Total Learning Architecture (TLA) Data Pillars and their Applicability to Adaptive Instructional Systems.

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Abstract. Since 2016, the Advanced Distributed Learning (ADL) Initiative has been developing the Total Learning Architecture (TLA), a 4-pillar data strategy for managing lifelong learning. Each pillar describes a type of learning-related data that needs to be captured, managed, and shared across an organization. Each data pillar is built on a set of international data standards that combine to increase the granularity and fidelity of learner data. Reusable Competency Definitions (IEEE 1484.20.1 RCD) are used to describe the Knowledge, Skills, Abilities, and Other behaviors (KSAOs) that are required in the workplace (e.g., the operational environment). Learning Activity Metadata (IEEE P2881 Learning Activity Metadata) is used to describe the various learning resources an organization uses to train and educate its people. The Experience API (IEEE 9274.1 xAPI) is used to track and manage learner performance both inside and outside a learning activity. An Enterprise Learner Record, currently an IEEE study group, is used to track and manage each learner's level of competency within the organization.

Together, this data enables a ledger of learner performance that ties all learning activities that a learner completes to competencies, credentials, and ultimately to the different career trajectories that a learner may pursue. The TLA data strategy includes linkages across the different standards listed above and collectively provide a data foundation for adaptive systems to build upon. This paper and discussion will walk viewers through the different data models that are being used to drive development of these standards.

Keywords: Total Learning Architecture, Adaptive Instructional Systems, Data Strategy,

1 Introduction to the TLA

The human capital supply chain is a complex system with inherent challenges to accommodating interoperability between organizations. The Advanced Distributed Learning (ADL) Initiative started the TLA project in 2016 with the goal of establishing a common data strategy across the education and training industry that enables lifelong learning. The TLA benefits from modern computing technologies, such as cloud-based deployments, microservices, and high Quality of Service (QoS) messaging services. Its capabilities come not from individual components or databases, but the enterprise-level collection, sharing, dissemination, and analysis of learner data [1].

The TLA defines a set of policies, specifications, and standards for enabling a future learning ecosystem. TLA standards help organize the learning-related data required to support lifelong learning and enable defense-wide interoperability across DoD learning tools, products, and data [2]. Business rules and governance strategies enable the management of this data across connected systems. The TLA relies on common data standards and exposed data interfaces to enable a wide range of functions. This abstracts away any dependencies on a single component and enables these functions to be performed by any connected component.

As a policy driven architecture, the TLA does not require any mandatory components. There are only required functions, organized into microservices and data stores. Each functional area must be exposed through common interfaces, asynchronous services, and standard data formats for communicating and storing data. Interfaces between components and data stores use the Secure Hypertext Transfer Protocol (HTTPS – part of an architectural pattern called Representational State Transfer or REST).

Message payloads are described using JavaScript Object Notation (JSON) and interfaces may be exposed at any point or points, depending on the physical components being used. The value of this strategy is that it supports the immediate and cost-effective reuse of legacy systems, while affording a gradual migration to a fully TLA compliant learning stack.

1.1 The TLA Data Strategy

Key to the human capital supply chain, learner data is a critical asset that enables effective decision making for both trainees to identify gaps in competencies, and for organizations to track employee capabilities across emerging needs. The key to managing lifelong learning data within the TLA is the interoperability afforded through the technical standards, specifications, and practices that underpin an integrated data strategy. The TLA Data Strategy is necessary to provide the semantic interoperability required for enterprise-level analysis and decision support. Data-driven decisions are enabled through enterprise-level analyses of learning data, supporting the continual refinement of occupational skills and the creation, selection, and maintenance of learning activities necessary to achieve proficiency.

The TLA Data Strategy provides a common set data standards and technical specifications designed to be implemented across DoD's education and training community. This overarching strategy will ensure that all data resources are designed in a way that they can be used, shared, and moved efficiently across the organization. The ADL Initiative is working with the Institute of Electrical and Electronics Engineers (IEEE), an internationally recognized standards-development organization, to formally establish the data standards required for successful TLA implementation. While these standards will continue to evolve, DoD education and training communities are urged to adopt and employ them now. These commercial standards describe the data within the four pillars of the TLA Data Strategy:

- **IEEE P9274.1 Experience API.** Learner performance tracking within different learning activities use the Experience API (xAPI) to capture learning activity streams [3]. This standard defines how learner performance is captured, communicated, and shared via a Learner Record Store (LRS), the server-side implementation of xAPI. The xAPI standard also includes xAPI profiles [4] such as cmi5 [5] and the TLA's Master Object Model. xAPI 2.0 is targeted for approval by IEEE in 2021.

- **IEEE P2881 Learning Activity Metadata.** Descriptions of learning activities and their associated content are stored in the TLA's Experience Index (XI). This draft standard builds upon IEEE 1484.12.1 Learning Object Metadata (LOM) to increase the granularity of how learning resources are defined [6]. It was developed by harmonizing with other educational data standards such as the Common Educational Data Standards (CEDS) project, the Postsecondary Educational Standards Council (PESC), Credential Engine's Learning Opportunity Type, the Learning Resource Metadata Initiative (LRMI), and Schema.org. The data model that informs the draft standard also includes numerous data types and properties that were derived from MILHDBK 29612, TRADOC FM 350-70, and the USAF 36-2235 Instructional Systems Design guidebook.

