Proceedings of the Human Factors and Ergonomics Society Annual Meeting
1–6

DOI: 10.1177/21695067231192886
journals.sagepub.com/home/pro
Sage

Learning Engineering Perspectives for Supporting Educational Systems

Scotty D. Craig[1], Jim Goodell[2], Erin Czerwinski[3], Jodi Lis[4], and Rod D. Roscoe[1]

Abstract

This panel will focus on the emerging area of Learning Engineering. Learning Engineering is a transdisciplinary area focusing on the systematic application of evidence-based principles from science of learning disciplines to create effective learning experiences, addressing the challenges of learners. During the panel, examples of Learning Engineering will be presented of interest to anyone within human factors and ergonomics with interest in education, training, or usability/design science. The panel will represent experience from both academia and industry. The goal of this panel is to foster dialog between the IEEE Industry Connections Industry Consortium on Learning Engineering (ICICLE) and HFES members in the hope of increasing knowledge of Learning Engineering and creating ties between the two organizations.

Keywords

Learning Engineering, Education, Educational Systems

Summary

Learning engineering is a transdisciplinary area focusing on the systematic application of evidence-based principles from science of learning disciplines to create effective learning experiences, addressing the challenges of learners. While learning engineering was first proposed in 1967 as a method for improving the basic efficiency for learning organizations (Simon, 1967), the professional practice of the area has just started forming (Goodell & Craig, 2022) and basic principles of the area are summarized in a book covering the discipline, Learning Engineering Toolkit (Goodell & Kolodner, 2023). The emerging area uses skills from multiple disciples to tackle educational issues (e.g., scaling-up online learning) that are too large or complicated to be solved by one skillset (Kessler et al. 2023). As shown in Figure 1, this new area encompasses systems engineering (Barr et al. 2023), learning sciences, cognitive sciences, design sciences (Roscoe et al., 2018; Thai et al., 2023) as well as both data science (Barrett et al., 2023) and evaluation (Czerwinski et al., 2023).

This panel will be a discussion between Human Factors and Ergonomics members and representatives from IEEE Industry Connections Industry Consortium on Learning Engineering (ICICLE). ICICLE is a professional organization that seeks to define a new profession and support working learning engineers (ICICLE, N.D). We hope the panel will help to explore the synergy between the two organizations. While there are potential connections throughout HFES due to learning engineering focus on Systems Engineering/ Systems Thinking (e.g., Cognitive Engineering and Decision

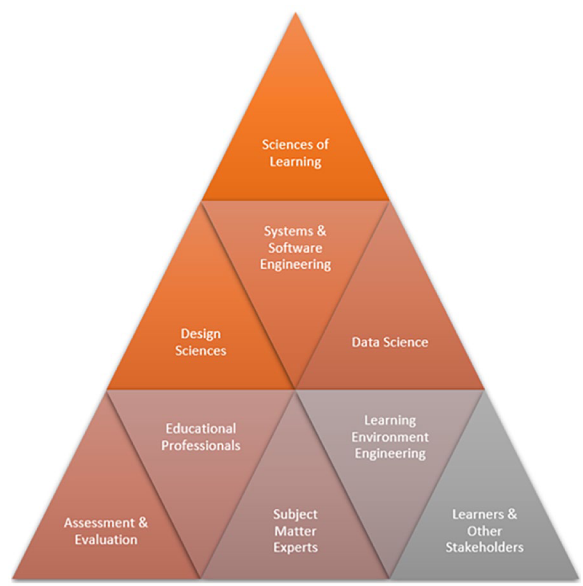

Figure 1. Example Areas within Learning Engineering Teams.

[1]Arizona State University, Mesa, AZ, USA
[2]Quality Information Partners Inc., Fairfax, VA, USA
[3]The Simon Initiative, Carnegie Mellon University, Pittsburgh, PA, USA
[4]IntraHealth International, Chapel Hill, NC, USA

Corresponding Author:
Scotty D. Craig, Arizona State University, 7271 E. Sonoran Arroyo Mall, Santa Catalina Hall, Suite 150g, Mesa, AZ 85212, USA.
Email: scotty.craig@asu.edu

Making and System Development Technical groups), there are also more direct connections to education and training areas (e.g., Education, Training, and Extended Reality technical groups) and human Centered evaluation areas (i.e., Usability and System Evaluation).

