Generalizable Learning Engineering Adoption Maturity Model

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ABSTRACT

In this paper we provide a generalizable learning engineering adoption maturity model for appraising an organization's or enterprise's maturity in adoption of learning engineering practices. Learning engineering is a process and practice that applies the learning sciences using human-centered, engineering, design principles and data-informed decision-making to support learners and their development.

This model draws concepts from previous work including the IEEE International Consortium for Innovation and Collaboration in Learning Engineering's definition of learning engineering as a process and practice, a maturity model for learning ecosystems, the ADL Initiative Distributed Learning Capability Maturity Model, a Learning Engineering Virtual Training Systems with Learning Science, Data Standards and a Capabilities Maturity Model) and the definition of learning engineering team member competencies by the IEEE ICICLE Competency, Curriculum, and Credentials Special Interest Group. The model is offered as a foundation for developing industry standard recommended practices for learning engineering that may be formalized through future work with standards development organizations.

We defer to other instruments to assess the capability, capacity, or readiness of any individual or organization in the competencies required for learning engineering. This model is designed to assess if an organization or enterprise has actually adopted learning engineering processes and practices to some degree and at some level of fidelity. This model attempts to answer the question, to what extent is the organization or enterprise **doing** learning engineering?

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INTRODUCTION

Learning engineering is an emerging professional practice that applies principles from the learning sciences, systems and implementation sciences, engineering, and data analytics to support effective learning experiences—particularly at scale. As a discipline, learning engineering is differentiated from related practices (such as instructional design) in several ways, including its multidisciplinary approach, emphasis on continuous improvement, incorporation of higher-level and longitudinal perspectives, extensive use of data-informed methods, and broad approach to outcome achievement.

As a new and complex discipline, however, organizations and multi-organization enterprises may find it difficult to implement learning engineering, evaluate their internal progress, and make systematic decisions on where to invest future resources. This is where a Maturity Model can help.

Maturity models are structured frameworks that describe what different levels of maturity look like. They serve as self-evaluation rubrics and roadmaps for organizations to improve their processes, products, and services. In the 1980s the United States Air Force funded a study at the Software Engineering Institute (SEI) to determine why software projects were failing and over budget. This work led by Watts Humphrey laid the groundwork for the Software Capability Maturity Model (CMM) (Carnegie Mellon University Software Engineering Institute, n.d.).

Maturity models are useful for several reasons: They offer a systematic approach to assess and enhance processes, leading to increased efficiency and quality. Through benchmarking against industry standards, maturity models help identify areas for improvement and prioritize efforts, and they can be useful tools to compare one organization against another or to compare one's own organization against prior versions of itself to document progress.

Maturity models, used to assess and improve organizational processes, may face critique for being too rigid. Critics may argue that these models may not fully capture the unique complexities and dynamics of different organizations, leading to a one-size-fits-all approach that can overlook context-specific needs. Additionally, maturity models might be implemented with a grading mentality, where the focus is on achieving a certain level rather than on genuine improvement. To mitigate these limitations, organizations should adapt maturity models to their specific contexts, using them as flexible frameworks rather than strict blueprints. Organizations may complement maturity models with other assessment tools for a more holistic view. Furthermore, organizations may consider maturity models as a tool to discover specific opportunities for growth rather than focusing on an overall level or score.

