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Editorial

Learning analytics of embodied design: Enhancing synergy

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ABSTRACT

Two nascent lines of inquiry in the Learning Sciences are contributing to research and development of interactive digital resources for STEM education. One is *embodied design*, a research program to create theoretically driven and empirically validated technological learning environments where students ground STEM concepts in new perceptual capacity they develop through solving motor-control problems. The other is *multimodal learning analytics*, a methodological approach to investigating learning processes through gathering, analyzing, triangulating, and presenting data from multiple measures of students' actions and sensations. This special issue looks at a set of articles reporting on pioneering efforts to coordinate these parallel lines of inquiry into a theoretically coherent research program informing an integrated design framework. The following editorial frames and motivates these research efforts, surveys the set of papers, and speculates on possible futures for the learning analytics of embodied design.

LA–ED: A Promising Discipline

Two thriving efforts in the field of educational research – embodied design and learning analytics – could benefit from greater philosophical, theoretical, and methodological synergy, with implications for research foci and methods, the educational practice of design and facilitation, and the training of graduate students in the learning sciences.

Drawing on embodiment theory from the cognitive sciences (Newen et al., 2018; Shapiro, 2014), *embodied design* (ED) is an educational research program, including a pedagogical design framework, oriented primarily on children's study of STEM concepts (science, technology, engineering, mathematics; see Abrahamson, 2009, 2014, 2015, 2019).[2] ED applications, pedagogies, heuristic principles, and theoretical models are developed through iterated cycles of design-based research studies (Cobb et al., 2003) of STEM cognition, teaching, and learning. ED's research-and-development process creates empirical contexts for mixed-methods investigation of students' learning through interacting with a variety of technological media, peers, and instructors. In ED activities, students work initially with non-symbolic objects. In their attempts to perform assigned tasks, students draw on their innate sensorimotor capacity. For example, to solve a motor-control problem, students develop new perceptions of the environment that enable them to coordinate the bimanual enactment of a complex movement instantiating a mathematical concept. Only later are disciplinary resources introduced into the situation that afford students perceptual transitions into formal re-conceptions of the situation. ED research tackles philosophical and theoretical questions related to the epistemic function of movement in the cognition, teaching, and learning of curricular content (Abrahamson & Bakker, 2016; Abrahamson & Sánchez–García, 2016; Abrahamson & Shulman, 2019). Combining clinical, action, and eye-tracking data, ED studies have documented the emergence of new perceptual structures that enable students to enact complex movements; these perceptual structures – *attentional anchors* (Hutto & Sánchez–García, 2015) – then become accessible to students' explicit reasoning as articulable ontologies (Abrahamson et al., 2016; Shvarts & Abrahamson, 2019). As such, ED is theoretically resonant with recent calls to favorably consider tenets of Piaget's 1968 genetic epistemology (Allen & Bickhard, 2013; Arsalidou & Pascual-Leone, 2016) as well as enactivist philosophy (Maturana & Varela, 1992) and dynamic system theory (Kelso, 1995; Thelen & Smith, 1994) in making sense of children's movement-based conceptual learning.

Learning Analytics (LA) seeks to study the implications of a digital world on learning. Contributions often focus on leveraging nascent data (Pardos, 2017) from digital systems (Siemens et al., 2011) to describe, explicate, or facilitate the learning process or shed light on digital learning environments. The call

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1 Guest Editors.

2 By way of introduction to embodied design, readers are referred to Abrahamson and Lindgren (in press), Abrahamson et al. (2020), Abrahamson et al. (under review), and Shvarts et al. (2021).

