvement.

Iterations appropriate for the challenge	**No iteration** (one and done)	**At-least one iteration** of improvement after initially implemented.	**Multiple data-informed iteration(s)** of improvement after initially implemented.	A process of **continuous improvement** (informed by learner experience data) continues for the life of the product.
Applies the Learning Sciences				
All team members have basic knowledge of learning science with at least one team member serving as an expert on the learning sciences and best practices.	No one on the team has a basic understanding of key learning sciences concepts. Principles or methods used are based on "faux science" - lore of how people learn best not supported by empirical science. Management direction is provided without learning science expertise being consulted or considered	One or some team members have some basic knowledge of learning sciences concepts but not expert-level competence.	At least one member has expert-competence in learning sciences and best practices. Not always consulted in all key design decisions or applied research methods appropriate to the context of the learning challenge.	All team members have working knowledge of key learning sciences concepts. At least one team member is a learning sciences subject matter expert. Is consulted in all key decisions and testing, and employs applied research methods appropriate to the context of the learning challenge.
Using Human-Centered Design Process				
Understanding learner and their use of learning solutions variability (use of personas and user journeys)	Solutions are developed without consideration of targeted learner persona or learner population, and use variability (e.g., prior training, environment and technology available and learning-related constraints and advantages.	Solutions are developed with a general idea of the target learner but not the contextual use of a solution in a user journey nor are solutions compared to iterative target learner or refined by the target learner feedback or use data…	Solutions are developed with a persona and user journey but solutions are not then compared to this profile or tested or refined by real user test data…	Learner personas and user journeys are used to guide design, and compare to and update based on new data results. Solutions are adapted to scaffold and make accessible to learner variability.
User-test prototypes with learners in iterative cycles that produces data to analyze and improving the released product	Few team members use a static "waterfall" ADDIE process of analyzing, then designing, then developing, then implementing, then evaluating the solutions based on initial requirements.	Team works more through different ADDIE stages at same time, across roles and lanes, with prototype learning solutions, then tests and iterates in each team lane	Team works more through different ADDIE stages at same time, across roles and lanes, with prototype learning solutions then tests and iterates as a team…	Team works more through different ADDIE stages at same time, across roles and lanes, with prototype learning solutions then tests and iterates with a target learner from the target population.
Using System Engineering Design Principles				
System-of-systems perspective	Team domains/roles focus only on assigned specific solutions or components of the overall learning solution design without consulting others. No preliminary analysis or prototyping done to show what areas are needed to be solved first and how.	Team domains/roles work from each other's ideas but don't understand the "bigger picture" of the overall vision or don't understand other assigned component-solutions enough to work toward that larger vision/solution.	Team roles all understand larger overall solution vision, and the component parts required of the architecture or curriculum but don't produce common interfaces or standards to integrate each solution	Team roles all understand larger overall solution vision, and the component parts required of the architecture or curriculum, and use common interfaces or standards to integrate each solution components
VTD as a closed-loop control system	No data is collected and analyzed from iterative prototype testing, or used to give team members feedback or to adjust and optimize current solution designs and development.	Data collected during iterative VTD testing with target learners not regularly briefed or not used by team members to adjust and optimize current solution designs and development.	Data collected during iterative VTD testing with target learners, and regularly briefed. Team members do adjust and optimize current solutions but the process does not continue after the initial	Data collected during iterative VTD testing with target learners, and regularly briefed. Team members do adjust and optimize current solutions and this data collection process continues

