Weaving the Fabric of Adaptive STEM Learning Environments Across Domains and Settings

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Abstract: What principles should guide the design of progressive, adaptable, distributed digital STEM learning environments that can personalize learning for diverse learners in individual and collaborative settings across multiple and varying domains of knowledge, learner interests, formal and informal contexts and time spans? This paper articulates six broad, high priority design principles for future integrated STEM learning environments that emerged from a 2019 interdisciplinary NSF-funded workshop involving leading learning scientists and researchers. We reflect on central tensions to be resolved for designing next-generation STEM learning.

Motivation and objectives

Mandates for education to prepare learners for 21st century life and work, and progressive standards for STEM subjects reflect an ***integrated*** STEM perspective (NGSS Lead States, 2013; NRC 2014) that integrates the four STEM domains, including computing and computational thinking (Grover & Pea, 2018). Additionally, there are opportunities to personalize learning with multi-modal analytics and machine learning (Worsley et al., 2016), and calls to attend to learner interests and STEM (Nasir et al., 2020). *What design principles for the next generation of digital STEM learning environments can we glean from the state-of-the-art in rich, adaptive, inclusive STEM learning?* To answer this question and develop guidelines for innovative designs for future integrated STEM learning in an era of big data, the authors convened a workshop with 25 leading learning scientists actively engaged in state-of-the-art advances in equity-focused, technology-enhanced STEM learning, measurement and assessment, and educational data mining and learning analytics. The workshop goal was articulating fundamental design principles that embody a transformative vision of future STEM learning for diverse learners across domains and settings. Taking an equity-first approach, interdisciplinary groups at the workshop identified and proposed progressive digitally augmented STEM environments bridging formal and informal learning contexts that are inclusively responsive to every learner's needs.

Deliberations and discussions at the workshop were 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 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? This paper synthesizes the group's recommendations into a set of design principles that reflect a future research agenda for STEM learning environments.

Design principles for future integrated STEM learning environments

This section outlines a set of principles that best frame the future of best-practices-informed technology-enhanced STEM education consonant with a vision of prospectively integrative STEM digitally augmented learning environments to bridge formal and informal learning contexts responsively for every learner.

Figure-ground flip principle

A centering consideration for integration of STEM education technology is brokering the relationships between technology and real-world experiences (Barron & Darling-Hammond, 2010; Dawley & Dede, 2014), in other words, to socialize augmentation of how we approach the knowledge transfer problem (Pea, 1987). Effective STEM education technology must carefully use the real world to ground sites for learning since, "Often, people can competently perform complex cognitive tasks outside school, but may not display these skills on school-type tasks" (Nasir, et al., 2014, p. 491). As technology brings applications of real-world inquiry into STEM classrooms, students will be provided opportunities to incorporate telepresence, virtual labs, augmented reality, virtual reality, and agent-based modeling (Wilensky & Rand, 2015) for better understanding their real-world phenomena and lived experiences. Although learnings with simulations of phenomena are useful, learning which situates new technologies in real world inquiry experiences becomes a priority (Blikstein, 2012; Scanlon et al., 2012).

Measurement principles

New technologies must incorporate the capacity for assessments-*of*-learning as well as assessments-*for*-learning (Gerard et al., 2015; Gobert et al., 2018; Yin, Tomita, & Shavelson, 2014). As back-end data analytics offer useful learning information, these assessments must be integrated into future STEM technology to allow for real-time assessment and iterative refinements of digitally enhanced instruction (e.g., Gane, Zaidi, Pellegrino, 2018). Further, the measurement principles must be extended to longitudinal performance assessments with technology. Embedding performance assessments in STEM learning technologies will enable tracking and promulgation of students' STEM interests and competency developments such as inquiry and argumentation-based thinking. As scholarship and technology improve in tandem, they must engage in multidimensional measurement incorporating both individual and group assessment practices.

Social and generative learning design principle

One fundamental issue with contemporary STEM technology is limited incorporation of our scientific understanding of learning processes (NRC, 2000; NRC, 2018)—that STEM learning must be designed with the intention of fostering generative student learning. Given that learning is active, socially constructed, and situated (Brown, Collins, & Duguid, 1989), emergent STEM learning technology must be intentionally designed for producing types of learner engagement that require 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), with a social design focus expanding learning opportunities for traditionally underrepresented students in STEM disciplines and which encompasses unconventional sites for STEM learning beyond school (e.g., Calabrese Barton & Tan, 2018; Gutiérrez & Jurow, 2016).

Distributed expertise principle

As learners engage with STEM technology, the learners and their communities must be included as learning agents (Barron & Bell, 2015; Brown et al., 1993). 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 learning environment design.

