Enhancing the Total Learning Architecture for Experiential Learning

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ABSTRACT

Defense-wide efforts are underway to modernize learning technologies and increase capabilities related to warfighter performance. Many investments focus on discrete training experiences, which does not provide a platform for longitudinally assessing the competencies and progression of learners or the efficacy of training systems. Longitudinal assessments are needed both for training purposes and to support the transfer of training systems into the acquisition process.

The STE (Synthetic Training Environment) Experiential Learning for Readiness (STEEL-R) project addresses the challenge of gathering and analyzing longitudinal training and performance data by establishing a common data interoperability layer that collects evidence through a competency-based experiential learning model. The STEEL-R architecture is based on and extends the US Advanced Distributed Learning (ADL) initiative's Total Learning Architecture (TLA) to function across an ecosystem of synthetic and live training environments. This approach provides data traceability, supports evidence-based training decisions, and results in datasets that can inform acquisition teams and reduce the need to manually collect data when transitioning from research to acquisition.

This paper starts by presenting the STEEL-R architecture, in which xAPI, the Generalized Intelligent Framework for Tutoring (GIFT), Learning Record Stores (LRSs), and the Competency and Skills System (CaSS) - all open source and developed for the DoD - play central roles. GIFT is used to orchestrate data from training exercises ranging from game-like VBS exercises to live field exercises in which soldiers are equipped with wearable sensors. The paper then discusses the data models used and data is collected over time and transformed into standardized patterns that can be used to produce fully traceable evidence-based decisions concerning trainees. The last section of the paper discusses the implications of this approach for evaluating system performance and how this work will aid DoD acquisition teams.

ABOUT THE AUTHORS

Mike Hernandez is the Director of Business Development at Eduworks and a learning engineer. He brings over a decade of Defense experience and has been a contributor to the Total Learning Architecture (TLA) effort since 2016. Throughout his career, he has stewarded the technical and programmatic development of multiple projects related to competency-based learning, performance tracking, and data analytics for the US Navy, US Army, US Air Force, and OSD**.**

Shelly Blake-Plock is co-founder, President and CEO of Yet Analytics, Inc. He has served as PI on key TLA-related projects sponsored by the Advanced Distributed Learning Initiative (ADL), including the Data and Training Analytics Simulated Input Modeler (DATASIM). He is a Senior Member of the IEEE where he is an officer of the Learning Technology Standards Committee and chairs both the P9274.4.2 working group on xAPI Cybersecurity and the Technical Advisory Group on xAPI. He serves as vice-chair of the working groups on Enterprise Learner Records and on AI Ethics for Adaptive Instructional Systems. Relevant projects include CASTLE at ADL.

Kevin Owens is an Engineering Scientist in Modeling and Simulation at the Applied Research Laboratories: The University of Texas at Austin (ARL: UT). Following a career in the US Navy, Kevin has been conducting learning engineering, and applied research in new warfighter training technologies and learning models for 21-years. Currently Mr. Owens is a member of the US Army PEO-STRI engineering team for the future Synthetic Training Environment (STE) program. He is also a principal researcher for the U.S. Army Combat Capabilities Development Command (DEVCOM) Soldier Center, Simulation and Training Technology Center (STTC) STEEL-R project.

Benjamin Goldberg, PhD is a senior research scientist at the U.S. Army Combat Capability Development Command – Soldier Center and is co-creator of the Generalized Intelligent Framework for Tutoring (GIFT). Dr. Goldberg is the technical team lead for a research program focused on the development and evaluation of Training Management Tools for future Army training systems. His research is focused on the application of intelligent tutoring and artificial intelligence techniques to build adaptive training programs that improve performance and accelerate mastery and readiness. Dr. Goldberg has researched adaptive instructional systems for the last 12 years and has been published across several high-impact proceedings. He holds a Ph.D. in Modeling & Simulation from the University of Central Florida.

Robby Robson, PhD is the Chief Science Officer and co-founder of Eduworks Corporation. He has led successful research and product development teams in industry and academia and is currently the Principal Investigator on the STEEL-R project discussed in this paper and on the National Science Foundation (NSF) SkillSync project that is using AI services to create efficiencies and analyze trends in the US talent pipeline ecosystem. In his volunteer life Dr. Robson is actively involved in governance within the IEEE, serving on boards and committees within the IEEE, the IEEE Standards Association, and the IEEE Computer Society. Dr. Robson holds a PhD in mathematics from Stanford University and has contributed to the fields of semi-algebraic geometry, computational number theory, online learning, competency management, and applications of AI to training and talent management.

Tim Welch is an instructional technologist focusing on innovative ways to improve the work performance of a wide variety of learners and instructors in academic, professional, and military environments. Tim has been a teacher, instructional designer, and evangelist for emerging learning technologies at many levels of multiple instructional organizations. Prior to joining Eduworks, Tim's roles at NAWCTSD included the Central Florida Tech Grove, Chief Scientist for the Learning Architecture for Defense Health Agency, Principal Investigator for the Avenger AI for LVC effort, Instructional Lead for the Modern Learning Strategies group, and Lead Instructional Technologist for the Sailor 2025 Read Relevant Learning Initiative.