- **IEEE 1484.20.1 Reusable Competency Definitions.** The RCD standard enables a common approach for describing competencies, aligning competencies to other related competencies in the context of a framework, and defining the assessment and evaluation criteria for the evidence a learner must demonstrate to help measure proficiency [7]. This standard is being designed to facilitate a common language for describing the knowledge, skills, abilities, and other behaviors (KSAOs) required for performing different jobs, duties, and tasks associated with an occupational specialty. Competencies provide a common approach for aligning education and training activities to the desired operational performance expected from learners to perform with proficiency.

- **IEEE Enterprise Learner Records (Study Group).** This draft standard is built around a data model created by the ADL Initiative to meet DoD requirements on the Enterprise Learner Record Repository project [8]. This model was informed by the T3 Innovation Network's Learning and Employment Records (LER) Resource Hub and the Data Ecosystem Schema Mapper [9]. The data model builds upon the work performed by the T3 Innovation network to meet the evidentiary requirements (e.g., ownership, stewardship, and management of raw learner data) that many DoD organizations adhere to. It also supports future artificial intelligence / machine learning solutions that enable instructor support tools, intelligent tutoring, and additional insight into each learner that can be used to optimize and tailor their continuum of learning.

1.2 The TLA Reference Implementation

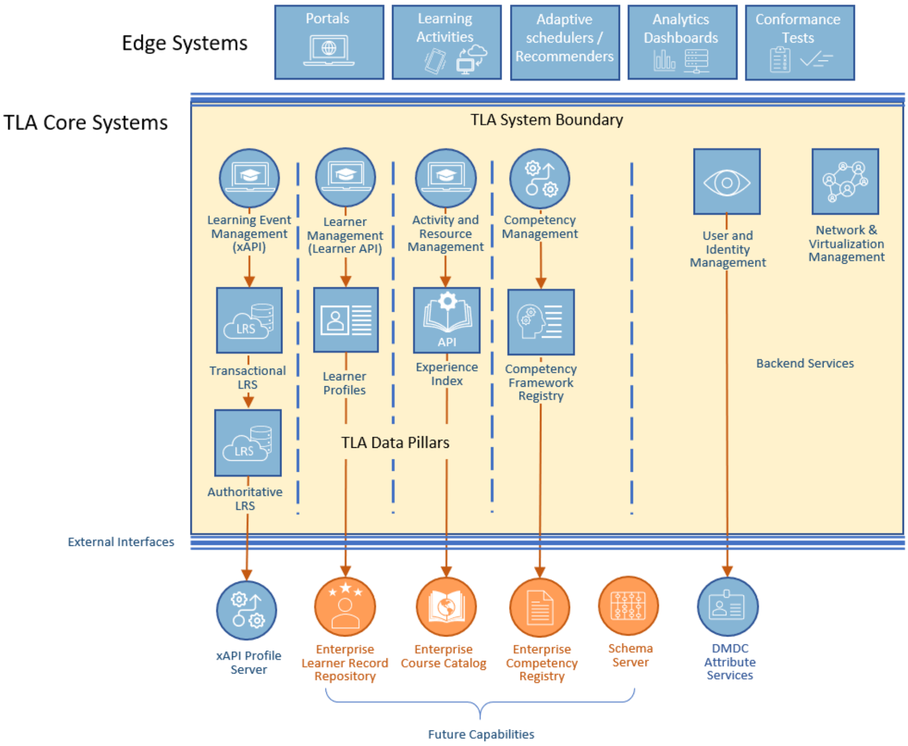

Fig. 1. Organization of Core and Edge Systems. The TLA's Core Services, required interfaces, and the data structures required for any TLA enclave align with the 4 TLA data pillars.

As shown in **Figure 1**, the TLA Reference Implementation adopts a core / edge paradigm that deconstructs the learning environment into core services, core data, and edge systems [10]. Core systems replicate key functionality that typically resides in a Learning Management System (LMS), e.g., student registration, student tracking, content presentation, performance tracking, etc. that are necessary for any learning environment.

Core services manage the learner bookkeeping functions, while back-end core services manage the virtual network bookkeeping functions necessary to operate in a distributed, cloud-based environment. The edge systems are the devices used to provide learning, which may include traditional LMSs, as well as handheld devices, intelligent tutors, electronic publications, simulators, and any other evolving learning technologies. Ancillary functions, like an access portal, data visualization tools, adaptive algorithms, and any attached learning device, are also edge systems that communicate to the core.

The TLA reference implementation exists as a continuously evolving framework of software components designed and built to process large volumes of data from connected core and edge systems. The Apache Kafka® platform provides a distributed publish/subscribe messaging topology built around streams of different data topics [11]. Connected TLA components are instrumented with a collection of microservices that use either HTTP/S over TCP/IP or by producing and consuming messages to the centralized Kafka cluster. The services layer acts as the bridge between learning devices, other TLA components, and shared data stores. Each service exposes the stored data to an application so that information can be transformed into other meaningful data used by other Reference Implementation components.