Learner empowerment principle

Given the reality that learning is far more than cognitive tasks, a future for STEM education 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. Special attention is vital for ensuring that technology supports full inclusivity of diversity with respect to gender, race, culture, abilities, and context. It will be essential to establish access to all learners including students and teachers with disabilities (Burgstahler & Thompson, 2019). Future STEM learning must be rich in opportunities allowing students to rethink who participates in STEM and provide students a sense of belonging embedded into the very design of the learning technology and its uses.

Human-Virtual Agent (VA) interaction co-evolution principle

Design investigations are needed of 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 engaged and deepening learning (Johnson & Lester, 2018). The aim has been to create intelligent systems for interacting with learners in natural, human-like ways to achieve better learning outcomes.

Tensions to be resolved in the design of next-generation STEM learning

The vision of adaptive integrative STEM technology enhanced learning embodying these design principles is one to be sought, nonetheless heeding the tensions and limitations inherent in taking an ambitious approach to improve STEM learning. We sketch tensions to be resolved through research in efforts to reach the desiderata above.

Knowledge Integration: Learning progressions (Wilson, 2009) have been conceived within specific domains only, yet the aim of NGSS-based science and NRC reports calls for adopting a more integrated approach to STEM teaching and learning. Given that learning goals should sustain the aim of integrating science learning that weaves together disciplinary topics, technology must attempt to walk the fine line between mapping learning progressions for linear growth and reflecting a more dynamic sense of the nexuses 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 or broadly used manner. As context drives learning, students will inevitably 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.

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. An inherent challenge in these data uses involves the need to store and have real time access to longitudinal data across settings for creating context-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), and run risks of providing 'algorithms of oppression' with discriminatory outcomes, reinforcing disempowering stereotypes (WEF, 2018).

The Inscrutability of the Artificial Intelligence Models: While teachers have the capacity to engage in differentiation and make real-time decisions about students' learning needs, an emergent use of AI to make learning recommendations for individual learners 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).

The Need for Data Interoperability In and Out of School: Contemporary research approaches too frequently presume a false division between STEM learning in and out of school. As future STEM learning technology is conceived, developers and educators must focus on ensuring data derived across learning contexts are connected meaningfully. As back-end databases are employed, they should allow integration of learning data procured from uses of software across settings.

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 undermining adoption and functionality of STEM technology. Increasingly, design-based research actively engages teachers in design and data-driven redesign efforts to foster effective, equitable learning designs (Leary et al., 2016). As user-centered educational technology develops, STEM technologists and scholars must embrace the foundational roles teachers play, as adaptive learning algorithms too oft neglect real time, face-to-face values of teachers in student learning.

Conclusion

Next generation K-12 STEM learning should be characterized by *integrated* multidomain learning across STEM subjects, *integrated* STEM learning across space and time and *integrated* learning and assessment to advance deeper learning. Human development and sociocultural theorists call for more expansive visions of how learning works than mere focus on cognitive tasks (Nasir et al., 2020). STEM learning must therefore also attend to developing STEM-linked interest and identity for diverse learners in diverse settings. The design principles outlined above describe a vision and lay out a learning sciences research agenda for the future of K-12 STEM learning that is rich, adaptive, supports integrated learning, and bridges contexts (digital and physical, formal and informal) to support deeper learning across space and time, for diverse individuals and groups of learners.

References

Bardini, T. (2000). *Bootstrapping: Douglas Engelbart, coevolution, and the origins of personal computing*. Stanford University Press.

Barron, B., & Bell, P. (2015). Learning environments in and out of school. In D. C. Berliner & R. C. Calfee (Eds.), *Handbook of educational psychology* (pp. 323–336). London, UK: Routledge.

Barron, B., & Darling-Hammond, L. (2010). Prospects and challenges for inquiry-based approaches to learning. *The nature of learning: Using research to inspire practice*, 199-225.

Barron, B., Gomez, K., Pinkard, N., & Martin, C. K. (2014). *The digital youth network: Cultivating digital media citizenship in urban communities*. Cambridge: MIT Press.

Blikstein, P. (2012). Bifocal modeling: a study on the learning outcomes of comparing physical and computational models linked in real time. In *Proceedings of the 14th ICMI* (pp. 257-264). NY: ACM.

Brown, A.L., Ash, D., Rutherford, M., Nakagawa, K., Gordon, A., & Campione, J.C. (1993). Distributed expertise in the classroom. *Distributed cognitions: Psychological and educational considerations*, 188-228.

Brown, J.S., Collins, A., & Duguid, P. (1989). Situated cognition and the culture of learning. *Educational Researcher*, *18*(1), 32–42.

Burgstahler, S., & Thompson, T. (Eds). (2019). *Accessible cyberlearning: A community report of the current state and recommendations for the future*. Seattle, WA: University of Washington.