Fritz Ray is Eduworks' CTO and lead contributor to Eduworks' CaSS project since its inception in 2015. He is the company's senior technical lead for MNL/STRMS where he oversees competency framework development, development of tools for data ingestion, the MNL API, and integration of CaSS within the MNL/STRMS architecture. Mr. Ray has over fifteen years' experience architecting, designing, and leading development of software used by the U.S. Navy, U.S. Advanced Distributed Learning (ADL) Initiative, the U.S. Army Research Laboratory, the U.S. Air Force, and industry partners in the fields of readiness, training, and talent management.

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INTRODUCTION

In this paper we present a data strategy for measuring the longitudinal impact of synthetic, semi-synthetic, and live training experiences on individual and team competency development. The strategy presented was developed in conjunction with the STE Experiential Learning - Readiness (STEEL-R; Goldberg et al., 2021) project led by the US Army DEVCOM Soldier Center and represents a Science and Technology (S&T) investment that supports the US Army Synthetic Training Environment (STE) modernization effort. Although presented in an Army context, the capabilities and business rules described within are applicable to similar programs in Department of Defense (DoD) agencies seeking to modernize their training infrastructure. This is enabled through data-driven learning that aligns with acquisition strategy and building for a future training and education ecosystem.

Collecting longitudinal data and emphasizing experiential learning enables training systems to be continuously validated in mission contexts. Traditionally, acquisition programs verify that systems perform their intended function, validate those systems solve a targeted problem, and transition verified and validated systems to warfighters (Department of Defense (DoD), 2022). Once deployed, their outputs are monitored to ensure continued operation. In the case of training systems, these are high-level outputs such as credentials earned, pass rates, and hours of training. In fact, data standards for Live Virtual and Constructive (LVC) training are not designed to capture richer data to drive performance assessment and evaluation (Robson & Barr, 2019; Sottilare, Long & Goldberg, 2017).). This is problematic because the value and efficacy of simulation-based environments cannot be evaluated without considering the long-term impact on learner proficiency and without understanding the effects of fine-grained training activities on skill acquisition and retention.

Capturing the required data goes beyond creating high fidelity practice environments. It involves identifying the skills and competencies that warfighters require and establishing evidence-centered metrics to assess proficiency at all phases of skill acquisition. This includes observing how skills and competencies improve, decay, and build upon each other over periods of weeks/months and, when analyzing generational changes, over many years. To accomplish this, learning environments, including the STE, must measure and track longitudinal learning gains. Given the variety of systems and modes of training in a STE, data standards are needed for architectural compatibility and interoperability and to record and exchange data in common formats. In this paper we argue that acquisition teams should ensure that these systems:

- Use common definitions of human performance at the organizational proponent level;
- Enable these definitions to evolve as doctrine and job requirements adapt to emerging capabilities and threats;
- Produce data that can be stored in and retrieved from enterprise repositories and that conform with open standards so that these data can be analyzed in the present and in the future;
- Measure and track the effects of the systems on human performance and skill acquisition through evidence centered design; and
- Include data strategy and the above measures as key components of system evaluation.

The US Army's STE is an important acquisition program influencing this research (Goldberg et al., 2021). STE is a collective training solution that delivers multi-domain exercises across reconfigurable ground, air, and dismounted assets. It leverages a core STE Information System (STE IS) with three primary components that enable a Plan, Prepare, Execute and Assess cycle for STE-enabled exercises. The STE-IS components include: One-World Terrain (OWT), Training Support Software (TSS) and Training Management Tools (TMT). These are described in detail at https://armyfuturescommand.com/ste/. With TMT, the US Army will have the means to automatically collect and persistently track data that supports the approach recommended in this paper. To take full advantage of STE's investments in data-rich systems, it is necessary to have a uniform data strategy and the means to translate these data into (trusted) statements about competencies and skills. According to DoD policy (DoD, 2017), this should be provided by an architecture that builds from underpinnings established in the Total Learning Architecture (TLA) (Advanced Distributed Learning Initiative (ADL), 2021). This paper will describe how a program like the STE, and capabilities being researched in STEEL-R, will extend the existing TLA to influence skill acquisition through theories grounded in experiential learning and deliberate practice.

EXPERIENTIAL LEARNING IN STEEL-R

A key concept of the STEEL-R project is the implementation of a data strategy guided by the theory of Experiential Learning (Kolb & Kolb 2017; Owens et al., 2020). This approach breaks away from an instructor centered, group-paced, and curriculum-based learning model, with an emphasis on 'learning by doing' across an ecosystem of resources. Experiential Learning infuses many modern-day theories, practices, and concepts to drive knowledge and skill acquisition through active learning and deliberate practice principles (Ericsson, 2006). Learning, measured as a change in knowledge, skill, and behavior, occurs through tension and conflict between a learner's current state of competence and what impact an experience stimulates them with in the form of a task, a problem to solve, or a skill to perform. Once a learner reflects on their performance and understands that change is required, they should form a means to change their knowledge, skill, and attitude for that task or problem in the future. That realization is the key moment to then provide the opportunity to provide a similar experience and then test the change in competence. With the advancements and eventual proliferation of synthetic and extended reality learning resources, establishing best practice methodologies for designing and tracking experiential learning events can produce a major alternative to the traditional course-centric learning method.

