Weaving the Fabric of Adaptive STEM Learning Environments Across Domains and Settings (aka 'Adaptive STEM LEADS'): The Stanford-DCL-Workshop White Paper

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I. Goals and Approach

This workshop was funded through the "Dear Colleague Letter (DCL): Principles for the Design of Digital Science, Technology, Engineering, and Mathematics (STEM) Learning Environments (NSF 18-017)." The goal of this workshop was to articulate a transformative vision of future STEM learning for diverse learners across domains and settings. We sought to forge a nexus among the emerging (a) sciences of learning, (b) assessment, and (c) data-intensive research (aka 'big data') to formulate frameworks and tools for designing STEM learning environments. Taking an equity-first approach for broadening participation through innovative designs, this project convened interdisciplinary teams to identify and propose forward-looking digitally-augmented STEM environments that bridge formal and informal learning contexts and which are inclusively responsive to the needs of every learner. The white paper articulates a future research agenda that could lead to new breakthroughs at the Human-Technology Frontier. The open-invitation design workshop, strategically located at Stanford University, and dissemination through a public website and community outreach activities at key conferences in which these scholarly communities convene was designed to ensure broad awareness of and access to these models, tools, frameworks, design principles, and research priorities for educators, researchers, and technologists.

The workshop was designed to construct needed new collaborations with the learning sciences, assessment, and computer science communities to design integrative STEM learning environments with robust in-process measures of adaptive learning that address key aspects of deeper learning, with a strong focus on learning that is NOT limited to a single setting or STEM subject—expanding across time, across settings, and to related STEM subjects (NRC, 2014). It convened innovators advancing the state-of-the-art in equity-focused, technology- enhanced STEM learning, educational data mining and learning analytics (Dede, 2015; Niemi et al., 2018), and educational measurement, to develop innovative ways to design and scale for a future of integrated STEM learning in an era of big data. An infrastructure of generative new algorithms and knowledge models, psychometric models, and learner pathway models will emerge from project activities at the intersection of such interdisciplinary perspectives to transform learning and assessment designs by incorporating signals from emerging designs from multimodal learning analytics (e.g. Chan et al., 2020; Davis et al., 2017; Ochoa & Worsley, 2016; Worsley et al., 2016) and software for multi-faceted, multi-contextual measurement of social-emotional learning indicators and academic competencies.

The project scope was guided by three questions:

1. How can learning environments for integrated STEM learning scale successful efforts across diverse student populations and bridge formal and informal learning contexts?
2. What innovative research methods, statistical techniques and modeling formalisms are necessary to embed theoretical models in data-driven computational approaches in order to capture, characterize and support causal claims about individual and team-based learning, especially for complex, multi-source streaming data?
3. How can multi-domain threaded learning progressions be created for integrated learning and assessment of STEM subjects?

II. **Key findings and syntheses on existing state of the art** (from workshop participants[1])

1. Workshop participants provided examples of learning that bridge K-12 formal/informal learning (e.g., Barron, 2010; Barron, Gomez, Pinkard & Martin, 2014; Cabrera et al., 2018; Sharples et al., 2015) and/or which integrates STEM disciplines and rich data capture in industry of learning-on-the-job (Boeing). Participants created a shared repository of key papers on workshop-relevant topics (see bibliography below), gave talks drawn from their work that connected to o workshop goals, and shared elements of a vision of expansive learning. These were considered in cross-specialization group discussions, report outs, and collaborative writing processes, resulting in design principles (see below) and associated Learning Environment Vignettes.

2. Interdisciplinary groups from learning sciences, assessment, and computer science designed learning environment vignettes comprising integrative STEM learning environments over space and time. The centrality of persistence and depth of learning for interest-driven learning was common to vignettes from all subgroups.

3. Participants concurred on their frustrations over the lack of longitudinal STEM learning data on interests, achievements, socio-emotional learning (SEL: Osher et al., 2016) across domains and settings to support the desired vision of adaptive integrated STEM learning.

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4. Participants' felt need centered on the importance of advancing the state-of-the-art of knowledge mapping which serves to articulate relationships between learning progressions across multiple domains. Our highly experienced researchers could not identify any integrated STEM learning examples yet of such multi-dimensional alignments of curricula and assessments. Yet weaving together data-driven integrated learning and assessment-for-learning-experiences across multiple STEM domains into threaded learning progressions of STEM subjects will be vital for learners' developing adaptive expertise across STEM domains, rather than only within-domain learning progress.