The data contracts between data and service layers are based on the nature of the data exchanged. The behavior and functionality of each service is defined and aligned with TLA business functions. Input/output data flows are identified and aligned with the required TLA data stores. Data models and protocols are defined around the IEEE standards. Each microservice is independently deployable and reduces the complexity of managing and testing updates to the Reference Implementation. The performance of these microservices can be extended horizontally by cloning the processes on multiple server instances using cloud-based technology like Microsoft ®Azure Apache Hadoop and dynamic load balancing. Core services include:

Learning Event Management. Within the TLA, each learning activity generates xAPI statements using one or more xAPI Profiles. xAPI Profiles are used to help guide the implementation of xAPI into specific types of learning activities or for specific domains. Each profile is a collection of vocabularies, statement templates, and patterns that describe the relationship between xAPI statements and govern how xAPI statements are implemented into an activity.

Once an xAPI instrumented learning activity is connected to the TLA reference implementation (via the Learning Record Store (LRS)), other connected systems can glean insights from the learner performance data generated by that activity. The raw data collected in the LRS provides valuable insights into the learner pathways and decisions made within the context of each learning activity. This data can be used to provide adaptive feedback, remediation, instructor support, and can provide an understanding of how and why a learner performed the way they did within a single learning activity.

Given the diversity of different learning activities, occupational domains, and the xAPI Profiles that govern the xAPI Implementation within those systems, the TLA needs a way to normalize the data coming out of each activity. The TLA Master Object Model (MOM) is used to roll up the raw learner data into meaningful information that other connected systems can use [12]. The TLA MOM includes xAPI statements that describe key learner milestones for tracking and managing learner progression across all learning activities they encounter. The TLA MOM normalizes the xAPI statements coming out of a learning activity, as well as other learning systems such as schedulers, competency management systems, and career field planning tools.

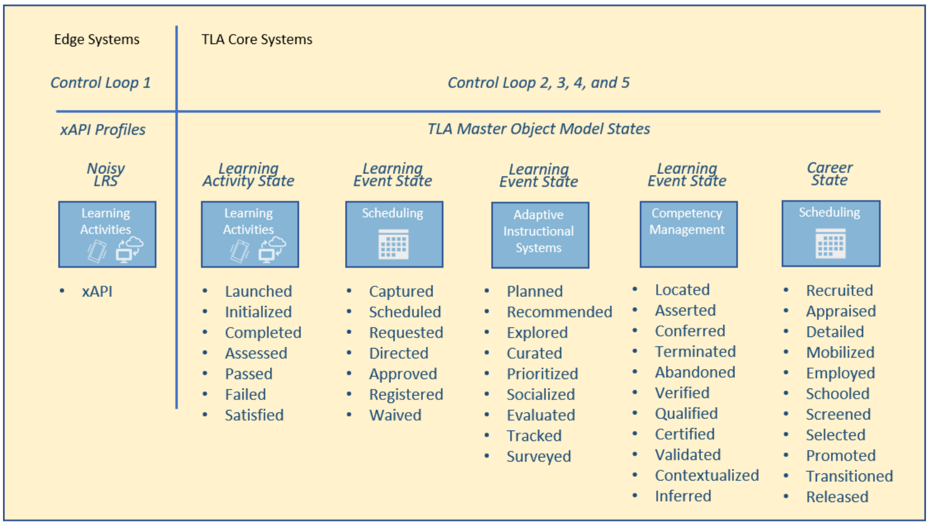

Fig. 2. TLA MOM Verbs. The TLA MOM defines the object life cycle of learners executing a single "thread of learning" that culminates in the reporting and evaluation of a learning event.

As shown in **Figure 2, t**he lifecycle of a learning event is defined by a series of learner-state transitions that are generated as a learner interacts with different systems used to schedule, deliver, and evaluate each instructional activity. The TLA MOM is implemented as an xAPI profile that generates xAPI statements at key points in the learner lifecycle and includes pointers to the raw learner data for systems that need it.

The TLA MOM's Learning Activity State defines the learner interactions a user will perform in a learning activity from initialization to completion or termination [13]. TLA MOM verbs in this state conform to the cmi5 Specification, which follows the lifecycle of the legacy SCORM cmi.core run-time data model. The use of cmi5 normalizes performance data and allows edge systems to perform their own adjudication so there are no conflicts within the TLA core data of what "correct performance" looks like.

The Learning Event State is associated with the activities that occur before a learner has interacted with a learning activity (e.g., requested, approved, scheduled, recommended, among others). It describes the context under which the learner pursued their learning. TLA verbs for this state are also generated after learner performance evidence has been generated or when an activity has been completed. These verbs are used to contextualize learner performance against a related set of competencies (e.g., validated, qualified, conferred, inferred, among others).

Career States are the verbs associated with moving to or progressing towards jobs on a career arc. These MOM statements would be generated by career field management tools, human resource systems, or other personnel systems. Career State change slowly over time as a learner moves from job to job and meets different career milestones (e.g., promoted, detailed, selected, among others).

Federated Learner Record Stores. The TLA uses a federated set of LRS solutions within the TLA Sandbox. This approach stores all raw learner data in the noisy LRS and maintains data ownership with the owners of the learning activity. The transactional LRS collects TLA MOM statements that 'roll up' and normalize the learner performance data coming out of each activity. TLA MOM statements are formatted using xAPI to include the following information:

- Actor: Unique User ID (e.g., DoD ID) used to track an individual across all connected learning activities.

- Verb: Track and Manage the context of how a learning activity was scheduled, completed, and evaluations throughout the life of the learner

- Object: Each Learning Activity has a unique identifier (i.e., Activity ID) that is used to associate that activity with its metadata.