Experiential learning also feeds the assertion of competence, which is dependent on longitudinal performance gains across several structured practice opportunities with scaffolds and feedback to guide the learning process. To support this requirement, STEEL-R builds on many components of the TLA, as well as existing Army Adaptive Instructional System (AIS) technology. The capabilities are combined to manage data capture and production of granular evidence-based performance evaluations that are stored long term; and to use this persistent data to track competence development and atrophy of skills. STEEL-R defines experimental competence based on three parameters of performance monitored concurrently, and is represented in the WHO model:

- how **W**ELL someone performs over time,
- how **H**ARD the conditions that they performed against, and
- how **O**FTEN they have performed that task or applied that competency, that well, and at that same level of difficulty.

We also postulate that attained competence from experiences natural atrophy or decay as a result of inactivity. The rate at which skill decay will occur will be based on task and skill dependent characteristics and based on existing modeling techniques that target multi-factor atrophy (Robson et al., 2022). With STEEL-R, if a team or person does not continue training with evaluation at varying levels of difficulty, and data is not collected on those events, the default assumption is that the team or persons will fall prey to not only well documented knowledge and/or skill decay that humans are known to experience over time.

STEEL-R, THE SYNTHETIC TRAINING ENVIRONMENT, AND THE TLA

STEEL-R's data and data exchange strategy builds on the TLA. The TLA provides a collection of specifications and practices for interoperability among learning technologies (ADL, 2018). Multi-year investments in the TLA have created a foundation for formatting, exchanging, storing, and analyzing learning-related data over time across many different learning experiences. To date, however, the TLA has primarily been applied to data generated by individual learners interacting with traditional learning content. There are no established practices for extracting task and procedure level performance statements and team-level data from more operational military simulation and gaming environments. Repeatable and proven methods for doing this are required to fully realize the benefits of the STE, for which we found it necessary to extend the TLA in order to retain its core capabilities.

The STEEL-R data strategy includes technologies from the S&T community that have been developed for transition and that inform future STE requirements. Leveraging these technologies, and the TLA, has accelerated STEEL-R prototype development and will simplify its transition into the STE.

STEEL-R's Competency Based Experiential Learning as an Implementation of the TLA

STEEL-R currently focuses on creating experiential learning opportunities in a way that scales through all echelons in the US Army and that enables Soldiers to properly progress through developmental phases from crawl to walk to run and from untrained to expert within each phase. This progression is the internal view and the commander's view of STEEL-R (Goldberg et al, 2021). From an external perspective, a convenient way of conceptualizing STEEL-R is via a set of control loops that were initially defined for the TLA (ADL, 2020). As shown in Figure 1, STEEL-R extends this TLA control loop approach with principles driven by experiential learning. Data from formal training, informal training, and credentials are still very much part of this approach, but the structure shown in Fig. 1 shifts the focus of training from traditional single-person, course-based credentials to evidence collected on individual and team competency over time.