5. There is a general lack of uses in STEM learning research of good/varied measurement methods for capturing multiple forms of data from which we can derive socio-emotional learning (SEL) constructs (self-management and emotion regulation; self-efficacy, social-awareness and empathy; identity; mindsets) related to STEM learning achievements. For example, the belief that effort will lead to increased competence defines a growth mindset, found to foster greater achievement and well-being across academic, emotional, and social domains. Although there are robust SEL Measurement Instruments (Durlak et al., 2011; Dweck, 2017; Taylor et al., 2017; Yeager & Walton, 2011), what is missing is their usage by researchers in relation to STEM learning, much less integrative STEM Learning. Yet innovative research methods, statistical techniques and modeling formalisms will be necessary to embed theoretical models in data-driven computational approaches for capturing data and characterizing and supporting causal claims about individual and team-based learning and SEL profiles, especially when inferred from interpretations of complex, multi-source streaming data.

III. Insights for Adaptive STEM LEADS

The workshop participants generated a series of principles that best frame the future of technology-enhanced STEM education consonant with the workshop vision of forward-looking, integrative STEM digitally-augmented learning environments that bridge formal and informal learning contexts and which are responsive to the needs of every learner. These principles reflect the need to merge best practices in teaching and learning (Darling-Hammond et al., 2019) with innovative technology (Baran, 2014; Clark & Mayer, 2016). These principles included: (1) *Figure-Ground Flip Principle*, (2) *Measurement Principle*, (3) *Social and Generative Learning Principle*, (4) *Distributed Expertise Principle*, (5) *Learning Empowerment Principle*, and (6) *The Human-Virtual Agent (VA) Interaction Co-Evolution Principle.* Together each of the principles described below reflected the workshop participants' vision of how learning technology can improve with a careful reconsideration of ways to integrate technology into learning spaces with a reinvigorated vision of the dynamic nature of learning across disciplines and contexts.

1. **Figure-Ground Flip Principle**: One of the first considerations to be made in the integration of STEM education technology involves the need to broker the relationships between technology and real-world experiences (Barron & Darling-Hammond, 2010; Dawley & Dede, 2014), in other words, to socialize the knowledge transfer problem (Pea, 1987). Effective STEM education technology must carefully use the real-world as locale to ground sites for learning: Nasir and colleagues highlight how, "Often, people can competently perform complex cognitive tasks outside of school, but may not display these skills on school-type tasks" (Nasir, et al., 2014, p. 491). As technology brings real world STEM inquiry into schools in relation to real-world application and utility, students will be provided opportunities to incorporate telepresence, virtual labs, augmented reality, and virtual reality and agent-based modeling (Blikstein, 2012; Wilensky & Rand, 2015) as a means to better understand their lived experiences and real-world phenomenon. While learning with simulations and models of phenomenon is useful, learning which situates new technologies in real-world inquiry experiences must emerge as a priority (e.g., Blikstein, 2012; Lee & Drake, 2013; Pea, et al, 2011; Sharples et al., 2015).

2. **Measurement Principle:** As new technologies emerge, these technologies must incorporate the capacity not only to make assessments-*of*-learning, but to broadly and effectively serve to support assessments-*for*-learning (Gerard et al., 2015; Gobert et al., 2018; Huda et al., 2018; Kippers, Wolterinck, Schildkamp, Poortman, & Visscher, 2018; Pellegrino, diBello & Goldman, 2016; Yin, Tomita, & Shavelson, 2014). As back-end data analytics continue to provide useful learning information, these assessments must be integrated into the STEM technology of the future to allow for real-time assessment and iterative refinements of digitally-enhanced instruction (Gaine, Zaidi, Pellegrino, 2018; Gerard et al., 2015). Additionally, the measurements principle must be extended to the use of long-term performance assessment with technology. Embedding performance assessments in STEM learning technology will enable STEM technology to track and support students' STEM interest and development of their competencies such as inquiry and argumentation-based thinking over time (Gobert et al., 2018). As scholarship and technology improve in parallel, they must engage in multidimensional measurement that incorporates both individual and group assessment practices.