- Context: MOM statements include context that provides additional insight into how a learning resources was used in the context of individual learner experience. This data is used to build insights into each individual's learning path and learning velocity to inform future adaptive instructional systems.

The authoritative LRS only includes verified competency assertions which will be discussed in the next chapter. This approach provides traceability of learner data for all learning activities that a learner encounters within an organization. Using this information, other connected systems can identify what training and education activities a learner has completed, use catalog descriptions to learn more about each activity, and evaluate learner performance in those activities.

Activity and Resource Management. Within the TLA, each learning resource (course, publication, activity) is described using the draft P2881 Learning Activity Metadata standard. Each learning activity has a unique, organizational identifier (ActivityID) that is used to update and manage these descriptions. As shown in **Figure 3,** the draft P2881 standard includes data elements that enable other TLA systems to link learning outcomes to raw learner records (e.g., LRS endpoints, alignments, competencies). Other metadata elements are used to support lifecycle planning, adaptive instructional systems, and other elements that describe its fitness for use in an instructional setting.

Learning Activity Metadata is stored in an 'Experience Index'. Experience indices are maintained locally so that organizations can add additional metadata attributes as needed. P2881 Metadata governance allows for the promotion of locally created metadata attributes to the standard data model. Learning Activity Metadata attributes may be populated during development of the learning resource or they may be populated using values that are derived from other connects systems [14]. For example, a course survey system might allow a learner to rate their experience, when combined with other learner ratings, an 'AggregateRating' value can be calculated.

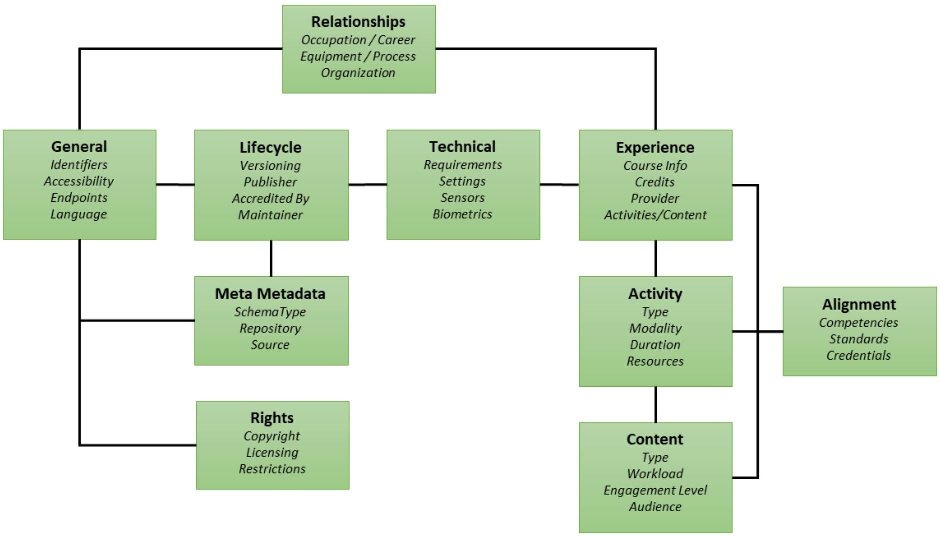

Fig. 3. Draft P2881 Learning Activity Metadata. The TLA uses a standardized data model for organizing one or more local course catalogs into a network of federated course catalogs.

The data model that the TLA's P2881 draft was derived from increases the granularity and fidelity for how we describe learning resources. Learning experiences (e.g., courses, seminars, classes) are decomposed into course sections, learning activities, and instructional content that comprise each course.

An Activity and Resource Management (ARM) service is associated with capturing, connecting, and sharing data about learning resources available within the TLA enclave. Key features include the ability to generate and manage metadata about each learning activity. The ARM functions of the TLA are associated with the creation, review, update, and deletion of Learning Activity Metadata (e.g., activities, courses), as well as the publishing those experiences to other connected systems (e.g., Enterprise Course Catalog). Learning experiences are initially defined as the different training and education resources that an organization has available; however, they may also represent other unique opportunities to enhance or demonstrate learning.

The Resource Management services are concerned with computational or physical assets, infrastructure, consumables, and staffing (e.g., observers, instructors) required to conduct a learning activity. Devices are registered as part of a Zero-Trust Network (ZTN) architecture. Device registration works with the identity and virtualization management services for security and integrity of the data generated and processed from each device. Devices include anything from an LMS or other Learning Experience Providers to mobile platforms and any number of future technologies. This allows users to use the organization's computational resources or their own personal devices once registered.

Competency Management. Competency management includes the process for evaluating learner performance and predicting proficiency levels for individual's teams, and organizations. Learner performance is collected using training and education activities that have been instrumented with the xAPI standard and the TLA MOM to federate learner data across multiple LRSs.

As shown in **Figure 4,** competency definitions describe the specific details, contexts, related standards, mastery levels, and credentials required to successfully demonstrate the *knowledge, skills, abilities and other* (KSAO) behaviors necessary to successfully perform a job in an operational environment. Competency frameworks are used to define the relationships between defined competencies [15]. They are hierarchical in nature, but a single competency may be used across numerous occupations (e.g., jobs) so a 'many-to-many' relationship between many of the competency elements is required. The development of these models requires expertise in the science of learning, instructional design, and operational experience to accurately define each measure of competency, acceptable assessment strategies, and evidentiary requirements.