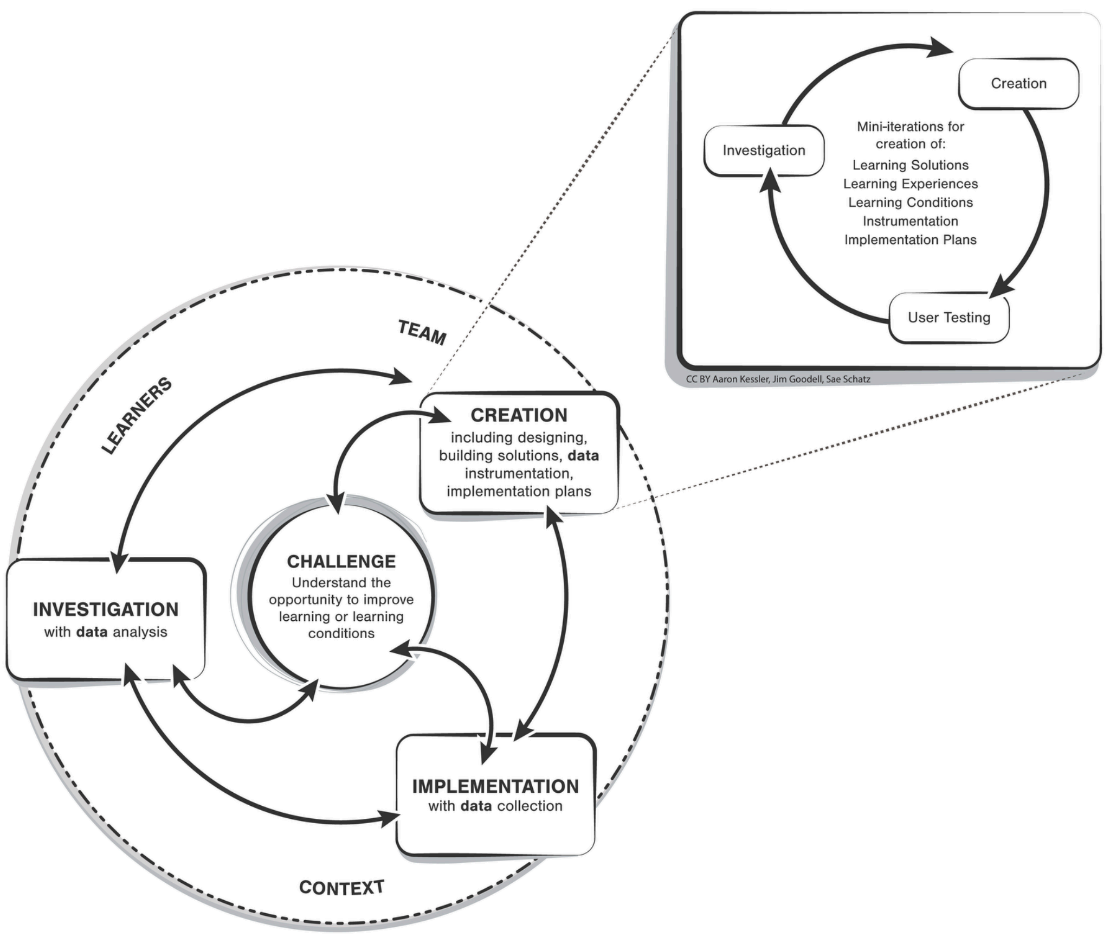
The learning engineering adoption maturity model presented in this paper has been developed for ease of use through iterative development with potential end users; it has value for large businesses, government programs, and academic institutions, all of which may use it to guide their adoption of the learning engineering process. It is being offered as a baseline for further iterative development by standards organizations to build future industry best practices for learning engineering and its systematic implementation.

LEARNING ENGINEERING

> *"Learning engineering is a process and a practice that applies the learning sciences, using human-centered engineering design methodologies and data-informed decision-making, to support learners and their development."*
>
> (IEEE Industry Connections Industry Consortium on Learning Engineering, 2019)

Learning engineering is a growing applied discipline and process. It can be conceptualized as a 21st century evolution of the original ideas that produced the Instructional Systems Design / Development (ISD) process for the military in the late 20th century – a process that was intended to help industry create and sustain training for the systems they were building for DoD in a systematic process – using data from learning and performance outcomes to improve upon the original learning content. Learning engineering maintains the systemic nature of learning design and development that ISD introduced, but requires a more robust, data-informed iterative model of design and development than is often employed. Figure 1 shows a conceptual model of the learning engineering process (Kessler, Goodell, & Schatz, 2022; Kessler et. al., 2022).

Figure 1. The Learning Engineering Process



This process is suited to modern learning solutions that are no longer just products of paper media, instructor guides and trainee guides or textbooks that follow a single script of instruction. Learning engineering adopts the culture and practices of modern "agile" engineering, emphasizing systems thinking and data-informed engineering for rapid development of quality learning solutions. The learning engineering process considers data at each step. This may include data instrumentation using sensors and data pipelines, and learning analytics to support data-informed iterative improvement. As such, learning engineering can be thought of as both a modern mindset and process based on the best of what was and what is: an aggregation and assimilation of many disciplines, ideas and practices. From this, learning engineering will likely further evolve.