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for LAK (2011) – the 1st international Conference on Learning Analytics and Knowledge – states that "Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Siemens, 2013). One way that Learning Analytics (LA) and ED have begun to interface is in the form of *multimodal* learning analytics (MMLA). Inspired by micro-ethnographic and interaction-analysis methodologies, MMLA aims to harness the affordances of multimodal sensors and computational analysis to better understand and support student learning. MMLA involves principled, yet emerging, methods for gathering, analyzing, coordinating, and presenting visual, aural, gestural, spatial, linguistic, and other data of students' cognitive, affective, behavioral, and physiological processes in online and offline learning environments, as they engage in instructional tasks (Worsley et al., 2016; Worsley & Blikstein, 2014b). MMLA is conceptualized as aligning with the embodied and multimodal nature of learning as well as the complementary diversity in contexts where students may individually or collectively experience learning. Importantly, MMLA represents a variety of strategies for drawing inferences about the student's learning experience. For example, some prior work has demonstrated how computational algorithms can surface hard-to-see patterns within human annotated data (Worsley & Blikstein, 2014a). Other research takes a more automated approach, explicitly introducing researcher inference only after the computational techniques have annotated and clustered the data (Huang et al., 2019; Worsley & Blikstein, 2018). Still others utilize multimodal features and artificial intelligence to augment video analysis (i.e., overlaying eye-tracking, gestures, or electrodermal activation data in videos) or to segment continuous data into meaningful segments (Worsley et al., 2015). Collectively, these approaches welcome a careful and thoughtful application of multimodal sensor data and computing to enhance student and researcher sense-making.

Up to this point in the editorial, we have discussed embodied design and learning analytics as relatively intact research programs. This special issue, however, is about how these efforts could (and, we submit, should) be mutually informing and even interleaved and united into a single coherent research program of the learning sciences. Granted, there have been a number of collaborative efforts, where educational designers, often design-based researchers of STEM teaching and learning, worked with learning analytics specialists to evaluate artifacts and activities (Pardos & Horodyskyj, 2019). For example, educational designers of movement-based learning have shared their data with learning-analytics experts who applied machine-learning algorithms and statistical methods to detect and classify microprocesses of skill development (e.g., Pardos et al., 2018). Also, data-driven quantitative and qualitative insights about students' behavior have been drawn to inform the development of new ED applications for personalized learning (Ou et al., 2020). Still, it is our reading of the field that ED and LA communities mostly operate from distinct, often non-overlapping intellectual bases, secluded in their own associations, special interest groups, conferences, journals, and online activities. When they do collaborate, it is often across a professional divide, where each researcher appreciates but may not completely understand the other's intellectual foundation, making the joint work piecemeal and "inorganic." As such, LA techniques may be applied to ED data only after a research design has been charted out and implemented. In like vein, graduate-school course offerings often compartmentalize design-oriented seminars as satisfying requirements of cognition, curriculum, and/or theories of learning, whereas learning-analytics and/or educational data mining (Fischer et al., 2020) courses fall under the division of quantitative methods.

The vision of this special issue is to stimulate the field to foster "organic" relations between the camps, for the edification of all stakeholders. Thus, *we are looking to boost a conception of LA–ED no longer as interdisciplinary but as disciplinary*. One way forward, we believe, is integrating LA considerations and utilities into ED technology to build research designs optimized for the technical capacity, rigor, and scope of MMLA. More broadly, we are hoping to foster a community of LA–ED researchers who combine both forms of expertise in their methodological palette. Doing so would require of graduate programs in academic schools of education to align with contemporary paradigms in the cognitive sciences in terms of the intellectual rationales, pedagogical objectives, and investigative toolset represented in design-based research courses on STEM teaching and learning.

As a first step in that direction, this special issue called for state-of-the-art articles that: (1) report on empirical research projects where multimodal interaction data were collected to investigate the micro-process of teaching and learning grounded in movement; (2) present philosophical, theoretical, and/or critical-pedagogy review work that contemplates, evaluates, elaborates, and/or challenges premises of LA–ED; or (3) offer reflections from researchers who analyze their project procedure to understand opportunities, challenges, and solutions for this line of collaborative work. We particularly sought articles that would bridge the learning design and learning analytics camps. That is, we invited projects from LA experts that are presented so as to be accessible to learning-science readers interested primarily in design-based research of theoretically informed learning environments, and projects from ED experts that are, in turn, presented so as to be accessible to ED-curious LA readers. As such, we were less interested in computationally-heavy LA papers that use learning designs only as their host context and would be inscrutable and perhaps irrelevant to ED scholars, just as we were equally less interested in ED papers that include a LA facet as an afterthought. Ideally, we hoped, contributions to the SI would come from LA–ED collaborations. Accordingly, our call encouraged the submission of outstanding articles concerned with *integrating* LA–ED themes, such as the following: (a) underrepresented content domain (on beyond STEM, e.g., literacy, the arts, history); (b) underrepresented theoretical foundations (on beyond Piaget and Vygotsky, such as dynamic systems theory); (c) underrepresented participants, such as differently abled students, remote rural students; and (d) underrepresented settings, such as remote instruction for a/synchronous learning. In sum, we were looking for contributions demonstrating the possibility of deep dialogue among these not-yet-quite-convergent tributaries of educational research, LA and ED. Submitted papers were to ideally help the field answer questions such as these:

- How does applying LA methodologies to ED contribute to the evaluation of contemporary paradigms in the cognitive sciences?
- What new disciplinary constructs come forth as instrumental to the productive collaboration of experts in the respective areas of ED and LA?
- What graduate-level courses train learning sciences students to understand and use learning analytics in the DBR of learning environments?

In This Special Issue

Our call and review process yielded four articles: Lee-Cultura et al. (in this issue), Closser et al. (in this issue), Pardos et al. (in this issue), and Tancredi et al. (in this issue). Below, we offer overviews of each paper.

The introduction of MMLA (multi-modal learning analytics) into the learning-sciences investigative toolkit has demanded of design-based researchers new forms of technical expertise, mathematical fluency, and statistical prowess. As with any innovative digital technology, early adopters are paving the way, through proof-of-concept studies, toward integrating these new digital affordances into more familiar research practice. However, a lingering paradigm schism still inhibits many learning scientists from interleaving MMLA techniques into their laboratories' perspectives and operations. In *Children's Play and Problem-Solving in Motion-Based Learning Technologies Using a Multi-Modal Mixed Methods Approach*, Lee-Cultura et al. (in this issue) take on the methodological problem of integrating MMLA with the historically more robust research tradition of coding-based qualitative micro-ethnography on video data. As a case in point, their study contributes to the special issue an exemplary development and implementation of an analytic coding scheme that, while derived from qualitative examination of children's interaction with a geometry learning activity, can readily be populated with relevant MMLA data drawn from the same events. The resulting form, named SP3, is suitable for deploying quantitative data from the multimodal gambit of embodied interaction, such as eye-trackers, wristbands, and Kinect joint tracking, into a contextually articulated network of qualitatively encoded pigeonholes. This integrated analytic form, the authors argue, facilitates the detection of multimodal behaviors correlated with actions, utterances, and affective markers implicated as instrumental for learning processes.

In their stimulating paper, *Blending Learning Analytics and Embodied Design to Model Students' Comprehension of Measurement Using Their Actions, Speech, and Gestures*, Closser et al. (in this issue) look at multimodal data from educational episodes in the mathematical domain of measurement to demonstrate the predictive capacity of MMLA to anticipate and characterize microprocesses of students' conceptual gains. The authors' findings from machine-learning analysis of actions, speech, and gesture reveal implicit behavioral patterns that, in turn, may drive new theoretical insight on embodiment, development of domain-specific and generalizable design principles, and methodological innovation for increasing statistical power. Ultimately, applying learning analytics to embodied design sheds new light on nuances of media engineering and instructional facilitation to enhance student development of new embodied–enactive skills constituting content domain knowledge. The paper also offers a fine diagnostic typology of gestures as they pertain to specific domain learning. Embedded as real-time augmentation into the instructional modules, we submit, MMLA information could support student learning through personalized feedback and teacher dashboard cues. Reflecting on their own journey, the authors "implore learning scientists to consider the potential benefits of cross-disciplinary collaborations by blending theories of embodied cognition with learning analytics to pose new research questions and impact future research directions."