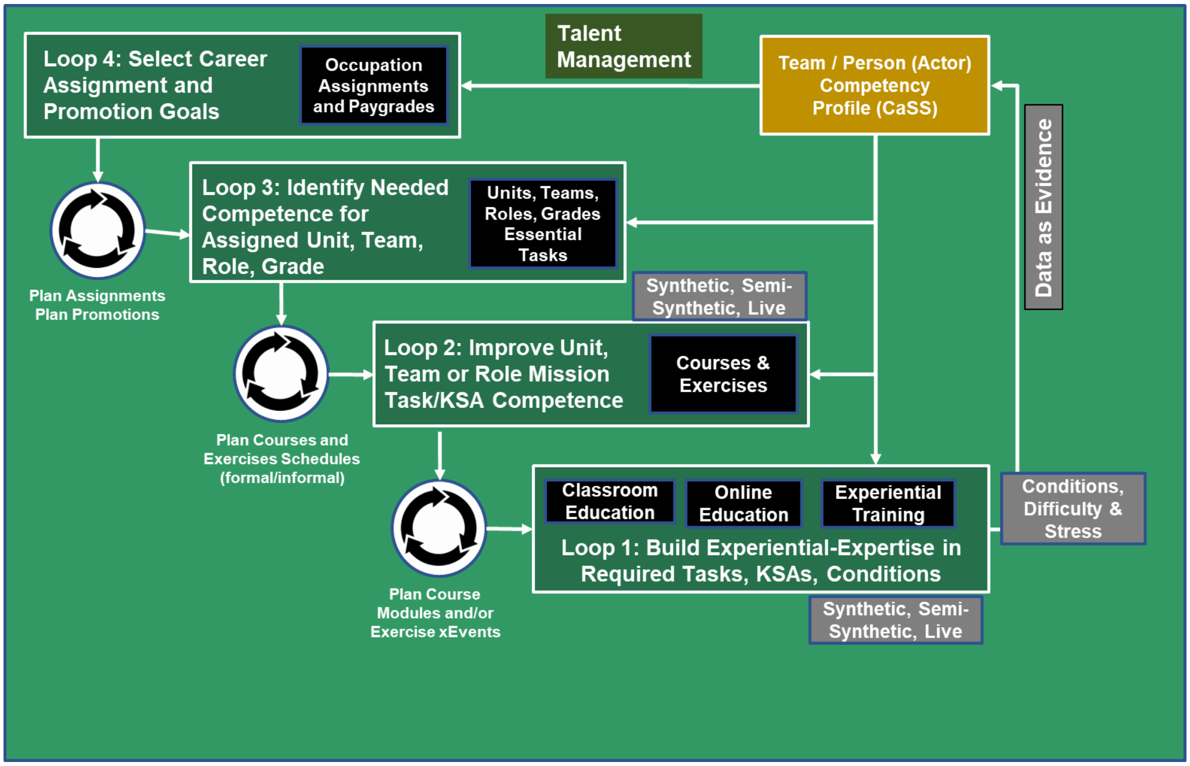

Figure 1, STEEL-R Extension of TLA Control Loop

In the current TLA model control loop 1 optimizes the current training session. Control Loop 2 optimizes progress towards a credential. Control loop 3 in the TLA is described as "...the data to optimize competencies and credentials of an individual's current job." Control Loop 4 in the TLA supports the career arc of an individual in the context of the needs of their organization.

In its current state, STEEL-R has implemented analogs of the first two loops. Loop 1 still optimizes the current training session within a specific learning system (synthetic, semi-synthetic, or live). Loop 2 optimizes the selection of the next activity as individuals and teams' cycle through synthetic, semi-synthetic, and live training. Loop 3 in STEEL-R emphasizes competencies and skills instead of credentials. It includes skill decay and skill fade and considers their impact on the ability of a person or team to execute tasks within a role or job. This is the primary departure from the TLA approach. We envision the STEEL-R loop 4 as being similar to the TLA loop 4, with the differences that (a) STEEL-R includes team performance and (b) STEEL-R focuses on mission readiness as opposed to mission qualifications.

STEEL-R Implementation

STEEL-R uses multiple open-source technologies within a Modular Open Systems Architecture (MOSA) to create an interoperable system of systems (Owens, K.P., et.al. 2020). Although currently configured for squad-level training, this architecture will enable the data strategy to scale to all echelons in the US Army. Fig. 2 depicts the STEEL-R architecture.

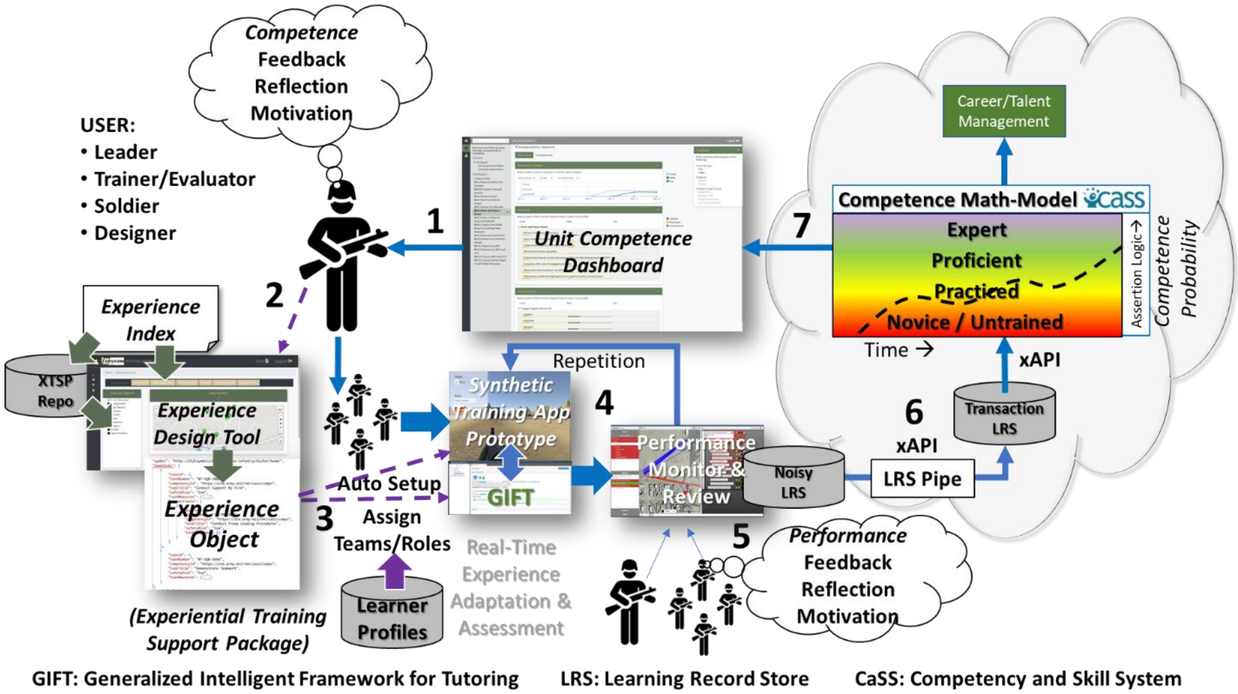

Figure 2 STEEL-R Modular Open Systems Architecture

Experience Design Tool, Experience Objects, and Experience Events

The Experience Design Tool (XDT) is an extension of existing tools used to author synthetic training exercises, often referred to as exercise design tools (EDTs). The XDT extends the traditional EDT by providing a consistent machine-readable output that can be shared, modified, and used to automatically set up both training applications and intelligent tutoring systems, as well as to define reporting standards for performance data.