Learning engineering is an applied discipline that fuses together established disciplines, including learning science, human-centered design, engineering methods, data engineering and analytics, and principles of organizational performance and implementation science. It's also an emerging professional discipline with shared principles, practices, ethics, and terminology.

The principles of learning engineering include tenets such as these:

- Be data-driven throughout the entire learning lifecycle
- Continuously improve learning activities – like development operations (DevOps) for learning
- Incorporate UI/UX throughout all aspects (human-centered design)
- Use learning activities to reach a goal (not solely an end to themselves)
- Actively intertwine learning science, technology, data, UI/UX, and organizational performance principles.

Learning engineering extends to the learning environment and contextual factors that impact learning. For example, the learning engineering process might improve a training program's outcomes simply by addressing a faulty wi-fi network in an office space, if that was identified as the main bottleneck preventing improvements to workers' learning and performance.

Learning engineering takes into account collecting data from a wide range of sources. It goes beyond the focus of explicit assessments in learning settings. It emphasizes data-driven processes. It includes sources such as clickstream behaviors (taps or clicks), trace data (digital 'fingerprints' generated through a person's interactions, such as dwell-time on an e-book page or a response to a forum post), and implicit estimations (such as using algorithms to predict learner engagement, frustration, boredom, or confusion).

LEARNING ENGINEERING ADOPTION MATURITY MODEL

Purpose and Approach

The tool defined in this paper is designed to assess the level at which an organization or enterprise has adopted learning engineering processes and practices, i.e. the extent to which the organization ***is doing*** learning engineering.

This tool is intended to work with other tools that assess an organization or enterprise's capabilities or readiness to do learning engineering. For example, a subgroup of the IEEE International Consortium for Innovation and Collaboration in Learning Engineering (IEEE ICICLE) is developing competency frameworks for the various roles on learning engineering teams. The tool is not intended to score or grade an organization. It is rather intended to be an easy to consume (text light) and easy to use formative tool that organizations can use to determine next steps and areas for improvement on a pathway toward full adoption of learning engineering.

Design Goals

Priority design goals for the tool were utility and usability, making it as easy as possible to assess generally where an organization is on a continuum from non-adoption to full-adoption of key learning engineering practices.

Design Process

The Adoption Maturity Model is being generated through iterative design, publication, and open discussion at conferences and through the IEEE ICICLE community of practice. Our process has been to iteratively build on concepts discovered through more contextualized prior work to inform a new generalizable high level archetype model with input and feedback from representatives of people and organizations that might use the tool in the future.

PRIOR WORK

The tool has been informed by concepts from previous work, as described below, including the definition of learning engineering as a process and practice (IEEE ICICLE, n.d.), the ADL Initiative *Distributed Learning Capability Maturity Model* (Malone et al., 2020), "Learning Engineering Virtual Training Systems with Learning Science, Data Standards and a Capabilities Maturity Model" (Owens, et al., 2023) and the IEEE ICICLE Competency, Curriculum, and Credentials Special Interest Group's definition of learning engineering competencies.

Definitions of Learning Engineering

The IEEE International Consortium for Innovation and Collaboration in Learning Engineering defines learning engineering as "a process and practice that applies the learning sciences using human-centered, engineering, design principles and data-informed decision-making to support learners and their development (IEEE ICICLE, 2018)." In addition, IEEE ICICLE (n.d.) defines learning engineering as a process with which "the people on the team will differ depending on the challenge or problem to be addressed. It may be a single person with a broad set of skills or an interdisciplinary team of professionals with expertise in a range of areas."

ADL Initiative Distributed Learning Capability Maturity Model

The current model, particularly the rubric for data instrumentation, is informed by the ADL Initiative Distributed Learning Capability Maturity Model (DL-CMM). The DL-CMM shows the resources, expertise and capabilities an organization needs to optimize its use of distributed learning. The rubric criteria for an organization's infrastructure and data strategy to promote data sharing and usage in distributed learning is similar to the criteria for data instrumentation to support data-informed decision-making in adoption of the learning engineering process.

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

The current model is informed by a prior capability model (Owens, Blake-Plock, & Goodell, 2023) that was more narrowly scoped for virtual training device (VTD) programs, and used the US Government Accountability Office (GAO) recommendations to the Department of Defense (DoD) services for virtual training devices as a theoretical framework. That decision-aid was organized according to subprocesses of learning engineering and data standards.