As students interact with digital technologies designed for enactive mathematics learning, can these technologies "know" what students are thinking? That could be beneficial for ongoing efforts both to model the learning process theoretically and to develop artificially intelligent tutoring systems that respond in real time to students' actions in ways that best support embodied grounding of curricular content. Attentive human tutors of embodied learning appear to glean students' mathematical thinking from observing their actions and then steer those actions toward expert performance, just as music or sports instructors assess and modify students' actions on the fly (Flood et al., 2020; Newell & Ranganathan, 2010). Can we automatize this intuitive human capacity for noticing in the form of responsive computational algorithms? In their paper, *Characterizing Learner Behavior From Touchscreen Data*, Pardos et al. (in this issue) use neural networks in an effort to detect and proceduralize what it is that humans diagnose as they monitor students' enactive mathematics learning. The researchers trained the artificial intelligence on student touchscreen actions that had been classified by human tutors, and then evaluated the utility of this machine learning by assessing its precision in classifying another set of data. The algorithms achieved moderate parity with human classification of student actions. In turn, visually examining what the neural networks had learned from the data revealed nuances of student behavior that the qualitative analysis had not detected, advancing the greater research program to theorize and serve enactive learning.

In *Modeling Nonlinear Dynamics of Fluency Development in an Embodied-Design Mathematics Learning Environment With Recurrence Quantification Analysis*, Tancredi et al. (in this issue) use analytic perspectives and methodological tools from dynamic systems theory to characterize the process by which students develop capacity to perform motor-control tasks believed to ground mathematical concepts. The case in point is young students figuring out how to move their hands simultaneously, each hand operating one tablet cursor, so that the movement pattern of the two cursors maintains a favorable feedback. The students are not told or shown the goal movement—they must discover it. This challenging bimanual coordination, it will later turn out, is a conceptual choreography of a specific proportional relation. A Cross-Recurrence Quantification Analysis (cRQA) comparing students' bimanual actions across three learning phases (Exploration, Discovery, and Fluency) revealed quantitative markers characteristic of dynamic systems in flux, including phase transitions. A pair of follow-up qualitative analyses then contextualizes the cRQA results in light of the students' verbal–gestural interactions with a human tutor. The study is perhaps the first documentation of nonlinear processes in multimodal mathematics learning. It sets the stage for the research team's subsequent analysis of the role that perception plays in organizing bimanual coordination (Abdu et al., 2021).

Taken as a whole, these four papers engage a range of theoretical, methodological, and design matters attending the prospective marriage of learning analytics and embodied design. Notably, the papers demonstrate how learning scientists who have been citing complex empirical evaluations of embodiment theories need not shy away from utilizing the methods employed in those investigations to collect and analyze multimodal data of participants' neuro-physiological activity. So doing, the researchers' analytic and descriptive capacity will increasingly match the phenomenological richness of the bio–cognitive–social–material phenomena they purport to model. As often is the case, the LA–ED paradigm will evolve from interdisciplinary to disciplinary through graduate training by professors alert to the promise of these developments.

Following the four papers are two commentaries, each from a leading scholar in the cognitive sciences with expertise in embodiment theory, Anthony Chemero and Arthur Glenberg.

Avenues of Future Research

We hope you will find these articles and commentaries as inspiring as we do, and we look forward to working together with you to build our community of LA–ED learning scientists. As they enter in deep conversation, experts in multimodal learning analytics and experts in embodied design could deliberate over the following issues:

- *Intellectual substrate*. What philosophical approaches, theories of learning, and methodological frameworks best enable the coherent integration of LA–ED? To begin with, what are the *sine qua non* literature sources that each camp wishes to share with the other?

- *Technical considerations*. How could ED learning activities best offer LA researchers the data they need? How early in the design process should ED designers include LA considerations? How can we seamlessly integrate LA instruments into ED activities?
- *Transforming educational practice.* How might LA findings inform ED activities in real time? Plausibly, computational inferences from LA data could automatically customize and update task criteria, such as adjusting goals, offering feedback, highlighting relevant sensorial information bearing solution cues, and surfacing LA data for students' self-monitoring. How could human teachers accommodate their facilitation expertise to assimilate these LA–ED classroom activities?
- *Training*. How might graduate schools organize their course offerings and programmatic requirements so as to foster a generation of technologically savvy and theoretically informed design-based researchers capable of building and running LA–ED studies? For example, could LA and ED colleagues figure out how to interleave their respective syllabi into an integrated project-based LA–ED practicum?
- *Growth, community, support*. The future of LA–ED depends on a degree of receptivity in the field. How best could LA–ED researchers promote their scholarship in the field's journals, conferences, and workshops? How should we make our case to federal and private foundations who would fund this line of work?

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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