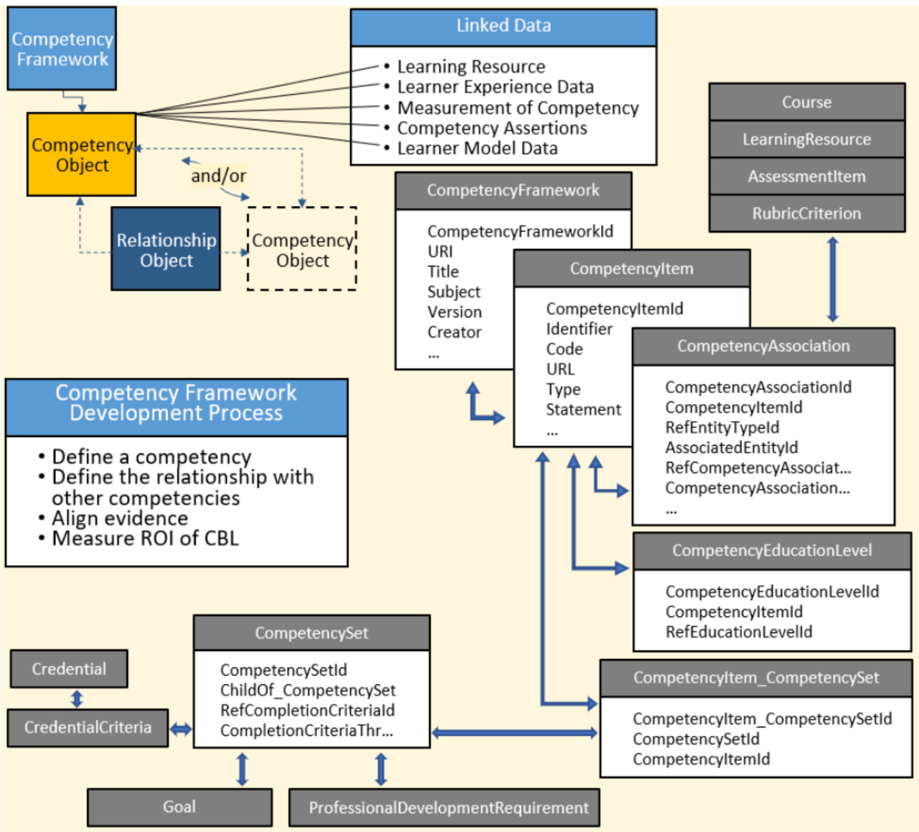

Fig. 4. Reusable Competency Definitions. RCDs formalize the way competencies, their relationships, and proficiency requirements are communicated to other TLA components.

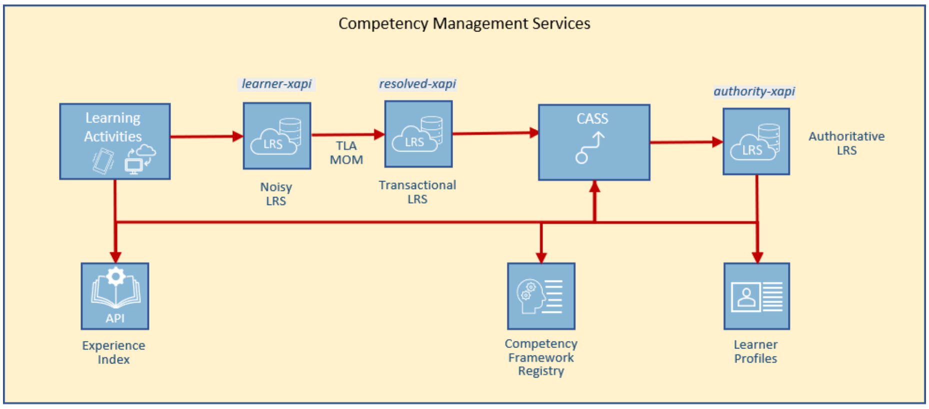

Fig. 5. Reusable Competency Definitions. RCDs formalize the way competencies, their relationships, and proficiency requirements are communicated to other TLA components.

Within the TLA, the competency management service manages evidence of an individual's knowledge, skills, abilities, attributes, experiences, personality traits, and motivators to predict their value toward effective performance. **Figure** 5 shows the flow of learner performance data from the learning activity to the noisy LRS, and over to the transactional LRS using the TLA MOM. The TLA MOM statements stored in the Transactional LRS provide the evidence upon which competency assertions are made.

To generate assertions of competency, the TLA's competency management service reads the TLA MOM statements that are stored in the Transactional LRS and parses each TLA MOM statement. The <xAPI Actor> field is correlated with the learner profile using the learner's UUID and the <xAPI Object> field is correlated with the activity's metadata using the unique Activity ID. Each learning activity's metadata file includes unique competency identifiers that tells the competency services which competency definitions need to be pulled from the Competency Registry. Using the learner profile, learning activity metadata, and relevant competency definitions, The TLA competency management system can estimate proficiency levels for each competency.\

A credential is issued by an entity with authoritative power and provides proof of an individual's qualification or competence in a subject. A network of competencies typically has varying mastery levels as part of its credentialing model. Previous levels contribute to the next level of mastery, and competency elements within the various levels may atrophy over time from disuse. Each credential is defined using the *Credential Transparency Description Language (CTDL).* CTDL decomposes the credential into the competencies that it represents using the same unique identifiers for each competency definition [16]. These artifacts range widely from a college degree to a professional certificate to a badge or a micro-credential. Possessing a credential not only helps one to prove competency and capability within a field, but it also serves as verification that the individual is properly trained and equipped to carry out their duties within their specific vocations or disciplines.