Learning Engineering Team Competencies – Work of the ICICLE CCC SIG

The Competencies, Curriculum, and Credentials (CCC) Special Interest Group of ICICLE is developing competency frameworks for learning engineering disciplines. The work informs this model's rubric criteria through insights about multidisciplinary collaboration and effective team practices. For example, while examining the various disciplines contributing to successful learning engineering teams, the group has discovered ways that effective and mature teams work together across disciplines for shared understanding of learning engineering challenges and collaboration through iterative cycles of the learning engineering process. The most mature teams continuously improve through cross-training and team performance optimization.

DIMENSIONS OF LEARNING ENGINEERING ADOPTION

The dimensions of the Generalizable Learning Engineering Adoption Maturity Model are from the official definition of learning engineering adopted by IEEE ICICLE with an added dimension reflecting the multidisciplinary nature of learning engineering. These dimensions have been vetted through iterative design, publication, and open discussion at conferences and through the IEEE ICICLE community of practice.

The maturity model is divided into six separate rubric criterion (presented as tables rows) used to indicate:

A. maturity of an organization in adopting learning engineering as a multidisciplinary practice
B. maturity of an organization in adopting the learning engineering process
C. maturity of an organization in adopting and applying the learning sciences
D. maturity of an organization in adopting human-centered design practices
E. maturity of an organization in adopting systems engineering
F. maturity of an organization in adopting data-informed decision-making

Each rubric offers criteria to indicate to what extent is the organization or enterprise ***doing*** the dimension of learning engineering, from "**indicators of no adoption**" to "**indicators of mature adoption**." This is a *formative* tool for organizations to discover areas for further development rather than to generate a score for comparison.

Indicators of No Adoption	Indicators of Some Adoption	Indicators of Maturing Adoption	Indicators of Mature Adoption
A. Adoption of Learning Engineering as a Multidisciplinary Practice			
The organization has not adopted a multidisciplinary approach or mindset.	The organization draws from multiple areas of expertise when developing learning solutions, but work is handed-off across different functional or domain-based people or teams without much interaction within stages of the process.	The organization employs multidisciplinary teams (or accesses multidisciplinary expertise) to address learning engineering challenges. When a team is required, the team members may contribute different levels of effort at different stages but continue to meet regularly and make shared design and development decisions based on data and insights gained from end-users of the experience or solution.	The organization employs a*ll indicators in the previous column* plus cross-training and team performance optimization. Team members are continuously learning from each other and developing skills in other domains of learning engineering. Data are used to continuously improve the learning engineering process. (*Teams may include humans working with AI agents learning from each other to optimize performance of the learning engineering process.)*
B. Adoption of the Learning Engineering Process			
The organization uses a waterfall, non-iterative process. That process does not start by defining a challenge. That process does not sufficiently consider contexts, resources, or constraints. The decisions made are not informed by data.	The organization uses a process that does not support iteration and/or lacks elements of the learning engineering process, e.g., challenge centric, iteration, human centered, data instrumentation, data analytics.	The organization only partially uses the learning engineering process, e.g. in only some parts of the enterprise, for only some projects, without full fidelity or limited by constraints of the enterprise policy structure.	The organization uses the learning engineering process enterprise-wide and with full fidelity. It is fully supported by the enterprise policy, e.g., budgets and procurement policies support iteration for continuous improvement. The full iterative, data-informed, multi-cycle process is used that includes defining the challenge in context, considering resources and constraints, iterative design-development cycles, implementation with instrumentation, investigation to inform the next cycle or next challenge.
C. Applies the Learning Sciences			
The organization is not able to defend design decisions with sound learning sciences concepts and there are no records showing that learning sciences concepts have informed design decisions. Decisions may be based on "faux science" about how people learn. Management direction is provided without learning science expertise being consulted or considered.	The organization is sometimes able to defend design decisions with sound learning sciences concepts. Management direction is provided without learning science expertise being consulted or considered.	The organization is able to defend many design decisions with sound learning sciences concepts. Management decisions may be informed by some level of learning science awareness.	The organization maintains logs of key design decisions with justification of those decisions supported by sound learning science. Management direction is informed by learning sciences expertise. The team employs applied research methods when the prevailing science is not sufficient to inform design decisions.