The panel will represent a broad-spectrum experience that spans practitioner and researcher in both organizations. HFES will be represented by two HFES members. Scotty Craig, current Education Technical Group Chair, and Rod Roscoe, former chair of the societal impact committee. Drs Craig and Roscoe are also associate directors of the Learning Engineering Institute at Arizona State University serving under Dr. Danielle McNamara, executive director. Dr. Craig will serve as the panel chair. Dr. Roscoe will serve as a panelist and discuss diversity, equity, inclusion, and belonging (DEIB) within Learning engineering will provide connections to HFES affinity groups. The three panelists will be from ICICLE. Jim Goodell, Erin Czerwinski, and Jodi Lis will offer industry perspectives of Learning engineering and provide concrete examples of Learning engineering in practice. Jim Goodell will discuss the role of intelligence augmentation and how that can impact workforce training and performance. Erin Czerwinski will discuss the role of data within learning design. Jodi Lis will provide examples of how learning engineering can be used to meet educational needs within low-resource environments.

Panel Chair

Scotty D. Craig, PhD Associate Professor of Human Systems Engineering at Arizona State University. I came to the learning engineering area as an academic researcher from the domain areas spanning the science of learning, assessment and evaluation, and design sciences. I also serve as the Director of the ASU Advanced Distributed Learning Partnership Lab where we work to apply those areas to improve learning ecosystems. I am currently one of the associate directors of the Learning Engineering Institute at ASU helping to create educational and applied opportunities within learning engineering.

Panel Presentations

Learning Engineering for Intelligence Augmentation in the Flow of Work

Jim Goodell, Director of Innovation at QIP. I come to the learning engineering area as lead editor and co-author of Learning Engineering Toolkit and a learning technology expert. I also work with the US Chamber of Commerce Foundation on projects that support improved systems for talent development and competency-based hiring and advancement. I also serve as Chair of the IEEE Learning Technology Standards Committee and on steering several related steering committees including IEEE ICICLE.

"Learning engineering is a process and practice that applies the learning sciences using human-centered engineering design methodologies and data-informed decision making to support learners and their development." (IEEE ICICLE)

The definition of learning engineering was developed by multidisciplinary experts with an eye to the future. The products of learning engineering are broadly defined "to support learners and their development" rather than being constrained to the development of specific things like courses and technology platforms. This is important in 2023 because how and when people learn is changing.

The lines are blurring between working and learning, just as the lines are blurring between the work done by humans and work done by machines. AI agents are becoming our coworkers and learning is happening everywhere and all the time. While AI can outperform humans at many tasks, some tasks, like the game of chess (Huang, 2022), are best when done by humans with AI assistance. At a meta level this may also be true for the task of learning. As humans can learn with assistance from AI, machine learning may be most effective with humans in the loop. (Mosqueira-Rey, et al. 2022)

Learning engineering is a process that supports this new reality, where humans and machines work together to support learning and productivity. It is an approach that is grounded in the learning sciences and uses human-centered engineering design methodologies and data-informed decision making. Learning engineering is an iterative team-oriented process in which teams use data to discover any opportunity for improvement (Goodell & Kolodner, 2023). Goals for each iteration of the learning engineering process are defined based on qualitative and quantitative analysis and team insights on possible changes in conditions or experiences that might improve learning.

Increasingly as work becomes a collaboration between humans and AI agents, micro learning experiences that are tailored to the learner's just-in-time needs will likely replace much of course-based learning as a more effective and efficient alternative. This has implications for higher education and corporate learning and development contexts.

Individual instructors, instructional designers, instructional system designers and other sometimes solo practitioners in siloed practices will need to retool their practice for a new model of collaboration. This approach, that is grounded in the learning sciences and uses human-centered engineering design methodologies and data-informed decision making, will increasingly require sets of skills unlikely to be held by any one individual.

Learning engineering as a discipline is also iteratively improving itself through development of new tools, engineering design patterns, and reusable components, including AI components. At a meta-meta level, we can envision the work of learning engineering as blurring lines between work and learning, and where AI agents will become coworkers on learning engineering teams.