3. **Social and Generative Learning Design Principle:** One of the fundamental limitations of contemporary STEM technology is a limited incorporation of our scientific understanding of learning processes (NRC, 2000, NRC, 2018). As such, emergent STEM technology must be designed with the intention of fostering generative student learning. Given our knowledge of learning as *active*, *socially constructed*, and *situated* (Brown, Collins, & Duguid, 1989), emergent STEM technology must be intentionally designed to produce the types of learner engagement that requires them to explain,

argue, and share their STEM knowledge between learners, with teachers, and within their broader social communities (e.g., Barron et al., 2014; Fields et al., 2017; Litts et al., 2016), with a social design focus which expands learning opportunities for traditionally under-represented students in STEM disciplines (e.g., Calabrese Barton et al., 2017, 2018; Esmonde & Booker, 2016; Gutiérrez & Jurow, 2016; Martin & Barron, 2016).

4. **Distributed Expertise Principle:** As learners engage with STEM technology, the learners and participants in their communities must be included as learning agents (Barron & Bell, 2015; Brown et al., 1993; Pea, 1994), as 'actors' in an actor-network theory of learning (Barab et al., 2001). As knowledge is distributed among a dynamic set of contributors, STEM technology must carefully integrate expertise from all students and communities. Instead of offering a one-way transmission of knowledge, an informed conception of STEM technology-enhanced learning will benefit from adopting a distributed expertise approach to design.

5. **Learner Empowerment Principle:** Learning is far more than a simple cognitive task. Psychologists and sociocultural theorists have called for more expansive visions of how learning works (Ambady, Shih, Kim, & Pittinsky, 2001; Gutierrez & Rogoff, 2003; Ladson-Billings, 1995; Purdie-Vaughns, Steele, Davies, Ditlmann, & Crosby, 2008). Given that reality, a future of STEM technology must apply a more dynamic and culturally-inclusive conception of learning and allow technology to foster STEM learning agency and self-efficacy for equitable participation. As technology is developed, special attention must be paid to ensuring that the technology supports full inclusivity of diversity with respect to gender, race, ethnicity, culture, (dis)abilities, and context. It will be vitally important to establish inclusivity of access so that all learners including students and teachers with disabilities can benefit from cyberlearning opportunities (Burgstahler & Thompson, 2019). The STEM technology of the future must be one rich in learning opportunities that allows students to rethink who participates in STEM and provides students a sense of belonging that is embedded in the design of the learning technology and its uses for building STEM competencies and identities (Cheryan et al., 2015).

6. **Human-Virtual Agent (VA) Interaction Co-Evolution Principle:** Human-VA interactions for supporting the development of STEM skills and competencies across settings and disciplines. At the dawn of personal computing, Douglas Engelbart established a vision of human-machine systems co-evolving with the distinctive strengths of each form of intelligence being leveraged (Bardini, 2000). In recent years, virtual pedagogical agents have been providing many learning-support-relevant interactive features that can serve to backstop human teachers or otherwise support processes for engaging and deepening learning (Johnson & Lester, 2018, Mudrick et al., 2017). The aim has been to

create intelligent systems that can interact with learners in natural, human-like ways to achieve better learning outcomes.

IV: Tensions & Surprises

The vision of adaptive integrative STEM technology-enhanced learning is one that must be approached with respect to the tensions and limitations inherent in taking an ambitious approach to improve STEM learning with advanced technologies. The participants outlined six primary tensions that must be explored in an effort to reach the idealized goals outlined above.