Indicators of No Adoption	Indicators of Some Adoption	Indicators of Maturing Adoption	Indicators of Mature Adoption
D. Using Human-Centered Design Process			
The organization develops learning solutions without consideration of targeted learner background and context, human-factors principles or use of variability, e.g., factors such as prior knowledge /experiences, learning environments, technology available and learning-related constraints or advantages are not considered.	The organization develops learning solutions designed to consider some variation in target learner populations but may not consider learner contexts, have knowledge of human factors principles and/or variability dimensions.	The organization develops learning solutions using processes to identify target learners, human factors principles, learner contexts, and variability based on empathy from iterative engagements with learners. Teams may also design adaptations for some key factors of learner variability within those populations.	The organization develops learning solutions with input from learners using human-centered design processes and best practices–including using processes to identify target learners, human factors principles, learner contexts, and variability based on empathy from iterative engagements with learners–and builds solutions that adapt, scaffold, and make accessible learning experiences for a full range of learners and context variability factors.
E. Using System Engineering			
The organization develops learning content in isolation without considering contexts. The organizational mindset is focussed on content delivery rather than addressing human learning as a complex system of systems. No preliminary analysis or prototyping is done to show what areas are needed to be solved first and how.	The organization considers learning contexts but fails to consider the "bigger picture" of factors that impact learning.	The organization considers learning engineering from an engineering mindset as a system of systems, and considers a multitude of factors that impact learning including environmental conditions, contexts, learner variability. The organization develops component solutions but without fully employing common interfaces or standards to integrate each solution.	The organization applies system engineering design principles, including systems thinking and modularization, addressing component solutions as part of a larger overall solution, using common interfaces or standards to integrate each of the solution components. The organization addresses learning and learning solutions as data-informed closed loop control systems.
F. Data Informed Decision-Making			
INSTRUMENTATION: The organization does not capture learner experience data or data are captured using disparate tools and technologies with proprietary data formats. DATA USE: The organization develops learning solutions or content based on subjective assumptions that are not supported by empirical data analytics of targeted users, environments and context.	INSTRUMENTATION: The organization captures data using a data instrumentation standard (e.g. xAPI) format but the activity log data are not useful for analyzing the learning analytics that could be used to inform iterative improvement of the solution. DATA USE: The organization develops learning solutions or content based on limited available data from existing legacy platforms. During data analysis, single-point outlier data are filtered out as statistical anomalies. The organization claims success if the solution works on average in controlled conditions.	INSTRUMENTATION: The organization develops new instrumentation when needed to inform iterative improvement of the solution using open source data standards (e.g., xAPI), including linked metadata for learning resources and competency definitions (e.g. IEEE 2881, IEEE 1484.20.3). DATA USE: The organization develops each iteration of learning solutions or content based on investigation and data analysis from previous trials. Team occasionally examines outlier conditions then works to determine root causes and adjusts the solution accordingly	INSTRUMENTATION: The organization develops new instrumentation when needed using open source data standards (e.g., xAPI), including linked metadata for learning resources and competency definitions (e.g. IEEE 2881, IEEE 1484.20.3). Data instrumentation is developed while creating the solution and is designed to capture data needed to fully meet the feedback requirements of the solution and data to inform decisions about the current solution (e.g. for A/B testing solution alternatives). DATA USE: The organization develops each iteration of learning solutions or content based on A/B testing of the solution or intervention with targeted users, environments and context; using well formulated data questions; high-quality data; and appropriate learning analytics methods. Findings from data are used to define the challenges for future iterations of the learning engineering process. Team uses outlier data for failure mode analysis to determine areas for improvement.

ITERATING FOR A MORE USABLE MODEL

With the primary design goal of "utility and usability" in mind the authors reviewed the rubrics above and considered alternative formats. One format included only the "Indicators of No Adoption" and "Indicators of Mature Adoption" columns. The next iteration focussed on observable "Indicators of Mature Adoption." The following further simplified checklist format includes all of the "Indicators of Mature Adoption" from the above rubrics. *When using this checklist, unchecked boxes represent potential areas for developing greater maturity.*