			solution is delivered to learners.	after the initial solution is delivered to learners.
Consider outlier data, conditions and failure workarounds	Team screens or throws out single-point outlier data or conditions as statistical anomalies that will not impact core solutions.	Team saves and looks at data and considerations more longitudinally and latitudinally but screens or dismisses without thinking about impact to learning if they happen during use.	Team saves and looks at data more longitudinally and latitudinally, saves outlier data for revealing possible impacts to learning but doesn't build in alternative or back-up learning options.	Team uses outlier data to detect failure modes and produce back-up or alternative learning features to circumvent these failures, and produce future solution improvements.
Data Informed Decision-Making				
Instrumented learning experiences and environments.	The training device is not instrumented to collect learner experience data.	Team designs instrumentation that relies on limited proprietary "readers" or special-access / licensed software (e.g., software development kit) to access. The log data is not useful for analyzing the learning analytics that could be used to inform iterative improvement of the solution.	Team develops instrumentation using standard protocols (e.g., xAPI) and open-access well-defined access points. Data captured is limited in insightful sources, extensible access sources. Creates data output feature (e.g., after action review tool" that isn't related to all min performance or learning outcomes, and/or only captures activity launch and completion events.	Team develops scalable instrumentation API that uses standard open-source protocols (e.g., xAPI) and can be expanded to capture more insightful sources that can be translated to assessing any min performance or learning event outcomes
Appropriate analytics at various stages of the learning engineering process.	The learning solution is developed based on subjective assumptions that are not supported by empirical data analytics of targeted users, environments and context.	Initial learning solution design is based on data from existing legacy solutions that clearly reveals gaps in minimum performance standards or learning outcomes (criteria) and/or data sources to determine those standards and criteria.	Learning solutions are based on empirical data (from R&D or other projects) collected from legacy solutions that reveal new learning solutions to achieve required standards and learning outcomes. Not continued after the solution is delivered.	Learning solutions are based on empirical data (from R&D or other projects) collected from legacy solutions that reveal new learning solutions to achieve required standards and learning outcomes. data collection and improvement continue after the solution is delivered to target learners.

CONCLUSION

While reportedly the DoD services have made progress in the noted GAO recommended actions since 2017, it is suggested they may still need evolve, especially with the advent of a recent growing professional discipline focused exclusively on the domain of optimizing experiences, content and technology for human learning and performance – i.e., Learning Engineering – and new DoD data requirements, technologies, standards. This paper has provided some discussion on why VTD features need to be specified and designed from the latest information provided from learning science. We have also endeavored to provide rational explanations as to why the learning engineering and data standardization enterprises have direct application to support military service VTD production, as defined in the cited GAO recommendations. Finally, this paper provides specific recommendations directly to the program leadership and life-cycle management of VTD programs. As always, more research, discussion and collaboration will likely be needed to ensure these recommendations are refined to address each military service's unique problem space.

REFERENCES

Barr, A., Dargue, B., Goodell, J., & Redd, B. (2023). Learning Engineering is Engineering. In Learning Engineering Toolkit (pp. 125-152). Routledge.

Barrett, M., Czerwinski, E., Goodell, J., Jacobs, D., Ritter, S., Sottilare, R., & Thai, K. P. (2023). Learning engineering uses data (part 2): analytics. In Learning Engineering Toolkit (pp. 175-198). Routledge.

Blake-Plock, S., Owens, K., Goodell, J. (2023). The Value Proposition of GIFT for the Field of Learning Engineering. Proceedings of the Eleventh Annual GIFT Users Symposium. US Army Combat Capabilities Development Command - Soldier Center. Orlando, FL.

Charters, W. W. (1951). The Era of the Educational Engineer. *Educational Research Bulletin*, *30*(9), 230-237+246.

Czerwinski, E., Goodell, J., Ritter, S., Sottilare, R., Thai, K. P., & Jacobs, D. (2023). Learning Engineering Uses Data (Part 1): Instrumentation. In Learning Engineering Toolkit (pp. 153-174). Routledge.

Ebbinghaus, H. (1885). Memory: A Contribution to Experimental Psychology. Translated and published by Teachers College, Columbia University. http://psychclassics.yorku.ca/Ebbinghaus/index.htm

Glassgow, S.D., Labrecque, S., Beamish, I.V., et.al. (2018). Activity-Dependent Netrin-1 Secretion Drives Synaptic Insertion of GluA1-Containing AMPA Receptors in the Hippocampus. Cell Reports (Open Access) 25, (pp 168-182)

Goldberg, B., Owens, K., Gupton, K., Hellman, K., Robson, R., Blake-Plock, S., Hoffman, M. (2021). Forging Competency and Proficiency through the Synthetic Training Environment with an Experiential Learning for Readiness Strategy. I/ITSEC. National Training and Simulation Association. Orlando, FL.