1. **Tension - Knowledge Integration:** Learning progressions have been conceived primarily within specific domains only, yet the aim of NGSS-based science and NRC reports (2012a, 2014b) calls for adopting a more integrated approach to STEM teaching and learning. Given that the learning goals should sustain the aim of integrating science learning that weaves together disciplinary topics, technology must attempt to successfully walk the fine line between mapping learning progressions for linear growth and reflecting a more dynamic sense of interdisciplinary learning. For example, we know certain math competencies (e.g., proportional reasoning) are required for learning of specific topics and competencies in science, but mappings that articulate prerequisites/relationships and their integral interconnections are as yet unspecified in any standard, broadly-useful or broadly-used manner. As context drives learning, students may arrive with expertise outside of the frameworks of learning progression guidelines. As such, technology must balance the dueling goals of providing trajectories of cognition with the capacity to identify context-specific knowledge that may bridge understanding.
2. **Tension - Capturing and Storing Multimedia Data:** A foundational principle described above focused on the careful and intentional use of back-end data to build better, more adaptively- responsive learning technology (Natriello, 2013). Sensing technology developments and expertise spanning a range of socio-technical fields is lowering barriers to investigating such interactions in authentic learning and work environments. An inherent challenge in these data uses involves the need to store and have real-time access to longitudinal data across settings for creating comprehensive learner profiles to better serve learning needs. While many agree with the goals of data capture and use to support learning, the inherent concerns of data privacy and risks of stereotyping due to labeling must be carefully considered as data are increasingly used to build improved learning environments (Niemi, Pea, Saxberg & Clark, 2018; Pea, 2014), and run risks of providing, without critical reflections, ‘algorithms of oppression’ with discriminatory outcomes, reinforcing disempowering biases and stereotypes (Noble, 2018; WEF, 2018).

3. **Tension - The Inscrutability of the Artificial Intelligence Models:** As technology adopts machine learning and artificial intelligence (AI) models, care must be given to how AI is used to make specific learning recommendations for learning. While teachers have the capacity to engage in differentiation and make real-time decisions about students' learning needs, an emergent use of AI must carefully assess when and how AI databases make recommendations for what to learn, when to learn it, and why a learner should be learning a given topic. The cyberlearning field would do well to heed the insightful observation that: "Effective governance of algorithms comes from demanding rigorous science and engineering in system design, operation and evaluation to make systems verifiably trustworthy" (Kroll, 2018).

4. **Tension - The Need for Data Interoperability In and Out of School:** A limitation of contemporary approaches to research is the false division between learning STEM in school and learning STEM in out of school contexts. As the STEM education technology of the future is conceived, developers and educators must pay more attention to ensuring the data that is derived from in school and out of school learning contexts are connected in a meaningful way. As back-end databases are employed, they must be done in a manner that allows for the integration of learning data collected during software use both in school and out of school environments (Behrens et al., 2019).

5. **Tension - The Integration of STEM Teachers in Technology Development**. Years of research have implicated a lack of cooperation between teachers and educational technology developers as a factor that undermines the adoption and functionality of STEM technology. Increasingly, design-based implementation research is actively engaging teachers in design and data-driven redesign efforts to foster effective, equitable learning designs (e,g. Leary et al., 2016; Tissenbaum et al., 2012). As educational technology improves in the years to come, STEM technology developers and scholars must focus on the foundational role that teachers play but which is often ignored by AI in education discourse, where 'adaptive learning algorithms' tend to neglect the real-time and face-to-face values of teachers in student learning.

V. Distinguishing near, medium and long-term research priorities

In their collaborative reflections, workshop participants sought to differentiate distinctive temporal levels for fulfillment of aspects of the workshop's vision, that is, we asked which aspects are sufficiently mature to inform near-term design of learning environments (*immediate future); which aspects would require additional design and development research (**medium-term, 1-to-3 years); and which aspects would require basic or foundational research (***longer-term, 3-to-5+years).

There were a variety of constructs that workshop groups surfaced as needing specification and cumulative knowledge building at each of these three programmatic temporal levels. We now describe five goal categories, note the programmatic temporal level for the pursuit of each of these goals, and note that some of the subgoals within the five goal categories have more future-oriented research needs to fulfill the workshop vision, which we accordingly demarcate with ** or ***.