Learner Management. The TLA's Learner Management functions are associated with the ledgering of all learning and development activities that a learner encounters within an organization. Learner management includes the administration, delivery, reporting, and assessment of a learner's progression through the myriad of different learning experiences they encounter. TLA MOM messages are used to define the context around the different learning activities that a learner completes and are also used to preserves learner performance evidence across the TLA's federated LRS structure.

Learner management functions work with other TLA data pillars to convert TLA MOM statements into the different competencies and credentials that each learning activity confers. This is the primary data pipeline for tracking and managing lifelong learning; and correlating learner performance with career field competencies and required credentials.

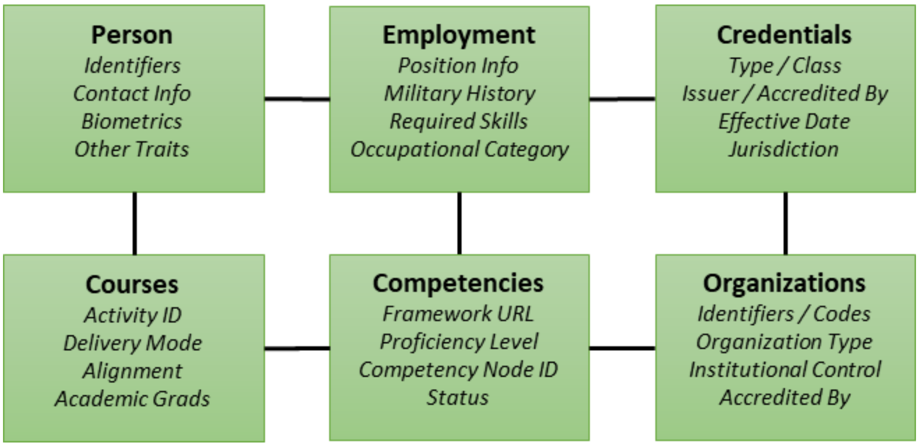

Fig. 6. Draft Enterprise Learner Record Data Model. Each learner record also includes a global registration of all places holding subordinate data about the learner, including learner attributes, learner performance records using xAPI, assessment data, and other related information.

A Learner Profile is used to record learner competency and credential history, aptitudes, local and global preferences, career trajectory and progress against learner goals. **Figure 6** shows the different categories of data that are tracked within the Enterprise Learner Record data model. A unique user ID is used to track learner performance across all connected activities using xAPI statements. xAPI statements include linkages to the other core data repositories to provide additional information to any connected system that requires it.

A Learner profile is used to aggregate this information and a broad range of other data including demographic data, data about student interests, learning preferences, learning goals, career trajectories, and other relevant learner attributes. Connected TLA systems use the Learner API to communicate with the learner profile.

Learner profiles act as the data fabric "connector" and make learner records within the profile globally discoverable through an Enterprise Learning Record Repository (ELRR). The goal of the ELRR is to ensure globally relevant data about individual learners and teams is available to any command, learning system, or activity across the DoD. These data may be used to support adaptive instruction, improved decision making, and analytical insights into learners and the systems they interact with. These data also facilitate the longitudinal analysis of a military career to evaluate systemic readiness issues, efficiency of education/training activities, completeness of standards, and media efficacy.

2 Supporting Adaptive Instructional Systems

Adaptive Instructional Systems, when developed with the TLA Data Pillars, can leverage the resultant data to support a number of different adaptive capabilities. Figure 7 describes these capabilities through a series of 'control loops'. At the first level, the learner's data can be used to adjust scaffolding within a specific learning activity (control loop 1). The activity may scale in difficulty, performance conditions, or the amount and type of feedback received. At a more complex level, learner data can be used to adapt across several different types of learning activities (control loop 2). For example, if there are identified gaps in learner knowledge, a path can be taken to provide supplemental learning activities before moving on to the next step towards achieving a credential.

Third, from an active learner's perspective, longitudinal data can be leveraged to compare several potential paths to get to a credential goal. Courses may vary in length, in ratings, or other factors that allow a learner to make decisions of how to structure their learning experience (control loop 3). Fourth (control loop 4), talent managers can work with learners to lay out long term plans to meet not only current career goals, but also to allow a career pivot to address emerging DoD mission needs (control loop 5), that leverages past learner credentials and competencies, or provides a new path.

The raw learner data from each learning activity can be connected to build learner insights beyond what a single learning activity is capable of. The TLA uses the concept of Control Loops, as shown in **Figure 7**, to delineate how this 'lifelong' learner data might be used by different systems and at different levels of granularity across different time horizons. In other words, the same data collected from a learning activity may be used in different ways depending on the purpose for which it is being used.

The control loops show that learning data may be viewed from different perspectives requiring different levels of granularity and fidelity over different time horizons. For example, a learner may be pursuing a specific job credential required for promotion. They need to participate in one of more courses (e.g., a sequence of learning activities) in support of their career trajectory. This example can be viewed in the context of control loops 2,3, and 4.

