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Aligning the Goals of Learning Analytics with its Research Scholarship: An Open Peer Commentary Approach

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Keywords
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1. Introduction

To promote cross-community dialogue on matters of significance within the field of learning analytics (LA), we as editors-in-chief of the *Journal of Learning Analytics* (JLA) have introduced a section for papers that are open to peer commentary. The first of these papers, "A LAK of Direction: Misalignment Between the Goals of Learning Analytics and its Research Scholarship" by Motz et al. (2023), appeared in the journal's early access section in March 2023, a few days before the start of the 13th International Learning Analytics and Knowledge Conference (LAK '23).

"A LAK of Direction" takes as its starting point the definition of learning analytics used in the call for papers of the first LAK conference (LAK '11) and used since then by the Society for Learning Analytics Research (SoLAR): "Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Long & Siemens, 2011, p. 24). This definition was adapted from the definition of web analytics that had been added to Wikipedia in December 2008: "Web analytics is the measurement, collection, analysis and reporting of internet data for purposes of understanding and optimizing web usage" (Belmond, 2008).

Motz and colleagues (2023) argue that this definition of learning analytics implies that research in this area "ideally, should make use of data from learners engaged in education systems, should measure student learning, and should improve these learning environments" (p. 1). However, their analysis of papers published from 2020–2022 in the LAK conference proceedings and in the JLA found that most of these papers neither included a measure of learning nor reported an attempt to intervene in the learning environment. The authors conclude that "LA research lacks clear direction toward addressing questions about learning, preferring instead to examine analytical approaches" (Motz et al., 2023, p. 8).

Discussion of the paper, its argument, and its conclusions began within the learning analytics community at LAK '23, a conference held both online and in Arlington, Texas. A hybrid JLA panel on the final day of the conference provided the paper's authors with an opportunity to share their findings before inviting questions and discussion from invited respondents as well as the audience.

Following the conference, an invitation to submit proposals for commentaries on the paper was released, and 12 of these proposals were accepted. The 26 authors of the accepted commentaries are based in Europe, North America, and Australia. They range in experience from PhD students and early-career researchers to some of the longest-standing, most senior members of the learning analytics community.

This paper brings those commentaries together, and we recommend reading it as a companion piece to the original paper by Motz et al. (2023), which also appears in this issue.

2. Overview of the Commentaries

One focus of the commentaries is on what LA is for. Manly and Ochoa (Commentary 1) argue that this is the only field researching ways of presenting analytic information to educational stakeholders in order to engage them in purposeful action. They provide a description of the "learning analytics loop," emphasizing the importance of presenting information back to stakeholders in order to support both their sense-making and their decision-making. In a similar fashion, Lodge (Commentary 2) points out that learning is a complex phenomenon involving both process and outcome. A focus only on learning outcomes

reveals just part of the picture. Learning analytics provides us with ways of gaining insight into real-world learning processes in ways that educational psychology largely does not.

Following these thoughts on what learning analytics can do, Tsai (Commentary 3) discusses what questions researchers should be asking. She outlines three mainstream learning theories that have helped shape practice — behaviourism, cognitivism, and constructivism — and suggests using these to both ask and answer meaningful questions about learning. Meaney (Commentary 4) looks beyond educational theory and argues that a comprehensive theoretical framework is required, taking into account the broader sociotechnical ecosystem in which learning analytics are embedded, including the existing biases and inequities in learning ecosystems.

This leads into a series of commentaries concerned with what learning analytics should do in the future. Williamson and colleagues (Commentary 5) return to the decade-old definition of learning analytics. They make the case for revising this to address objectives beyond understanding and optimizing learning. Like Meaney, they argue that researchers cannot effectively optimize learning for all learners without an in-depth exploration of how inequity and injustice manifest in the environment.