The XDT's main function is to produce an *Experience Object (xObject)* (Figure 3), which in the STEEL-R project is referred to as an Experiential Training Support Package (XTSP). The XTSP is based on the existing Army Warfighter Training Support Package requirements but is in a JavaScript Object Notation (JSON) format that can be used in the semantic web, in a local database, or in a portable file. Experience objects may be viewed as defining a curriculum for experiential learning and as a content type within control loop 1 of Figure 1. xObjects are machine-readable and syntactically normalized aggregations of the fundamental training elements produced by a traditional EDT plus measurable experiential learning events (called *experience events*, or *xEvents*) that are triggered manually or automatically in a training exercise. A critical function of an xObject is to ensure that performance measures apply consistent data sources, methods (manual or automated), and criteria across the various training environments that are planned for inclusion in the STE. xObjects are designed to automate many of the tasks needed to set up and adapt synthetic exercises that are currently performed manually and to facilitate portability and interoperability of EDTs.

xEvents are delineated by start trigger(s) and end trigger(s) within an xObject. Triggers provide context that is used in STEEL-R, where they define the points at which various competencies and skills are stimulated. xEvents can impact *data support functions* within a training environment. An example of a data support function is monitoring a sensor or the performance messages coming from a training application. These messages may include each trainee's activities and assessments of their performance on competencies and skills listed in the xEvent.

Figure 3. Experience Object with integrated Experience Events

Generalized Intelligent Framework for Tutoring (GIFT)

In STEEL-R, GIFT functions as an intelligent tutoring service that is directly integrated with learning environments. It is an open-source government-managed Adaptive Instructional System (AIS) that provides tools and methods for managing multi-modal data synchronization, real-time assessment, adaptive coaching, and integrated After Action Reviews (Owens, K.P. et al, 2022). Learning environments are connected to GIFT via gateway modules. Within GIFT, an extensible Domain Knowledge File (DKF) maintains a task tree schema that is used to create assessment models and adaptive strategies linked to learning environments through an established and reusable gateway module.

The DKF aligns with a scenario's embedded xEvents that are defined in an XDT. A DKF represents xEvents as a set of tasks represented within a scenario, with configurable start and end triggers that designate when a task is active. For each represented DKF, a set of concepts and sub-concepts define the skills, processes, and procedures being enacted and assessed during task execution. Task, concept, and sub-concept definitions are stored as templates in STEEL-R. The XDT interfaces with GIFT to calibrate a DKF template for use with each specific scenario. Templates are used to simplify the instantiation of controlled and maintainable assessment models (Goldberg et al., 2021). This architectural approach is designed to simplify the integration of existing and future learning experiences, whether live or synthetic, into a learning ecosystem.

An important requirement driving this work is using GIFT to output rich evidence-based performance statements that can be tracked longitudinally and used to provide evidence of competency at the skill interaction and procedure level. To meet this need, GIFT was extended to auto-generate xAPI data that aligns to task and competency structures managed in the DKF. For each task, concept, and sub-concept xEvent in GIFT, both formative and summative assessments are generated through a GIFT xAPI Profile. For the first time, this provides an extension to the TLA that is designed to produce continuous assessments of experiential learning using data streams from any training system. As a byproduct of implementing this strategy, STEEL-R has produced a library of gateway modules that connect to a broad range of learning technologies, including Virtual Battlespace 3, Unity, Engagement Skills Trainer 2, mobile apps, and Learning Management Systems.

xAPI Profiles and Learning Record Stores

xAPI Profiles (IEEE P9274.2.1) provide the ability to curate data as it flows through STEEL-R's implementation of the TLA. In particular, xAPI Profiles enable xAPI statements emitted by GIFT to be filtered and interpreted by the portion of STEEL-R that converts these statements into assertions of competency attainment (Blake-Plock, 2021).

The xAPI data emitted by GIFT follows the templates of the GIFT xAPI Profile (Blake-Plock, 2022). That data is validated, stored, and made accessible by a Noisy LRS. In future implementations there could be multiple Noisy LRSs set up at the edge of the STE for the purpose of validating and capturing xAPI data both online and offline. The xAPI Profiles designed for STEEL-R were tested and validated by the Data and Training Analytics Simulated Input Modeler (Blake-Plock & Hoyt, 2019; Blake-Plock, 2019) to ensure that the xAPI data in STEEL-R is aligned with the expectations of downstream applications.

To prepare this information for use by CaSS, xAPI data is forwarded through an LRS-Pipe statement filter depicted in Fig. 2 The filter provides the ability to configure and control the flow of data according to xAPI Profile statement templates. In this use case, the filter references the GIFT xAPI Profile. The configurable xAPI Profile data is validated against Data and Training Analytics Simulated Input Modeler (DATASIM) libraries, and only that data that is xAPI Profile conformant and that has been deemed useful in providing evidence to CaSS is passed through the filter.