Calabrese Barton, A., & Tan, E. (2018). A longitudinal study of equity-oriented STEM-rich making among youth from historically marginalized communities. *American Educational Research Journal,* 55(4), 761-800.

Dawley, L., & Dede, C. (2014). Situated learning in virtual worlds and immersive simulations. In *Handbook of research on educational communications and technology* (pp. 723-734). NY: Springer.

Fields, D. A., Kafai, Y. B., & Giang, M. T. (2017). Youth computational participation in the wild: Understanding experience and equity in participating and programming in the online scratch community. *ACM Transactions on Computing Education* (TOCE), 17(3), 15.

Gane, B. D., Zaidi, S. Z., & Pellegrino, J. W. (2018). Measuring what matters: Using technology to assess multidimensional learning. *European Journal of Education*, 53(2), 176-187.

Gerard, L., Matuk, C., McElhaney, K., & Linn, M. C. (2015). Automated, adaptive guidance for K-12 education. *Educational Research Review*, 15, 41-58.

Gobert, J. D., Moussavi, R., Li, H., Sao Pedro, M., & Dickler, R. (2018). Real-time scaffolding of students' online data interpretation during inquiry with Inq-ITS using educational data mining. In *Cyber-Physical Laboratories in Engineering and Science Education* (pp. 191-217). Cham, Switzerland: Springer.

Grover, S. & Pea, R. (2018). Computational Thinking: A competency whose time has come. In Sentance, S., Barendsen, E. & Carsten, S. (Eds.). *Computer science education: Perspectives on teaching and learning* (pp. 19–38). London: Bloomsbury.

Gutiérrez, K. D., & Jurow, A. S. (2016). Social design experiments: Toward equity by design. *Journal of the Learning Sciences*, 25(4), 565-598.

Johnson, W. L., & Lester, J. C. (2018). Pedagogical agents: back to the future. *AI Magazine*, 39(2).

Kroll, J. A. (2018). The fallacy of inscrutability. *Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences*, 376(2133), 20180084.

Leary, H., Severance, S., Penuel, W. R., Quigley, D., Sumner, T., & Devaul, H. (2016). Designing a deeply digital science curriculum: Supporting teacher learning and implementation with organizing technologies. *Journal of Science Teacher Education*, 27(1), 61-77.

Nasir, N. S., Rosebery, A. S., Warren, B., & Lee, C. D. (2014). Learning as a cultural process: achieving equity through diversity. In R. K. Sawyer (Ed.), *The Cambridge handbook of the learning science*s (pp. 686–706). New York: Cambridge University Press.

Nasir, N., Lee, C., Pea, R., & De Royston, M.M. (2020, to appear). (Eds.), *Routledge handbook of the cultural foundations of learning*. New York: Routledge.

National Academies of Sciences (NRC), 2000, 2018. *How people learn I and II.* The National Academies Press.

National Research Council (NRC). 2014. *STEM integration in K-12 education: status, prospects, and an agenda for research*. Washington, DC: The National Academies Press.

NGSS Lead States. (2013). *Next generation science standards: for states, by states*. Washington, DC: NAP.

Niemi, D., Pea, R. D., Saxberg, B., & Clark, R. E. (Eds.). (2018). *Learning analytics in education*. IAP.

Pea, R. D. (1987). Socializing the knowledge transfer problem. *Intl. Journal of Educ. Research*, *11*(6), 639-663.

Pellegrino, J. W., DiBello, L. V., & Goldman, S. R. (2016). A framework for conceptualizing and evaluating the validity of instructionally relevant assessments. *Educational Psychologist*, *51*(1), 59-81.

Scanlon, E., Sharples, M., & Littleton, K. (Eds.) (2012). *Orchestrating inquiry learning*. NY: Routledge.

Yin, Y., Tomita, M. K., & Shavelson, R. J. (2014). Using formal embedded formative assessments aligned with a short-term learning progression to promote conceptual change and achievement in science. *International Journal of Science Education*, *36*(4), 531-552.

Wilson, M. (2009). Measuring progressions: Assessment structures underlying a learning progression. *Journal of Research in Science Teaching: The Official Journal of NARST*, *46*(6), 716-730.

World Economic Forum/WEF (2018, March). *White paper: How to prevent discriminatory outcomes in machine learning*. Global Future Council on Human Rights 2016-2018.

Worsley, M., Abrahamson, D., Blikstein, P., Grover, S., Schneider, B., & Tissenbaum, M. (2016). Situating multimodal learning analytics. In *ICLS 2016. International Society of the Learning Sciences (ISLS)*.

Wilensky, U., & Rand, W. (2015). *An introduction to agent-based modeling: modeling natural, social, and engineered complex systems with NetLogo*. Cambridge: MIT Press.

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