Hicks and colleagues (Commentary 6) return to the subject of learning outcomes, noting that improving learning is one thing, but improving learning outcomes is something entirely different. They define learning as the cognitive process of understanding more about the world, and a learning outcome as an artefact of this process. They recommend making use of directed acyclic graphs to distinguish carefully between what we are intervening on and what we are measuring. Similarly, van Rijn and colleagues (Commentary 7) distinguish between learning process and learning outcomes. They define learning as a process of changing behaviour or dispositions while reflecting on experiences. Understanding and measuring learning processes make it possible to build tools to support students while learning takes place. They emphasize the need for continuing discourse to refine what the field understands as learning, how to impact it, and how to evaluate the community's goals.

Two commentaries also emphasize the importance of time when implementing and evaluating learning analytics. van Haastrecht, together with three colleagues from the Netherlands (Commentary 8), takes a structural realist view and highlights that generating new hypotheses about educational contexts can be just as valuable in the long run as direct improvements are in the short run. Although individual publications may not integrate learning interventions and outcomes, the extended work of projects carried out over several years is likely to do so.

Schuetze and Yan (Commentary 9) use findings from cognitive psychology to draw attention to a temporal aspect of learning: short-term performance is a poor proxy for long-term learning. They consider that meaningful definitions of learning should contain some kind of durability because learning is not useful unless it lasts. Like many of the commentary authors, they recognize problems with the use of learning outcomes as proxies for learning, pointing out that short-term performance can be inflated in ways that circumvent the deeper cognitive processing that supports true learning.

Aggarwal (Commentary 10) moves the discussion from the theoretical to the practical, suggesting steps that could be taken to address problems that have been identified. Ideas include awards, competitions, and different types of collaboration.

The final two commentaries take issue with specific points in the original paper. Chen (Commentary 11) highlights that many learning analytics studies are foundational or exploratory due to the nascent state of the field. She shows how the data in the paper can be used to provide starting points for new work. Finally, Matz and Hayward (Commentary 12) bring a perspective they characterize as in-between practitioner instructors and faculty doing basic research. They advocate for an approach that makes space for research and conversation about grading practices, grade outcomes, and student choices.

Together, the 12 commentaries that make up this paper, drawing on more than a decade of experience in the field, provide a series of promising ways forward for learning analytics. In seeking out theory and methods that can be applied to the LA field, applying practical experience in LA development, and expanding our understanding of the educational ecosystem as a whole — including its opportunities, its challenges, and its inequalities — these commentaries help point us toward the future of LA.

Declaration of Conflicting Interest

The Editors declare no potential conflicts of interest with respect to the research, authorship, or publication of this paper, independently of the declarations made in the commentary papers that follow.

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Open Peer Commentary 1

Building the Learning Analytics Loop: A Call for a More Comprehensive and Connected Approach to LA Research

Catherine A. Manly and Xavier Ochoa

Abstract
We argue against the view that learning analytics (LA) research is not fulfilling its original purpose, closing the LA loop. To close the loop, you need to build it first. This process requires (1) capturing data and mapping them to relevant educational constructs; (2) analyzing data to produce human-understandable information; (3) presenting this information, through indicators, visuals, or narratives, back to stakeholders to support their sense- and decision-making; and through this process (4) provoking and evaluating changes to improve learning. It is very difficult for an individual piece of research to address all parts of the loop in a meaningful way. LA research can be and has been produced about every part of the loop. To make it constructive, LA researchers should consciously connect their contribution to the LA loop so it is clear where their research fits. That being said, we consider that the third step, presenting information back to relevant stakeholders, is where the main body of LA theory should be created. In other parts of the loop, we can borrow and adapt existing theories generated by germane fields. However, LA is the only field responsible for the part of the loop that researches how to present analytic information to educational stakeholders to engage them in purposeful action. We propose that as a community, we should continue focusing on developing theoretical constructs and a rich research base focused on this third segment while not neglecting other parts of the loop.