The Learning Engineering Approach: Data-Generating Learning Design

Erin Czerwinski, Manager, Learning Engineering and Technology Enhanced Learning Product, The Simon Initiative, Carnegie Mellon University. I also serve on the steering committee of the IEEE ICICLE and authored several chapters in The Learning Engineering Toolkit. I come to learning engineering as a practitioner and a leader, by both producing data-generated learning designs, and leading teams of professionals to use sound learning science methodologies, best practices, and overall product quality guidelines to deliver impactful online learning experiences.

Data, and learning analytics, is driving the future of education. Learning engineering in practice produces learning experiences that generate data for the various feedback loops necessary for education: feedback to the learners to help them monitor their own progress and choose appropriate strategies, feedback to educators to know when students are struggling, and with which outcomes, feedback to learning designers to iterate on their designs toward student success, and feedback to the larger learning sciences community to drive new insights in teaching and learning. Learning Engineers employ many techniques and tools in their practice, including data-generating design to instrument learning experiences that will measure performance and progress of the stated learning outcomes. Without careful data collection and analysis, future advances in education such as personalized learning, augmented/virtual reality, artificial intelligence and machine-learning, universal transcripts, etc. are not possible.

Learning engineering draws on principles from the fields of psychology, neuroscience, education, engineering, and design to create interactive, engaging, and effective learning experiences. And like these other disciplines, LE aims to make the unobservable, observable, using scientific method-like practices, measurement, data collection, and analysis. Learning Engineers use techniques such as cognitive task analysis, user-centered design, and item-response theory, as a few examples, to develop learning solutions that solve particular learning problems and then optimize for performance.

LEs help to articulate the outcomes in a student-centered and measurable manner. Because we cannot see learning occurring in the brain itself, we must create cognitive models of what students need to learn, and then articulate those outcomes in a way that can be measured. Many times, outcomes come from standards or from an educator who remembers what and how they learned a similar concept. However, LEs know that experts cannot always articulate what and how they learned specific skills (Chi et al., 1981). Techniques like cognitive task analysis is one method that Learning Engineers employ to first create a model of learning. Cognitive tasks analysis can consist of carefully scripted interviews and think-aloud methods but can also be generated from analysis of data collected from instrumented systems. A cognitive model usually takes the form of stated outcomes, also known as learning objectives, skills, or knowledge components (Nguyen et. al., 2019).

Learning designs then becomes a hypothesis to test. Cognitive models are used to select the aligned activities, assessments and content to measure mastery. Available data and analytics from the learning sciences informs decisions about the learning solution, including the selection of topics, the structure of lessons, and the methods used to present information. Beyond aligning directly to the cognitive model, these data-generating designs are carefully selected and then instrumented to collect raw data from learner interactions. Raw data can be, for example, physical data collected from sensors, student inputs into a computer system, responses on paper surveys, or metadata collected about a particular experience. Raw data is then transformed by moving it through one or more pipelines for scrubbing, formatting, and quality reviews before it can be turned into analytics (Goodell & Kolodner 2023).

Analytics reveal patterns and trends gleaned from the raw data and used to power visualizations and dashboards. Learning analytics can be used in a number of ways. In real time (while students are working through a learning solution), these analytics can feed dashboards for the students themselves or to help instructors select just-in-time interventions. In the aggregate, they inform where and how to iteratively improve the learning design. And large datasets can be used by learning science researchers to gain new insights (or validate assumptions).

learning engineering processes are used to measure learning interventions in a rigorous and scientific manner. By integrating learning engineering practices, such as instrumentation, data collection, analysis, and iterative improvement into the design and development of learning products and systems, Learning Engineers can ensure that skills are acquired more effectively and efficiently, as well as validating the efficacy and contexts for new approaches to teaching and learning.

Learning Engineering Applications in Low-Resource Environments

Jodi Lis is a Digital Education Strategist. I came to learning engineering as Co-Chair of the IEEE ICICLE and as co-author of several chapters in the Learning Engineering Toolkit. I implement digital education interventions in Africa. I apply the learning engineering in low- and middle-income countries (LMICs) as a process to develop holistic solutions for workforce development, pre-service and capacity-building programs in health and education sectors to accelerate learning and performance outcomes at scale.