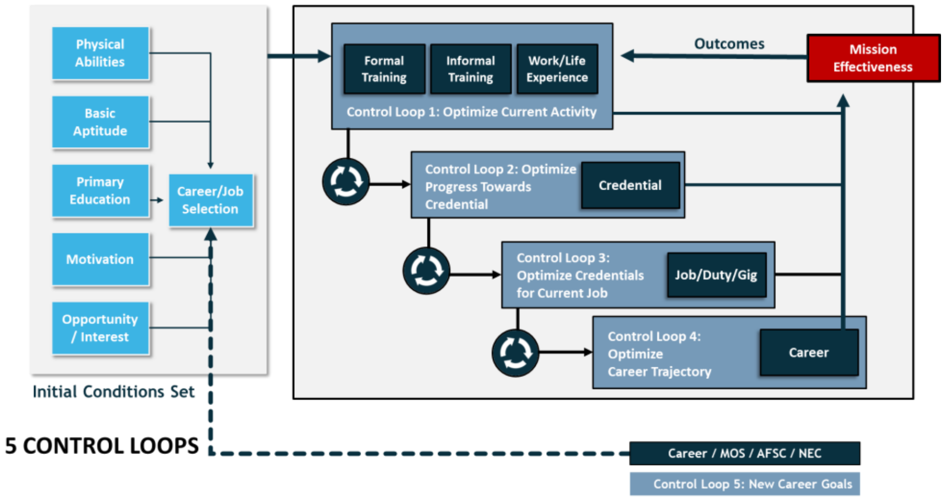

Fig. 7. TLA Control Loops. TLA MOM statements act as the sensors for the different control loops. The five control loops are constantly operating in parallel, but they provide a convenient way to categorize data.

This approach to learner management enables a system of digital trust that provides auditability, privacy, and data integrity for the chain of evidence (e.g., raw learner performance data) used to assert proficiency levels for individuals or teams against one or more competencies. The five control loops in order of ascending time horizons address:

- **Control Loop 1**: Using learner performance data to optimize the transfer of learning within the current learning activity (e.g., Intelligent Tutoring, Instructor Support).
- **Control Loop 2:** Using learner performance data across numerous learning activities to optimize a learner's progress toward a credential.
- **Control Loop 3:** Using longitudinal learner data to prioritize the pursuit of credentials or activities to meet requirements for a potential job.
- **Control Loop 4:** Lifelong learning data to support career field management and the planning of education and training goals for an overall career trajectory.
- **Control Loop 5:** Lifelong learning data to support the establishment of a new career.

2.1 The Sum is Greater Than its Parts.

Each TLA data pillar builds upon existing standards to increase the granularity and fidelity for how we describe learning resources, learners, their performance, and the competencies that need to be taught. The data models that drive the different TLA standards rely on other systems within the Human Capital Supply Chain to populate many of their data elements. Automation and a well-defined governance strategy are critical to updating and maintaining the data stored within each TLA data warehouse.

The TLA is asynchronous, and event driven. Every device or service in the ecosystem appears as either a learning record provider (LRP) and/or a learning record consumer (LRC). In many cases, a system may perform both roles (e.g., adaptive instructional systems). The use of APIs and microservices is designed to support modern high-performance messaging system and means that there is no single system responsible for coordinating the execution between components. This statelessness is essential for the loose coupling required to be a true ecosystem.

While most LRS solutions offer dashboards to view learner performance, they are commonly used to view xAPI statements that have been generated within a single learning activity. From an adaptation perspective, that data has great potential to automate remediation, feedback, or other optimizations that help expedite the transfer of learning.

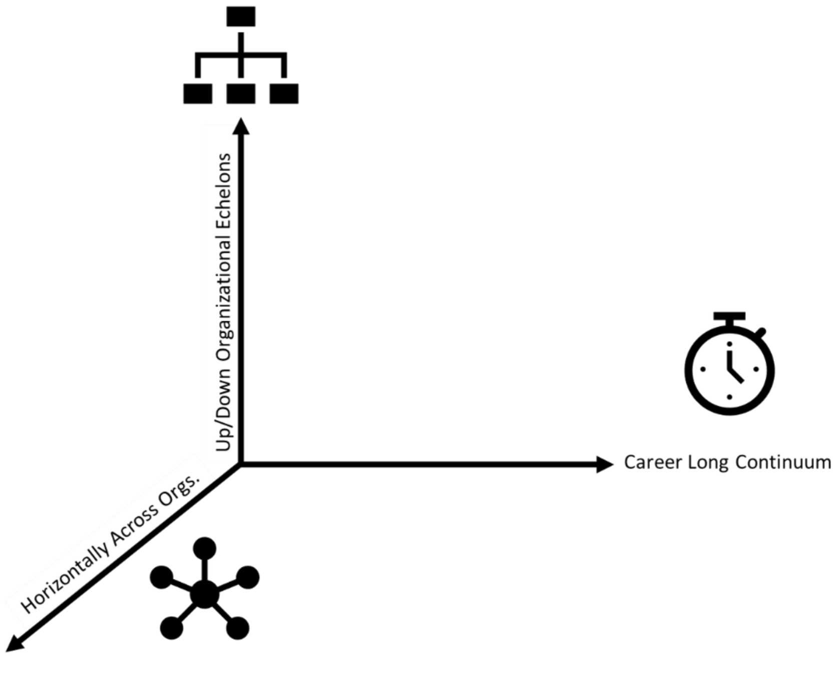

Fig. 8. Breadth and Scale of Learner Data. Learner data can be shared vertically within an organization, horizontally across other organizations, or longitudinally throughout a career.