Keywords
Learning analytics loop, learning analytics theory

The analysis published by Motz and colleagues (2023) advances the notion that by not focusing on studying interventions in real educational settings, learning analytics (LA) is not fulfilling its original purpose of closing the LA loop. Even though only 11% of articles they analyzed actually evaluated an intervention, we see the article distribution as a natural result of LA's nature rather than a problem. We argue that closing the LA loop requires research in each part, and interventions without a solid foundation in previous steps are not in the field's best interests. Using our own reinterpretation of Clow (2012)'s original proposal of the LA loop, it is easy to see the interdependence between steps, their importance in supporting successful interventions, and the difficulty of addressing all four steps in a single publication. The following list describes these steps and exemplary LA works that focus on them:

- **Data Step: Mapping data to relevant learning constructs.** Not all data are useful to understand or improve learning processes. An important avenue of LA research is finding what data are important to estimate or predict the cognitive and non-cognitive constructs related to the learning process. For example, Klebanov and colleagues' (2020) study used reading application data to estimate students' oral reading fluency, while Krumm and colleagues (2016) created a model to predict productive persistence out of LMS data.

- **Analysis Step: Analyzing data to produce human-understandable information.** During this step, the previously mapped data are often summarized or converted for human consumption. For example, Khosravi and Cooper (2018) generated and evaluated a topic-modelling visualization that could be useful for faculty to understand students' achievement across school terms. Similarly, Lin and colleagues (2019) analyzed and visualized communication between students of different genders during collaborative learning to better understand their interaction dynamics.

- **Feedback Design Step: Presenting data back to stakeholders to support sense- and decision-making.** This step focuses on using reports, dashboards, narratives, and other modalities to communicate analysis results to relevant stakeholders. This is the most well known and extensively researched part of LA, as reflected by several dashboard surveys (Bodily & Verbert, 2017; Matcha et al., 2019).

- **Intervention Step: Provoking and evaluating changes to improve the learning process.** Research in this final step focuses on studying the effects of presenting information back to relevant stakeholders on students' learning outcomes or other aspects of the learning process. For example, Dickler and colleagues (2021) studied the impact of an instructor alert system intervention on students' inquiry performance. In another example, Molenaar and colleagues (2020) described the effect of a personalized visualization dashboard on students' self-regulation of practice and transfer of learning.

It is very difficult for an individual piece of research to address all of the steps in the loop in a meaningful way, and we believe it is not necessary for authors to strive to address all loop parts in a single publication. As exemplified before, LA research can be and has been produced around every part of the loop, including work that crosses multiple steps of the loop. For example, Aguilar and Baek (2019) include both modelling and visualization (steps 2 and 3), while Ez-Zaouia and Lavoué (2017) include data collection and dashboards (steps 1 and 3). To the authors' knowledge, though, no papers effectively straddle all four steps at a deep enough level of detail to be considered to focus on all four simultaneously.

To reach the final desirable step of actually changing and improving the learning process, these type of studies should be supported in prior steps in the LA loop. Thus, valuable LA research can be focused on any part of the loop. However, to make research contributions as constructive as possible, LA researchers should explicitly position their contribution inside the LA loop, including building on previous step results and supporting the next steps. Even otherwise valuable LA research may not state or expressly imply that the results can be used for feedback to close the loop (e.g., Williams-Dobosz et al., 2021). We argue that it would be good reporting practice for all LA-oriented work to be situated within the LA loop and to clarify which steps are addressed.

With respect to theory generation, we see the third step of the LA loop (feedback design) as the place where the LA field has the potential for its most important contribution, since other steps typically draw on theories from other fields. Work on the first step (data) often borrows from educational psychology, such as work guided by self-regulated learning theories (Salehian Kia et al., 2021). Typically, the second step (analysis) makes heavy use of methodologies and techniques from data science and educational data mining but does not draw on theory per se, such as techniques modelling student knowledge (Slater et al., 2017). Research on the fourth step (intervention) may borrow from traditional research on educational interventions or theory of change, such as work using Universal Design for Learning (Manly, 2022). However, as the main educational research field that presents learning process information back to stakeholders (the third step), LA is responsible for generating theories guiding how data tools and feedback systems should be designed, deployed, and evaluated to actively engage stakeholders in sense- and decision-making. For example, work in this direction may further investigate how instructors interact with analytics to promote purposeful action (Li et al., 2022) or investigate how students use analytics to support self-regulated learning (Lim et al., 2021).