GENERALIZABLE LEARNING ENGINEERING ADOPTION MATURITY MODEL as a Checklist

Indicators of Adoption of Learning Engineering as a Multidisciplinary Practice

- ☐ The organization employs multidisciplinary teams (or accesses multidisciplinary expertise) to address learning engineering challenges.
- ☐ When employing a team, the team members may contribute different levels of effort at different stages but continue to meet regularly and make shared design and development decisions based on data and insights gained from end-users of the experience or solution.
- ☐ The organization employs cross-training and team performance optimization.
- ☐ Team members are continuously learning from each other and developing skills in other domains of learning engineering.
- ☐ Data are used to continuously improve the learning engineering process and team performance. (*Teams may include one or more humans working with AI agents learning from each other to optimize performance of the learning engineering process.)*

Indicators of Adoption of the Learning Engineering Process

- ☐ The organization uses the learning engineering process enterprise-wide and with full fidelity.
- ☐ It is fully supported by the enterprise policy, e.g., budgets and procurement policies support iteration for continuous improvement.
- ☐ The full iterative, data-informed, multi-cycle process is used that includes (a) defining the challenge in context, (b) considering resources and constraints, (c) iterative design-development cycles, (d) implementation with instrumentation, (e) investigation to inform the next cycle or next challenge.

Indicators of Adoption of Applying the Learning Sciences

- ☐ The organization is able to explain design decisions with sound learning sciences concepts.
- ☐ The organization maintains logs of key design decisions with justification of those decisions supported by sound learning sciences principles.
- ☐ Management direction is informed by learning sciences expertise.
- ☐ Learning engineering practitioners or teams employ applied research methods when the prevailing science is not sufficient to inform design decisions.

Indicators of Adoption of Human-Centered Design Practices

- ☐ The organization develops learning solutions with input from learners using human-centered design processes and best practices–including using processes to identify target learners, human factors principles, learner contexts, and variability based on empathy from iterative engagements with learners.
- ☐ The organization builds learning resources, events, and solutions that adapt, scaffold, and make accessible learning experiences for a full range of learners and context variability factors.

Indicators of Adoption of Systems Engineering Design

- ☐ The organization adopts an engineering mindset and systems thinking.
- ☐ The organization applies system engineering design principles to address complex problems, including modularization, i.e. addressing component solutions as part of a larger overall solution, using standard common interface protocols to integrate components.
- ☐ The organization addresses learning and learning solutions as data-informed closed loop control systems.

Indicators of Adoption of Data-Informed Decision-Making

Instrumentation

- ☐ The organization considers data instrumentation while creating the solution.
- ☐ The organization specifies the instrumentation to capture data needed to fully meet the feedback requirements of the solution (e.g. feedback to learners) and data to inform decisions about the current solution (e.g. for A/B testing solution alternatives).
- ☐ The organization configures or adapts data capture and logging (such as with sensors and data pipelines), or develops new instrumentation when needed using open data standards (e.g., xAPI).
- ☐ The organization uses instrumentation that includes linked learning resources and competency definition metadata (e.g. IEEE 2881, IEEE 1484.20.3).

Data Use

- ☐ The organization develops each iteration of learning solutions or content based on testing (which may include A/B testing of alternatives) of the solution or intervention with targeted users, environments and context.
- ☐ The organization uses well formulated data questions; high-quality data; and appropriate learning analytics methods.
- ☐ The organization adopts an iterative and data-driven approach, uses findings from data to improve and refine the solution as well as define the challenges for future iterations of the learning engineering process.
- ☐ The organization uses outlier data for failure mode analysis to determine areas for improvement.

RESEARCH NEEDED

Additional research is needed on several dimensions. First, from a human-centered design perspective, we have limited data from few non-author ICICLE participants pointing to the checklist as potentially the preferred format. More formal research is needed comparing the perceived and practical utility and usability of the proposed formats. Further testing will be needed to determine if a given iteration of the tool is valuable for formative feedback to the organization in its growth toward learning engineering maturity. While the authors had stories of exemplar organizations and the processes they use in mind, e.g. as documented in *Learning Engineering Toolkit* (Goodell, J., & Kolodner, J., 2022), we recognize the need for additional case studies on organizations that have adopted and are adopting learning engineering processes and practices, and more research on what makes them successful and what hinders success. This research could discover additional dimensions of mature and effective learning engineering organizations not covered in the current model. Furthermore, research is needed to identify characteristics of organizations that are at different levels of maturity and to develop additional tools that help organizations reach higher levels of maturity. Further development of standards could be paired with exemplar assessments for organizations in various contexts to review and use as a guide.

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