The inclusion of the TLA MOM provides additional insights into how learning activities are used to support training and education within an organization. Tracking this information provides insights into learner path, learner velocity, and overall effectiveness. The addition of learning activity metadata and competency definitions enhance these capabilities by affording opportunities to tie training and education outcomes to key performance indicators in the operational environment.

The totality of this data promotes adaptive systems beyond training and education and afford new opportunities for career field management, workforce planning, and cross-training. **Figure 8** shows the breadth and scale for how this data might be used to support the scope and breadth of DoD organizations from instructor dashboards to robust analytics for readiness and capable manpower. The data also supports the lifelong continuum of learning for all DoD personnel.

2.2 Data-driven Adaptation

Artificial intelligence (AI) and Machine Learning (ML) are becoming powerful tools for adapting instructional content to increase motivation, autonomy, effectiveness, and efficiency of learners and teachers [17]. Data driven learning can take place in traditional face-to-face learning settings, as well as in the technology-enhanced learning settings. The scope and scale for how adaptation is implemented within a course or activity spans a wide range of use cases. Learning analytics have long been used to inform instructors, improve course content, or adjust how the course is delivered [18].

Beyond the scope of a single learning activity, TLA data may be used to provide insights into students' learning trajectories. Reeves (19) discussed three approaches for assessing online learning environments in higher education. The cognitive assessment focuses on measuring the higher order thinking abilities of students, achieved through means such as concept mapping. Performance assessment can be done by looking into the learner's ability to apply knowledge in realistic contexts, done by requiring students to demonstrate their capabilities directly through product creation or through engagement. Finally, a portfolio is where the work of the student is stored over time so that it can be reviewed with respect to both process and product.

In recent years, progress has been made towards providing adaptivity and personalization in technology-enhanced learning environments. However, the breadth of data made available through the TLA standards supports adaptive systems that optimize or tailor instruction to support the needs of the organization. Well-defined competency definitions can be used to link training and education resources to key performance measures in the operational environment. This data provides has potential to provide a longitudinal analysis that links training and education activities to performance in the workplace.

Competency frameworks and their associated competency definitions can also be adapted to suite the needs of the organization. The tasks, conditions, and standards for demonstrating proficiency are highly dependent on the local context. Local weather conditions, geographic location, or the availability of learning resources, coupled with organization goals and/or mission parameters might drive adaptation around the sequence of learning interventions that a learner is provided. Alternatively, performance support tools may also adapt to provide just-in-time support to learners while doing their jobs.

The TLA project has established a foundational data strategy that supports adaptation for learners, instructors, and organizational needs. TLA data standards will continue to evolve and adapt to better support the needs of the future learning ecosystem. As adaptive instructional systems mature and refine their algorithms, new data elements may be required within certain standards. This requires changes to how we develop standards so they can be continuously managed, refined, and updated through a well-defined governance strategy.

2.3 Conclusions and Next Steps

The aggregation of TLA data provides a baseline for continuous process improvement across all aspects of training and education from scheduling and planning activities to evaluating their effectiveness against key performance indicators in the operational environment.

Increased fidelity of learner data also provides insights into the different paths different learners take to achieve proficiencies in their chosen careers. Learning trajectories within career trajectories can be tailored to support different groups of learners and improved insights into career progressions can help expedite growth across different to present new opportunities for employees. Senior leaders within an organization may also use this information to evaluate readiness towards achieving mission outcomes. Workforce planning and cross-training opportunities will converge to help organizations adapt to evolving requirements.

The different IEEE standards that the TLA is built around are at different stages of the standardization pipeline. The IEEE's xAPI 2.0 standard is due to be released in 2021; the update to the Reusable Competency Definition Standard (IEEE 1484.20.1) is also expected in 2021; the IEEE P2881 Working Group is actively developing their draft standard for Learning Activity Metadata and the IEEE Enterprise Learner Record Study group is actively evaluating a draft data model to evaluate its potential as an IEEE standard.

These data standards should be viewed as a foundation to be continuously improved upon as the tools and technologies used for training and education evolve. The aggregation of data collected by these standards will have increasingly important roles across organizational boundaries, thus enabling the future learning ecosystem.

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14. ABSTRACT
Since 2016, the Advanced Distributed Learning (ADL) Initiative has been developing the Total Learning Architecture (TLA), a 4-pillar data strategy for manag-ing lifelong learning. Each pillar describes a type of learning-related data that needs to be captured, managed, and shared across an organization. Each data pillar is built on a set of international data standards that combine to increase the granularity and fidelity of learner data. Reusable Competency Definitions (IEEE 1484.20.1 RCD) are used to describe the Knowledge, Skills, Abilities, and Other behaviors (KSAOs) that are re-quired in the workplace (e.g., the operational environment). Learning Activity Metadata (IEEE P2881 Learning Activity Metadata) is used to describe the various learning re-sources an organization uses to train and educate its people. The Experience API (IEEE 9274.1 xAPI) is used to track and manage learner performance both inside and outside a learning activity. An Enterprise Learner Record, currently an IEEE study group, is used to track and manage each learner’s level of competency within the organization.

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