Moving forward, while we believe meaningful LA research can continue to occur within any of the four steps in the LA loop, we also believe that the third step of the loop holds LA's key theoretical contribution overall. We propose that the LA community should turn their attention to developing a theoretical base focused on the best ways to give feedback to learning process stakeholders and validate these theories with empirical studies of LA interventions.

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JOURNAL OF LEARNING ANALYTICS

Open Peer Commentary 2

What Differentiates Learning Analytics from the Learning Sciences and Educational Psychology?

Jason M. Lodge

Abstract

This commentary examines the critique of the field of learning analytics (LA) by Motz et al. (2023), focusing on the perceived lack of emphasis on learning processes. In reconsidering LA's position within the broader educational research ecosystem, the importance of LA in gaining insights into real-world learning processes in ways that educational psychology often does not is discussed.

Keywords

Learning sciences, educational psychology, learning processes, learning outcomes, educational epidemiology

1. Commentary

Motz et al. (2023) scrutinize the effectiveness of learning analytics (LA) in leveraging data to facilitate learning. In the process, the authors have revealed an intrinsic issue with the field. This commentary aims to delve deeper into the authors' critical analysis, evaluate the fundamental assumptions underpinning their thesis, and attempt to map out one aspect of the educational research ecosystem to which LA is uniquely placed to contribute.

The principal concern illuminated by Motz et al. (2023) revolves around a lack of emphasis on learning outcomes or, indeed, on learning at all in LA research. While this is an important finding, it does relegate the critical processes of learning to the periphery. Learning is a complex phenomenon, it cannot be measured directly, and it involves both process and outcome (Soderstrom & Bjork, 2015). Learning cannot simply be measured by looking at the echoes of it in an outcome any more than it can be by looking at the parts of the brain. Presently, as generative artificial intelligence can produce learning "outcomes" without going through the learning processes necessary to produce these outcomes (Lodge et al., 2023), relying on outcomes to infer learning is even more fraught. The need to shift focus onto learning processes has become a pressing issue.

Motz et al. (2023) may have inadvertently captured the paradoxical nature of the LA discourse. The authors both decry the lack of emphasis on learning in the LA literature but also themselves primarily focus on learning outcomes and not explicitly on learning processes. The learning sciences and educational psychology have evolved beyond the crude concept of learning as merely an outcome (e.g., Fischer et al., 2018). However, it could be argued that these fields do not fully harness the capacity of LA to promote a more nuanced understanding of the learning process, though the field seems to be trending in that direction (e.g., Jarvela et al., 2020). The learning sciences in particular have much in common with LA but educational psychology, sharing a close connection with psychological science, could be seen as being not as well equipped to understand processes of learning in the wild. Psychological science relies heavily on controlled studies, often conducted in artificial learning situations. These studies do not easily translate to real students in real educational situations. The resulting translational distance underscores a significant gap in the educational research ecosystem, with LA potentially well-positioned to bridge this gap.

The conceptual fuzziness of LA is, therefore, an ongoing point of contention. The definition of LA provided by Motz et al. (2023) — "to understand and optimize learning" — ostensibly covers both learning processes and outcomes. However, the line separating LA from the learning sciences seems to be becoming increasingly blurred in this regard. Emerging work on artificial intelligence in education is poised to further add to the murkiness of the distinctiveness (or not) of LA as a field of study.