The data forwarded via LRS-Pipe is validated, stored, and made available in a Transactional LRS. From there, CaSS can retrieve filtered xAPI data and transform it into competency assertions. This entire process is automated and occurs in real-time.

Competency and Skills System (CaSS)

The open-source Competency and Skills System (CaSS) has been a central element of the TLA since the TLA was conceived as a universal architecture for learning systems in 2016 (ADL, 2018). CaSS has four primary functions: (1) authoring and maintaining competency frameworks; (2) translating evidence from diverse systems into assertions about competencies; (3) calculating competency states based on assertions and (4) sharing this data across technological and organizational boundaries.

In STEEL-R, CaSS frameworks have been developed to represent (1) doctrinal Army Tasks, (2) doctrinal structures that define individual soldier competencies (e.g., marksmanship), and (3) doctrinal structures that define echelon level competencies (e.g., communication and backup behavior). These frameworks define the competencies and skills that can be trained and possessed within an echelon and is designed to scale across all task and team structures. Current frameworks represent individual infantryman, fire teams, and squads.

A core research activity in STEEL-R is calculating the level at which an individual or team possesses a competency. This is done via a “math model” (Robson, R. et al, 2022) that is expected to evolve and incorporate more predictive analytics in the future. This is instantiated in a software module called a “cartridge”. From an acquisition perspective, CaSS cartridges are well-defined deliverables that simplify versioning and adapting open-source software to new requirements. To account for principles linked to experiential learning, deliberate practice and skill progression from untrained to expert, CaSS has recently integrated stress and difficulty into the assertions it records and into the computation of competency states.

Dashboard and future adaptive systems

To communicate with end-users, STEEL-R incorporates a dashboard that is populated by data from CaSS. The dashboard shows progression through developmental phases over time. This is a tool that commanders can use to adapt training exercises and that is described in more detail in (Owens, K.P. et al, 2022). As of this writing, the dashboard is being updated based on feedback from West Point Cadets. In addition to the dashboard, ongoing research is producing a *navigator* that provides deeper insight into what exercises, scenarios, and scenario configurations are appropriate for achieving a stated training objective.

STANDARDS USED IN STEEL-R

Across the DoD, acquisition standards are among the key driving factors that "…are intended to successfully guide the technical planning and execution of a program across the acquisition life cycle" (DoD, 2022). STEEL-R incorporates multiple published standards, emerging standards, and data formats. It also is entirely based on open-source software. This creates a data topology that is open (within cybersecurity constraints). The key data objects in STEEL-R and supporting standards are summarized in Table 1.

Table 1. Data Objects and Supporting Standards

Data Object	Description	Provenance
Experiential Training Support Package	A package of experience objects that can be used to implement experiential training scenarios	Developed in STEEL-R, built in Java Script Object Notation (JSON), ISO/IEC 21778:2017
GIFT's Adaptive Learning Service API	Reconfigured GIFT instance that exposes tutoring capabilities to an external system	Developed in GIFT, delivered to STE vendors, source code available via gifttutoring.org
Domain Knowledge Files	Defines task trees, concepts, concepts, and assessment rules. In STEEL-R, the data in the DKF can be specified in an XTSP	Developed in GIFT, open data structure authored in Extensible Markup Language (XML), W3C XML 1.1.
Assessment Condition Classes	A library of reusable algorithms and logic that use data from training exercises (obtained via a GIFT gateway module) to assess performance. Used in the DKF to provide automated assessments.	Developed in GIFT, open data structure authored in Java. Supports interoperability with External Assessment services through MOSA integration standards.
Experience Application Programming Interface (xAPI) Data	Statements that capture training events and GIFT-generated performance assessments. xAPI statements are stored in Learning Record Stores (LRSs) within STEEL-R.	Created by the ADL Initiative, standardized by the IEEE P9274.1.1.
xAPI Profiles	Specify the elements and semantics of xAPI statements.	Created by the ADL Initiative, standardized by IEEE P9274.2.1.
LRSPipe	Provides the ability to use xAPI Profiles to govern the business logic of data in a TLA implementation.	Created by Yet Analytics and published under the Apache 2.0 open-source license. First implemented in the STEEL-R project.
Competency Frameworks	Structured sets of competencies related to a specific battle drill, task, or mission. Frameworks include relations among competencies. Competencies are collections of knowledge, skills, abilities, and attitudes.	Stored and processed in the open source CaSS software, which is standards agnostic. CaSS frameworks can be imported and expired using a variety of extant standards.
CaSS Cartridge	Encapsulates logic and business rules specific to the application domain, learner model, and training model.	Developed by Eduworks CaSS Project. Enables severable extension of rules and models in different instantiations of CaSS and intended to facilitate open-source acquisition.