Introducing technology in education in low and lower-middle income countries has always been challenging due to lack of access to electricity and internet, low digital literacy, relevant digital resources, skills to incorporate technology into teaching and learning, and understanding by the administration and teachers of the value-add to using technology (Hamadeh et al., 2022). During the initial period of COVID-19, although similar issues came up in pockets of high-income countries, it is consistently more prevalent.

For years, ministries of education in these countries were told and therefore, assumed that putting any technology in classrooms will improve learning. As those involved in using educational technology well understand, it will not. COVID-19 clearly demonstrated that having available laptops in schools is not an appropriate solution. The World Bank has published its efforts on technology and education (Robert et al., 2020) and as part of this made it clear that human connections are necessary for technology to be a successful tool and resource in learning.

The Learning Engineering Toolkit describes how learning engineering is a team sport. It involves expertise from different fields, including learning sciences, learning experience design, education professionals, measurement and evaluation, data science, software engineering, and subject-matter experts. Education professionals in low-resource environments include the teachers and administrators at the schools. Although it is widely understood that for an education technology intervention to be successful the leader at the place of the intervention must be supportive and teachers properly trained, these lessons seem to be repeated over and over. In the referenced World Bank report (along with many other papers coming out since the start of COVID-19), an area of focus is to empower the teachers.

Yet the team also extends beyond the school. It involves the parents, caregivers and communities. The expression, "it takes a village," is accurate. As part of the learning engineering practice, Engaging parents, caregivers and the community are key to successful implementation and critical to learning.

The challenge within the learning engineering process here is to identify innovative solutions to engage these groups in their children's learning in environments with lack of access to consistent electricity, little to no access to the internet, and low literacy levels in these groups. Solutions include SMS and audio messages that would encourage caregivers to start new, simple habits such as asking questions, listening and storytelling to engage in learning at home. Entire curriculums with lessons and learning activities are developed and distributed via SMS, interactive voice response and WhatsApp on topics in formal and non-formal education.

Community volunteers are recruited to support children's learning. Local community radio stations slotted into their broadcasting recorded lessons. Communities brought students together to listen and work through the lesson togethers. To further engage people in the community with the schools, some became learning assistants at the schools and were provided support, tools and encouragement for them to become teachers themselves.

These are examples of how learning engineering is a team sport beyond the traditional team and types of solutions to the challenge of creating learning experiences to work in low-resource environments.

Equity-Centered Learning Engineering

Rod D. Roscoe, PhD, Associate Professor of Human Systems Engineering at Arizona State University. I came to the learning engineering area as a multidisciplinary scholar spanning learning science, cognitive science, design science, and computer science. I am currently an associate director of the new Learning Engineering Institute at ASU, which aims to use evidence-based and data-driven strategies to advance educational practice, assessment, technology, and equity. I am also affiliate faculty with the Mary Lou Fulton Teachers College, Center for Gender Equity in Science and Technology (CGEST), Research on Inclusive STEM Education (RISE) Center), and the Center for Human, Automation, and Robot Teaming (CHART). I am active in equity-centered research and advocacy across multiple organizations.

The foundations of learning engineering are diverse and deep, spanning (at least) data science, design science, computer science, and learning science (Goodell & Kolodner, 2023). Learning engineering thus inherits powerful expertise (i.e., theories, methods, and practices) from these participating disciplines. However, learning engineering also risks inheriting their challenges and problematic histories regarding diversity, equity, inclusion, and belonging (DEIB). At this moment of time—a period of self-determination, innovation, and vision—this nascent field has an opportunity to embrace DEIB as core or even defining tenets.

Equity begins by celebrating the meaningful variability among people with respect to identity and experience and continues by acknowledging how such factors participate in inequity: differential access (e.g., to decision-making power, opportunities, and resources) and differential outcomes (e.g., meaningful education, employment, health, and housing). To be equitable means to establish policies, procedures, and actions that reduce inequities and eliminate barriers to equity. Note that being equitable is not the same as "equality" or "fairness" where everyone is "treated the same." Being equitable also does not simply entail "fixing deficits" or "narrowing gaps" such that different people are now indistinguishable from each other. Diverse identities and cultures are assets that should be empowered to thrive without constraining access or outcomes.