Therefore, a pertinent question arises: is LA indeed a distinct discipline? Could it be regarded as the application of data science to the learning sciences, given the dominant theories such as self-regulated learning? Alternatively, could it be a sub-discipline of computer science applied to education? Such discussion is necessary since the academic positioning of LA holds implications for pedagogical strategies and broader educational policy and practice.

Considering these complexities, one can argue that LA's most significant contribution might emerge from a deeper understanding of the learning process in real-world and virtual learning environments. Traditional psychological science largely overlooks this aspect and is not well set up to explore it. LA could be the educational equivalent of quantitative

epidemiology in health research, compiling and analyzing real human data to comprehend processes, predict factor relationships, and subsequently enhance outcomes.

Motz et al. (2023) offer a valuable critique of LA that prompts broader conversations about the role and positioning of the field in the educational research landscape. By addressing the highlighted challenges, LA could live up to its potential, contributing to the evolution of the learning sciences. However, the positioning of LA relative to these other fields requires further consideration. Motz and colleagues appear to have overlooked the area where LA has perhaps the greatest potential given the pressure being applied to outcomes as a means of inferring learning by the emergence of generative artificial intelligence. LA can provide insights into learning processes in the real world in the way that quantitative epidemiology does about health. Within the ecosystem of research in education and learning, LA is uniquely placed to provide critical insight into the processes of learning as they are occurring in naturalistic learning settings.

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JOURNAL OF LEARNING ANALYTICS

Open Peer Commentary 3

Where is Learning in the Analytics?

Yi-Shan Tsai

Abstract

The article "Misalignment Between the Goals of Learning Analytics and its Research Scholarship" by Motz et al. (2023) reveals a misalignment between the goal of learning analytics and the current efforts in the field. This commentary explores this phenomenon further, positing that the learning analytics community is stuck in an exploratory phase of understanding how learning occurs with little progress on enhancing learning. Moving towards the goal of "optimizing learning," we need to ground the measurement of learning and intervention in learning theories. The commentary discusses three mainstream learning theories — behaviourism, cognitivism, and constructivism — that have shaped some learning analytics practices, and proposes reflection questions to align learning analytics with learning.

Keywords

Learning analytics, learning theories, behaviourism, cognitivism, constructivism

1. Commentary

Tracing the root of the misalignment between the current practice of learning analytics and the three defined elements (utilizing authentic learning data, measuring learning outcomes, and intervening in learning) discussed by Motz et al. (2023), we may blame the challenge of operationalizing learning analytics as part of core educational practices as a possible cause. A lack of leadership support to strategically integrate learning analytics into institution-wide teaching practice can significantly limit the range of data accessible to researchers. As a result, researchers turn to data at hand or seek new data sources such as through laboratory studies (Motz et al., 2023). In many cases, the latter may be the only possible way to innovate in learning analytics as justifications for more or new data collections from learners at scale can be difficult to create due to ethics and privacy implications. Even when researchers are granted access to data at the institutional level, there is often a disconnect between the purpose of data collection and learning design. The culture of asking "What is there in the data?" before asking "What is meaningful to measure?" has thus been perpetuated. As a result, the learning analytics community seems to be stuck in an exploratory phase of understanding how learning occurs with little progress on effective interventions to enhance learning.

Resolving the stagnation of progress from "understanding" to "optimizing" learning can nevertheless start from small-scale studies if we can resist the attraction of "things that we can do" and instead focus on "problems that we can solve" in answering meaningful questions about learning (Motz et al., 2023, p. 8). One may begin with the epistemic framing of a chosen pedagogical stance to identify suitable learning analytics approaches and questions to pursue (Knight et al., 2014). It is useful to start from the three main schools of learning theories: behaviourism, cognitivism, and constructivism. Behaviourism focuses on measuring observable behaviour and the cause-and-effect relationships of learning (Danver, 2016). The influence of behaviourism on the current practice of learning analytics is particularly notable, with its focus on capturing observable learning events and student responses to stimuli, such as email nudges. A typical question to ask is, "Has there been a change in learning behaviour?" It is worth noting that the promotion of behavioural change based on trace data may encourage surface learning or gaming systems. It is thus important to ask the following question:

Does the observed change of behaviour truly signal learning?