CAPTURING THE CHAIN OF EVIDENCE

Assertions of proficiency are based on "…elements such as the conditions, additional evidence, an expiration date, a confidence, and more elements" (Robson et al., 2021). The chain of evidence depicted in figure 3, represents the bi-directional data flow of STEEL-R. Users of STEEL-R author their XTSPs via the XDT as a series of xEvents to meet training requirements. As individuals and teams work through these events, which are defined by xAPI Profiles and DKFs, they generate xAPI data. That data is sampled by CaSS and results in evidence-based assertions of individual or team performance aligned to a competency framework. Linking conclusions about performance and competency levels to specific evidence from training systems establishes provenance of these conclusions. This, in turn, engenders trust in the conclusions and enables version control. Allowing assertions to change as definitions of proficiency and doctrine evolve over time. As shown in Figure 3, the chain of evidence from the core systems of STEEL-R is fully traceable through experience design, assessment methods, performance, reporting, computations, and dashboards.

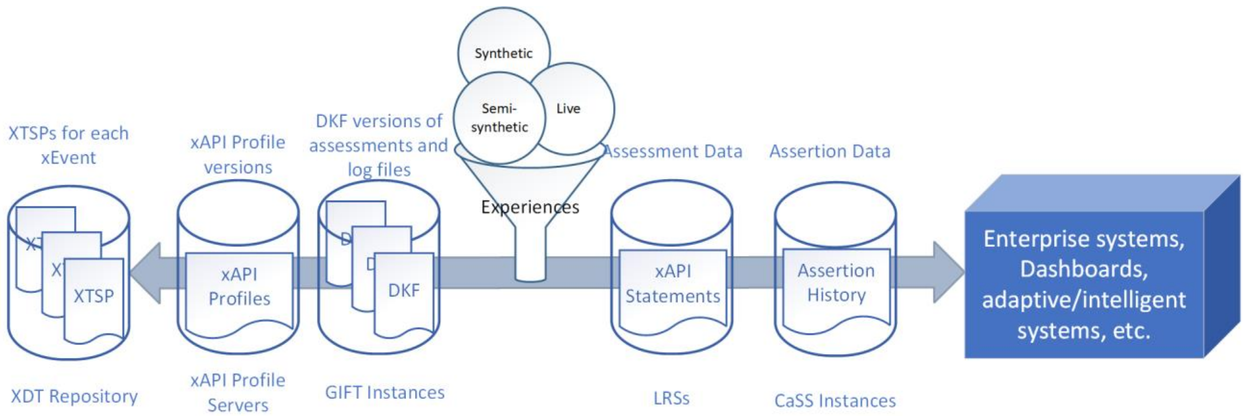

Figure 3 STEEL-R Chain of Evidence

The evidence gathered in the updated control loops will not replace credentials or traditional descriptions of roles (MOS, squad leader, etc.). It is intended to provide a broader and more nuanced view of how the previous investments made in readying someone to execute a mission have prepared them and have persisted as demonstrable, transferable skills and competencies. The data generated by each exercise will be available for recalculation as the models of proficiency and roles of individuals change over time. This persistent record will facilitate evaluation of past investments and inform future training selections.

There are multiple types of data in this chain of evidence that are not currently stored in an enterprise repository in the US Army and therefore do not have a single source of truth. To ensure consistent data structures are in place for use across STE, such repositories will need to be developed at the proponent level for storing xAPI profiles, competency frameworks, and assertions. These repositories will benefit from xAPI that is generated from systems across the enterprise. The next section discusses how these affordances can be put in place by the acquisition community.

TRANSITION TO THE ACQUISITION COMMUNITY

The STEEL-R data strategy captures the value of each training system's contribution to the development of proficiency in a Soldier. Transforming training systems validation into a continuous process will require new acquisition tools and a shift from credential-based to competency-based approaches. At this point in time, STEEL-R is an S&T project that requires additional work to be transitioned. For example, it must be accredited as conforming with the Risk Management Framework, and its ability to support all echelons within the US Army required further validation. Nonetheless, in its current form STEEL-R can offer technology, techniques, and lessons learned that acquisition teams can apply to increase the quality of their investments to support readiness. This section highlights these aspects of STEEL-R with a view towards providing current value as well as future transition.

STEEL-R as a Data Strategy

Standards

The use of standards is key to "Leveling the technology playing field and enabling innovation by all stakeholders, including large, medium, and small companies" (IEEE SA, 2020). Standards ensure that the outcomes of any system integrated within an acquisition program can be 1.) leveraged by vendors to produce the types of data required and 2.) that data will be in a format that is portable to other systems regardless of the involvement of any specific vendor. Standards bodies are public, and often have US Government participation in their development and eventual consensus. Through strategic planning, acquisition programs can influence the standards required over a system's lifecycle.

Assertions at the Enterprise Level

The final transformation of data sampled within a STEEL-R conformant system is the assertion of competence by CaSS. That assertion, derived from the chain of evidence described earlier, represents the measured impact of an experience within a given context and its contribution to the learner state. Longitudinally tracking assertions creates a measure of realized value at a point in time. Storing, and processing assertions will require interoperable connections to an enterprise level LRS and CaSS instance that consumes edge-generated assertions when a connection is available. Connections of this form will allow the various instances of STEEL-R in the field to exchange data with STE to track the impact of learning across the US Army and will preserve trusted evidence over time at the proponent level so that conclusions about readiness are traceable back to training experiences and their descriptive information.