1. *Construct specification and measurement goals:
    a. The field will need to define central constructs of Socio-Emotional Learning such as STEM Interest, STEM disciplinary Identity, STEM Learning Engagement, STEM Learning Self-Efficacy, and to develop and refine robust instruments for measuring them for domain-integrative STEM learning across learning times and locations.
    b. Further advances in weaving the Fabric of Adaptive STEM Learning Environments Across Domains and Settings will be achieved by identifying and measuring competencies that cross-cut STEM domains (e.g., Abstraction, Modeling, Spatial Reasoning, Algorithmic Thinking, Systems Thinking, Critical Thinking, as called for in NRC, 2012a).
2. *Identifying STEM learning interests for students/groups/classrooms and computing architecture which enables adaptive recommendations for learning pathways. Extensive research indicates the catalytic nature of student interest in a topic for their inquiries and depth of learning about it (Azevedo, 2018; Barron, 2006; Renninger & Hidi, 2017). Sparked interests for learning drive learning persistence and other consequential learning activities such as seeking learning resources, learning guidance and learning brokers that can serve these needs (Barron & Bell, 2015; Kafai & Peppler, 2010). Therefore, identifying STEM learning interests of students in learning environments is an important goal in learning environment design. Accordingly, anytime-anywhere integrative STEM learning requires computing architectures which will enable adaptive recommendations which can establish personalized learning pathways cued from identified learner interests to fulfill the aims of integrative STEM learning for all learners. In higher education, Jiang, Pardos & Wei (2019) have developed a novel recurrent neural network-based recommendation system for suggesting courses to help students prepare for target courses of interest, personalized to their estimated prior knowledge background and zone of proximal development.
3. **Identifying STEM learning interests creates the need for Instrumentation Goals, and integrative STEM Learning Progression Mapping Goals.

a. **We suggest the value of pursuing the topic of *Ubiquitous Interest Sensor*s, viz. how do we capture and make sense of signals of learner STEM interest for diverse learners across domains and settings? We presume the technical feasibility, if yet-to-be-resolved ethical and data privacy policies, of sensor instrumentation of learning environments inside and out of school and of learner activities in such distributed environments which employs their personal computing devices (e.g., Lee & Drake, 2013).
b. **Creation of Triggered Learning Pathway Openings based on sensings of learner interests: Presuming the provision of anytime-anywhere integrative STEM learning computing architectures, and the establishment of ubiquitous interest sensors, the technology-enhanced learning environments should be able to recommend learning pathway openings based on the learning interests inferred in learner models from data sensed for the learners interacting with those systems.
c. *Assessments 'for' learning progress (tied to topics/concepts in STEM domains and related standards) stemming from the nodes achieved in learners' progress through their **Longitudinal Integrative STEM Learning Progression Maps.

(4) **Defining multi-threaded learning progressions for integrated STEM. Learning progressions are the roadmaps seeking to align curriculum, pedagogy, and assessment (Black, Wilson & Yao, 2011; Wilson, 2009): They demarcate consequential locations on the learning journey from novice to expert by characterizing what a learner at each key location on the roadmap knows and is able to do. The descriptions highlight what is unique about each location, ensuring that differences between locations are emphasized so the transformations in skills and knowledge along the learning journey can be recognized. The hope is that by mapping the learning journey with such knowledge maps, learning progressions can create a common ground for the coordination of the works of curriculum developers, teachers, and assessment designers. Today we principally have available studies of learning progressions *within* STEM domains, as in mathematics (Confrey et al., 2013; Lehrer, et al., 2014; Maloney et al., 2014; Sztajn et al., 2012) and the sciences (e.g., Alonzo, A. C., & Gotwals, 2012; Berland & McNeill, 2010; Catley, et al., 2005; Duncan et al., 2009; Duncan et al., 2013; Duschl et al., 2011; Elmesky, 2013). In the case of computational thinking (Grover & Pea, 2013, 2018), in addition to theoretical definitions of learning trajectories of CT that need to be validated through empirical research (Kong, 2016; Rich et al., 2017; Seiter & Foreman, 2013), there have been attempts to define frameworks for integration with Science and Math (e.g. Weintrop et al., 2016) and what CT looks like from within other disciplines (e.g. Malyn-Smith et al., 2018). Given both NGSS and Common-Core calls for an integrated perspective on STEM learning, integrated learning progressions would provide a more dynamic version of how learning happens and arguably foster productive learner engagements and leveraging of their learning across STEM domains. It is unfortunately

the case for the workshop vision that multi-threaded learning progressions for integrated STEM learning remain to be investigated and refined from future programs seeking to advance such empirical and theoretical developments and breakthroughs.

(5) ***Integration of virtual companions in human teaching & learning environments (e.g., Johnson & Lester, 2018; Mudrick et al., 2017).

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