This leads to questions about whether learning does take place in one's brain and how. This is of interest to learning theorists of cognitivism, which draws attention to the mental processes activated during a learning process — attention, perception, memory, reflection, and motivation (Jordan et al., 2008). Examples of learning analytics research underlined by cognitivism include exploring self-regulated learning using trace data, understanding cognitive loads and attention using eye-tracking, and understanding how users perceive or make sense of dashboards using self-reported data. Guided by this school of thought, learning analytics researchers are interested in inferring mental activities from data. It is, therefore, important to ask these questions:

Is the data a true representative of the particular mental process that we are trying to observe?

Is there any mental activity that is not observable or interpretable based on the captured data?

With a shared interest in the cognitive process of learning, constructivism focuses on how learners make sense of information. Cognitive constructivism emphasizes that learners construct meanings by synthesizing new information and

existing knowledge. Building on cognitive constructivism, social constructivism zooms out from the view of the individual student to consider the social and cultural aspects of learning, such as learning with support from a "knowledgeable other" (Jordan et al., 2008). Studies on how learners can develop self-reflection abilities and devise actions based on interactions with learning analytics tools build on cognitive constructivism. Learning analytics that capture and analyze collaborative learning events and that provide feedback through a social comparison frame of reference are rooted in social constructivism. It is important to ask these questions:

How might existing knowledge and experience of learners affect their interpretations and experience of learning analytics?

How might learning differ among individuals as a result?

What roles can teachers and peers play to support learning?

How may learning analytics play the role of a "knowledgeable other" to scaffold learning?

Essentially, learning analytics as a process builds on all three schools of learning theories — relying on capturing observable learning behaviour (*behaviourism*) to understand how learning takes place inside a learner's brain (*cognitivism*), and supporting students to become reflective learners through the use of learning analytics (*constructivism*). However, depending on the theoretical perspectives that researchers and practitioners take to design or utilize learning analytics, the epistemological approaches to understanding learning vary. Thus, different questions need to be asked to guide the exploration of the ways learning occurs and thus ways to improve it.

Coming back to the common definition of learning analytics (Long et al., 2011), "optimizing learning" may seem aspirational, but it conveys the reason why we do what we do with data about learners and learning. Moving towards enhancing learning, it is important to recognize that learning can take different forms. We need to align measurement and intervention with learning theories, and to ask relevant questions that point us back, as well as lead us towards, learning.

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JOURNAL OF LEARNING ANALYTICS

Open Peer Commentary 4

From a Nominal to Normative Commitment: Liberating Learning Analytics from Embedded Biases Through a Sociotechnical Systems Approach

Michael J. Meaney

Abstract

The emphasis on "Can we do this thing with these data?" detracts from other important goals of learning analytics (LA) beyond understanding and optimizing student learning. It also undermines LA's ability to develop a coherent epistemology and be consistent with its stated values of openness, fairness, and justice, equity, diversity, and inclusion (JEDI). A comprehensive theoretical framework accounting for LA's macro, meso, and micro level domains would enable more epistemologically cohesive, sociotechnical system approaches to be taken, which could help shift nominal commitment to values to a normative one.