Simplifying Interoperability: Timing, Technology, and Data

The GIFT platform includes functionality that enables assessments generated by existing synthetic training systems to interoperate with the STEEL-R architecture. For xAPI to proliferate and enable the chain of evidence described in this paper, a platform for both existing and future learning systems must be in place to capture that data (Hernandez et al, 2019). Rather than instrumenting each training platform individually, GIFT presents an alternative which can save time and reduce costs during the acquisition lifecycle.

In STEEL-R the generation of xAPI statements is based on the relationship between the xEvents for a given XTSP, the xAPI Profiles selected to describe the data generated from that event, and the DKFs in GIFT that enable assessment of the connected learning platform. Since 2012 the GIFT project has evolved to use various standards and incorporate adaptive learning strategies into existing systems (Hoffman & Goldberg, 2022). For acquisition teams the potential to scale this model will simplify creating ubiquitous datasets to model human performance. An additional benefit in GIFT is the ability to generate multiple versions of assessments in its DKFs, without reengineering a learning platform or its associate xAPI profile associations.

Continuous Validation of Training Systems

The usage of any training system can be measured and generate digital records through the technologies described in this paper. To realize the potential return on investment that shifting from credential centric measures to CBEL requires the chain of evidence described in this paper. A key step to reaching this future state is creating common, and specific definitions across the learning ecosystem of STE and other DoD programs.

A COMPETENCY BASED EXPERIENTIAL LEARNING ACQUISITION PACKAGE

Learning engineering promises the ability to bridge the fields of instructional design and computer science to benefit DoD training and education (Bonnett, 2020). The current acquisition process leverages teams of ISDs, supplemented in some programs by engineers procuring simulation-based training. The traditional acquisition structure for instructional products includes a SOW establishing the work requirement, CDRLs establishing timing, and a DID for the format and content required (DoD 1999). To realize a Competency Based Experiential Learning (CBEL) additional DIDs must be established to bridge traditional software engineering and instructional design in acquisition with learning engineering. This is necessary to ensure that the chain of evidence is implemented. This will result in data to inform future investment and establish a learning engineering role in systems engineering. These recommendations are summarized in Table 2 Acquisition Documents for Learning Engineering Inclusion below.

Table 2 Acquisition Documents for Learning Engineering Inclusion

Deliverable	Acquisition Process	Purpose
Requirements (Redefine existing learning needs, data gaps, analysis processes, data strategy, etc.)	• DI-SESS-81518b, Data Item Description: Instructional Performance Requirements Document (IPRD)	Expand the IPRD as a foundational acquisition document beyond courseware and simulation to include an experiential learning focus.
CBEL Design (Instantiates the core XTSPs, DKFs, xAPI Profiles, Competency Framework, and Learning Models to start an experiential learning project)	• DI-SESS-81519C, Data Item Description: Instructional Media Requirements Document (IMRD) • DI-IPSC-81433 - Software Requirements Specification (SRS)	Evolution of the SRS and IMRD to combine their key data points and expand around specific functional qualities for experiential learning. This document will iterate over the lifecycle of a learning platform.
Learning Engineering (Expands the traditional software/systems engineering to include a CBEL product owner and their requirements)	• DI-IPSC-81431 - System/ Subsystem Specification (SSS) • DI-IPSC-81432 - System/Subsystem Design Description (SSDD) • DI-IPSC-81433 - Software Requirements Specification (SRS) • DI-IPSC-81435 - Software Design Description (SDD)	Bridging ISD with Computer Science establishes the value of learning engineering in the existing systems engineering processes of acquisition. Software acquisition materials adds specificity to the SSS, SSDD, SRS and SDD to develop software that incorporates the new learning specific design materials.
Continuous Validation (Supports independent reviewers seeing impacts of CBEL, ties data from schoolhouse to practice)	• DI-SESS-81697, Data Item Description: Instructional Design Documentation (IDD) • DI-IPSC-81438 - Software Test Plan (STP) • DI-IPSC-81439 - Software Test Description (STD)	Integrate item 3.7, measuring learning performance with data artifacts in systems engineering such as a Requirements Traceability and Verification Matrix DID DI-MGMT-8213

CONCLUSION

This paper has presented an approach where experiential learning and learning engineering can enhance DoD training and instructor centered, group-paced, and curriculum-based learning models. This will have far-ranging implications for how readiness is calculated and how skill decay and skill fade are digitally tracked as part of measuring proficiency. Data standards provide the foundation for a clear chain of evidence, providing traceability of learning goals to performance-based outcomes.

For the training acquisition community to take advantage of the opportunity presented in STEEL-R, investments must be made in transitioning the technologies and practices described in this paper. Such a transition will require close collaboration among the organizations and personnel who are developing new training methodologies and planning the future procurement of systems to support the STE. In particular, technical documentation and acquisition processes must more fully account for learning engineering and associated best practices. This will enable instructional designers and engineers to better articulate desired outcomes in learning engineering terms and to explicitly drive the type of competency-based experiential learning that lies at the heart of the STEEL-R approach.

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