Goodell, J., Kolodner, J., & Kessler, A. (2023). Learning Engineering Applies the Learning Sciences. In Learning Engineering Toolkit (pp. 47-82). Routledge.

Goodell, J., Kessler, A., & Schatz, S. (2023). Learning Engineering at a Glance: Based on the iFEST Poster. Journal of Military Learning — Conference Edition 2023, Army University Press. https://www.armyupress.army.mil/Journals/Journal-of-Military-Learning/Journal-of-Military-Learning-Archives/Conference-Edition-2023-Journal-of-Military-Learning/Engineering-at-a-Glance/

Goodell, J., Thai, KP.(. (2020). A Learning Engineering Model for Learner-Centered Adaptive Systems. In: , et al. HCI International 2020 – Late Breaking Papers: Cognition, Learning and Games. HCII 2020. Lecture Notes in Computer Science(), vol 12425. Springer, Cham. https://doi.org/10.1007/978-3-030-60128-7_41

GAO (2017). Defense: Defense Virtual Training (2017-02). (n.d.). https://www.gao.gov/action-tracker/defense-defense-virtual-training-2017-02

Goodell, J., Kolodner, J. (Eds.) (2023). Learning Engineering Toolkit: Evidence Based Practices from the Learning Sciences, Instructional Design, and Beyond. Routledge. New York.

Hernandez, M., Blake-Plock, S., Owens, K., Goldberg, B., Robson, R., Welch, T., Ray, F. (2022). Enhancing the Total Learning Architecture for Experiential Learning. I/ITSEC. National Training and Simulation Association. Orlando, FL.

IEEE SA. (2023, January 17). Industry Consortium on Learning Engineering (ICICLE) - IEEE Standards Association. https://standards.ieee.org/industry-connections/industry-consortium-learning-engineering

Kessler, A., Craig, S. D., Goodell, J., Kurzweil, D., & Greenwald, S. W. (2023). Learning Engineering is a Process. In Goodell, J., Kolodner, J. (Eds.) (2023). Learning Engineering Toolkit: Evidence Based Practices from the Learning Sciences, Instructional Design, and Beyond. Routledge. New York.

Koedinger, K. R., Carvalho, P. F., Liu, R., & Mclaughlin, E. (2023). An astonishing regularity in student learning rate. *Proceedings of the National Academy of Sciences of the United States of America*, 120(13). https://doi.org/10.1073/pnas.2221311120

Kolb, D. (1984). Experiential Learning as the Science of Learning and Development. Englewood Cliffs, NJ: Prentice Hall

Murnane K, Phelps MP, Malmberg K (1999). Context-dependent recognition memory: the ICE theory. J Exp Psychol Gen. Dec;128(4):403-15

Saxberg, B. (2018). "Executing the Change to Learning Engineering at Scale." In Dede, C., Richards, J., Saxberg, B. (eds.). Learning Engineering for Online Education: Theoretical Contexts and Design-Based Examples, 1st edition. New York: Routledge, 166–193. https://doi.org/10.4324/9781351186193

Schatz, S., & Goodell, J. (2022). 2022 Learning Engineering Tutorial. I/ITSEC. National Training and Simulation Association. Orlando, FL.

Simon, H. (1967). The Job of a College President: A memorandum written to the president of Carnegie Mellon University. Carnegie Mellon University website: https://www.cmu.edu/simon/what-is-simon/history.html

Stone, A. (2021). US Army makes headway on Synthetic Training Environment. Defense News. https://www.defensenews.com/training-sim/2021/09/30/us-army-makes-headway-on-synthetic-training-environment/

Soloway, E., Guzdial, M., & Hay, K.E. (1994). Learner-centered design: The challenge for human computer interaction in the 21st century. Interactions, 1, 36-48.

Thai, K. P., Craig, S. D., Goodell, J., Lis, J., Schoenherr, J. R., & Kolodner, J. (2022). Learning engineering is human-centered. In Learning Engineering Toolkit (pp. 83-123). Routledge.