Keywords

Distance education, massive open online courses, learning analytics, inequality

1. Limited Analysis of Demographic Subgroups

The focus on novel techniques in LA often neglects analysis of the composition of learners and their contexts and may inadvertently amplify biases and inequities in learning ecosystems (Uttamchandani & Quick, 2022; Sabnis et al., 2022). The LA community is too focused on what techniques are employed rather than on what questions can be answered (Motz et al., 2023; Wise et al., 2021). While a recent special issue in the *Journal of Learning Analytics* focused on fairness, equity, and inclusion, and these themes are nominally included as focus areas at top LA conferences annually, the field has under-considered the broader sociotechnical ecosystem in which LA are embedded (Wise et al., 2021; Meaney & Fikes, 2019), which may contribute to digital education systems reifying existing inequalities (Meaney, 2021; 2023). While these questions are of growing importance in the literature (Uttamchandani & Quick, 2022), they are noticeably absent in Motz et al. (2023). Without proper attention to these questions, LA risks reinforcing biases against certain kinds of learners and their contexts, namely those who are underrepresented in the data. The narrow focus of the field may sufficiently solve for a local maximum required for publication but may ignore important social questions raised about more global educational phenomena.

Re-emphasizing the values of openness, fairness, and JEDI in the epistemological approaches and research goals of LA could not only clarify the understanding and optimization of learning environments but help answer central questions of for whom and why.

Doing so may be difficult. Demographic data, critical to evaluating questions of openness, fairness, and JEDI, is often not collected or available, or analyzed when it is (Williamson & Kizilcec, 2022; Sabnis et al., 2022). A recent systematic review of the educational data mining literature, which overlaps considerably with LA, found that a mere 15% of papers used demographic variables in their analyses (Paquette et al., 2020).

Recent work attempts to fill this gap. Research that examines differences in procrastination behaviour (Sabnis et al., 2022), engagement with LA dashboards (Williamson & Kizilcec, 2022), and specific analysis of how demographic subgroups persist in open learning environments (Meaney & Fikes, 2023; Nguyen et al., 2020), have all explicitly collected relevant demographic variables and used them to analyze equity gaps along educational, racial, and socioeconomic lines, among others. More work along these lines is needed. Such work should be conducted with adequate attention to student privacy concerns and thoroughly explore the impact of including sensitive attributes in LA models (Deho et al., 2022). Even still, merely specifying demographic data and being thoughtful about how data biased toward a demographic group may inadvertently perpetuate inequality does not resolve the broader question of how to anchor the field to a more cohesive epistemology that can include the values of openness, fairness, and JEDI.

2. The Need for a Comprehensive Theoretical Framework

One way to do so is to call for more theoretical development; however, not just any theoretical development. LA is awash with ad-hoc theoretical models borrowed from the diverse fields that constitute its assemblage (Khalil et al., 2022; Wang et al., 2022; Ferguson et al., 2016). Developing a more comprehensive theoretical framework describing the overall ecosystem of domains and concepts that comprise LA would be more helpful.

The sister field of distance education provides an illustrative, analogous development cycle worth considering. Early in its development, distance education was described as fragmented and atheoretical (Perraton, 2000). To help resolve this, Zawacki-Richter (2009) proposed a comprehensive theoretical framework for approaching the literature. Through conducting a Delphi study, he developed the 3 M-Framework for Distance Education represented in Figure 1, which situated the research literature across relevant macro, meso, and micro level domains.

Research level	Research area
Macro-level: distance education systems and theories	1. Access, equity, and ethics 2. Globalization of education and cross-cultural aspects 3. Distance teaching systems and institutions 4. Theories and models 5. Research methods in distance education and knowledge transfer
Meso-level: management, organization, and technology	6. Management and organization 7. Costs and benefits 8. Educational technology 9. Innovation and change 10. Professional development and faculty support 11. Learner support services 12. Quality assurance
Micro-level: teaching and learning in distance education	13. Instructional design 14. Interaction and communication in learning communities 15. Learner characteristics

Figure 1. The 3 M-Framework for Distance Education (Zawacki-Richter & Bozkurt, 2022).

3. A Call for Sociotechnical Theory Building

The 3 M-Framework for Distance Education is an illustrative example of how LA can broaden its epistemology to consider questions beyond "Can we do this thing with these data?" A framework that includes relevant macro, meso, and micro level domains and concepts of the field would build upon early attempts to establish more cohesive epistemological frameworks (Buckingham Shum, 2012; Greller & Drachsler, 2012), the absence of which in recent work is noted in Motz et al. (2023). These frameworks could enable researchers to explore the broader sociotechnical systems in which LA are embedded, which has been called for in the literature (Wise et al., 2021).