Various fields have contended with inequity in parallel ways. For example, scholars have called for greater attention to equity, justice, and sociopolitical issues in learning sciences (Guttiérrez & Jurow, 2016; Sungupta-Irving & McKinney de Royston, 2020), data science (Green, 2021; Lewis & Stoyanovich, 2021), artificial intelligence in education (Lewis & Stoyanovich, 2021; Roscoe et al., 2022), and human factors and ergonomics (Roscoe et al., 2019), just to name a few. Such calls have been driven by rising awareness that inattention to DEIB results in potentially harmful outcomes, such as algorithmic bias in educational systems (Baker & Hawn, 2021) and excluding people from (or pushing them out) of relevant fields altogether (Roscoe, 2022).

I will invite the audience to envision ways that DEIB can be integrated in learning engineering "from the ground up." Integration might be ideological, conceptual, and methodological:

Ideological

- understanding that learning engineering cannot be "apolitical" or "neutral" in society
- commitment to equitable practices (e.g., how we work, network, and share work)
- commitment to equitable outputs (e.g., findings, technologies, and recommendations)

Conceptual

- defining knowledge, learning, and performance in terms of assets rather than deficits
- understanding learners and communities as complex systems facing systemic issues
- understanding differences beyond "demographic" categories (e.g., "race gaps")

Methodological

- innovating methods for intersectional data analysis (i.e., multiple identities)
- accounting for both intercategorical and intracategorical variance in analyses
- mixed method approaches for studying "small n" learner populations

ORCID iDs

Scotty D. Craig https://orcid.org/0000-0002-4103-5547
Jim Goodell https://orcid.org/0000-0002-8062-8740

References

Baker, R. S., & Hawn, A. (2021). Algorithmic bias in education. *International Journal of Artificial Intelligence in Education*, *32*, 1052-1092. https://doi.org/10.1007/s40593-021-00285-9

Barr, A., Dargue, B., Goodell, J., & Redd, B. (2023). Learning engineering is engineering. In J. Goodell & J. Kolodner (Eds.), *The Learning Engineering Toolkit: Evidence-Based Practices from the Learning Sciences, Instructional Design, and Beyond*. (pp. 125-152). Routledge

Barrett, M., Czerwinski, E., Goodell, J., Jacobs, D., Ritter, S., Sottilare, R., & Thai, K. P. (2023). Learning engineering uses data (Part 2): Analytics. In J. Goodell & J. Kolodner (Eds.), *The Learning Engineering Toolkit: Evidence-Based Practices from the Learning Sciences, Instructional Design, and Beyond*. (pp. 175-200). Routledge.

Chi, M.T.H., Feltovich, P.J., & Glaser, R. (1981), Categorization and representation of physics problems by experts and novices. *Cognitive Science*, *5*, 121-152. doi:10.1207/s15516709cog0502_2

Czerwinski, E., Goodell, J., Ritter, S., Sottilare, R., Thai, K.P., & Jacobs, D. (2023). Learning engineering uses data (part 1): Instrumentation. In J. Goodell & J. Kolodner (Eds.), *The Learning Engineering Toolkit: Evidence-Based Practices from the Learning Sciences, Instructional Design, and Beyond*. (pp. 153-174). Routledge

Goodell, J., & Craig, S. D. (2022, September). What does an emerging intelligence augmentation economy mean for HF/E? Can learning engineering help?. In *Proceedings of the Human Factors and Ergonomics Society Annual Meeting* (pp. 460-464). Sage CA: Los Angeles, CA: SAGE Publications.

Goodell, J., & Kolodner, J. (Eds.) (2023). Learning engineering toolkit: Evidence-based practices from the learning sciences, instructional design, and beyond. New York, NY: Routledge. https://doi.org/10.4324/9781003276579

Green, B. (2021). Data science as political action: Grounding data science in a politics of justice. *Journal of Social Computing*, *2*(3), 249-265. https://doi.org/10.23919/JSC.2021.0029

Guttiérrez, K. D., & Jurow, A. S. (2016). Social design experiments: Toward equity by design. *Journal of the Learning Sciences*, *25*(4), 565-598. https://doi.org/10.1080/10508406.2016.1204548

Hamadeh, N., Van Rompaey, C., Metreau, E., & Eapen, S. G. (2022, July 2022). *New World Bank country classifications by income level: 2022-2023*. World Bank Group. https://blogs.worldbank.org/opendata/new-world-bank-country-classifications-income-level-2022-2023

Hawkins, R. J., Trucano, M., Cobo Romani, J. C., Twinomugisha, A., & Sanchez Ciarrusta, I. A. (2020) *Reimagining human connections: Technology and innovation in education at the World Bank (English)*. World Bank Group. http://documents.worldbank.org/curated/en/829491606860379513/Reimagining-Human-Connections-Technology-and-Innovation-in-Education-at-the-World-Bank

Huang, T. (2022). *Chess: The ultimate AI challenge*. Retrieved from https://www.technologyreview.com/2021/04/30/1022755/ai-chess-game-challenge-deepmind-alphazero/

IEEE Industry Connections Industry Consortium on Learning Engineering (ICICLE). (n.d.). Learning engineering. Retrieved from https://www.ieeeicicle.org/learning-engineering/

Kessler, A., Craig, S. D., Goodell, J., Kurzweil, D., & Greenwald, S. W. (2023). Learning engineering is a process. In J. Goodell & J. Kolodner (Eds.), *The Learning Engineering Toolkit: Evidence-Based Practices from the Learning Sciences, Instructional Design, and Beyond*. (pp. 29-46). Routledge.

Lewis, A., & Stoyanovich, J. (2021). Teaching responsible data science: Charting new pedagogical territory. *International Journal of Artificial Intelligence in Education*. *32*, 783-807. https://doi.org/10.1007/s40593-021-00241-7

Mosqueira-Rey, E., Hernández-Pereira, E., Alonso-Ríos, D., Bobes-Bascaran, & Fernandez-Leal (2022). Human-in-the-loop machine learning: a state of the art. *Artificial Intelligence Review*, *56*, 3005-3054. https://doi.org/10.1007/s10462-022-10246-w

Nguyen, H., Wang, Y., Stamper, J., & McLaren, B. M. (2019). Using Knowledge Component Modeling to Increase Domain Understanding in a Digital Learning Game. In *Proceedings of International Conference on Educational Data Mining*, (pp. 139–148). EDM.

Roscoe, R. D. (2022). Please join me/us/them on my/our/their journey to justice in STEM. *Discourse Processes*, *59*(5-6), 345-360. https://doi.org/10.1080/0163853X.2022.2050084

Roscoe, R. D., Branaghan, R. J., Cooke, N. J., & Craig, S. D. (2018). Human systems engineering and educational technology. In R. D. Roscoe, S. D. Craig, & I. Douglas (Eds.), *End-user considerations in educational technology design* (pp. 1–34). IGI Global. https://doi.org/10.4018/978-1-5225-2639-1.ch001

Roscoe, R. D., Chiou, E. K., & Wooldridge, A. R. (2019). *Advancing diversity, inclusion, and social justice through human systems engineering*. Boca Raton, FL: CRC Press. https://doi.org/10.1201/9780429425905

Roscoe, R. D., Salehi, S., Dowell, N., Worsley, M., Piech, C., & Luckin, R. (2022). Inclusion and equity as a paradigm shift for artificial intelligence in education. F. Ouyang, P. Jiao, B. M. McLaren, & A. H. Alavi (Eds.), *Artificial intelligence in STEM education: The paradigmatic shifts in research, education, and technology* (pp. 359-374). Boca Raton, FL: CRC Press. https://doi.org/10.1201/9781003181187

Simon, H. A. (1967). Job of a college president. *Educational Record*, *48* (1), 68-78.

Sungupta-Irving, T., McKinney, de, & Royston, M. (2020). *STEM and the social good: Forwarding political and ethical perspectives in the learning sciences*. New York, NY: Routledge.

Thai, K. P., Craig, S. D., Goodell, J., Lis, J., Schoenherr, J. R., & Kolodner, J. (2023). Learning Engineering is Human-Centered. In J. Goodell & J. Kolodner (Eds.), *The Learning Engineering Toolkit: Evidence-Based Practices from the Learning Sciences, Instructional Design, and Beyond*. (pp. 83-124). Routledge.