Initial attempts at this kind of work are underway. One example is the development of Hegemonic Design Bias (Meaney, 2021; 2023), a sociotechnical framework that attempts to account for the macro, meso, and micro levels of the MOOC production ecosystem and how it perpetuates inequality.

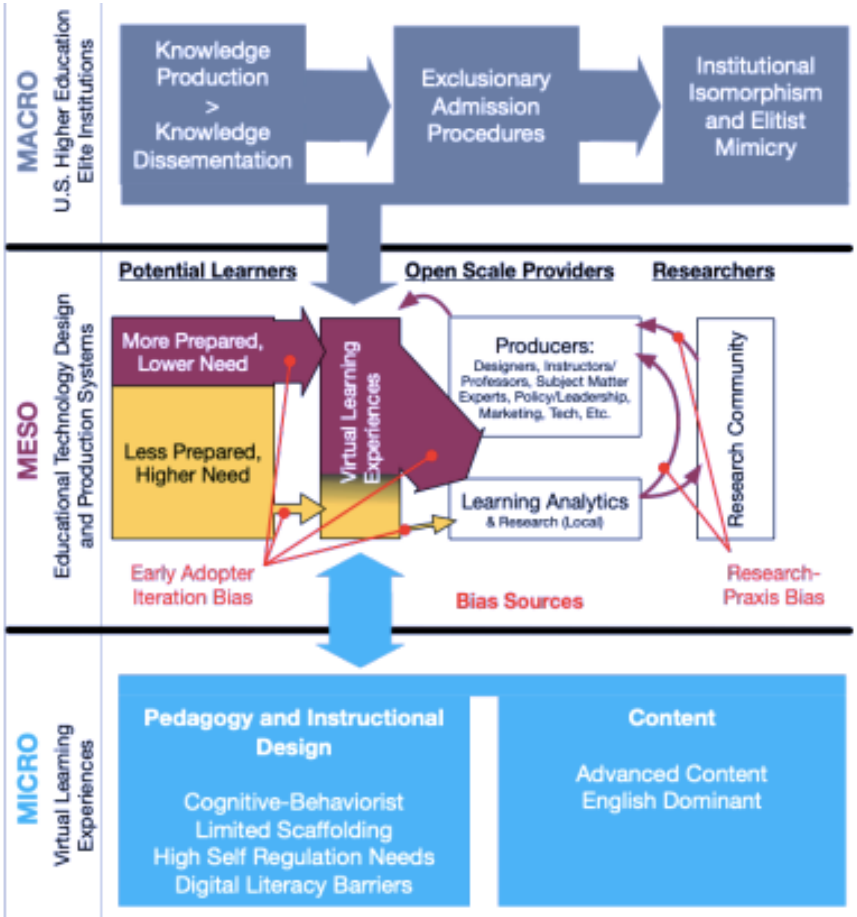

Figure 2. Hegemonic Design Bias: a sociotechnical framework describing the MOOC production ecosystem. At the macro level, the relative importance of knowledge production compared to knowledge dissemination among elite institutions of higher education, the tendency for this focus to produce exclusionary admissions standards, and elitist mimicry resulting in institutional isomorphism all influence the design of MOOCs. At the meso level, "early-adopter iteration bias" — whereby already educated users make up most MOOC participants and produce the data that researchers and practitioners analyse to iterate and improve MOOCs — skews this design further. A separate but related process, "research-praxis bias," further prevents MOOC development from meeting the needs of underserved learners. At the micro level, a series of pedagogical, curricular, and technological design processes compound these issues (Meaney 2021; 2023).

4. Moving from Nominal to Normative Commitments

Openness, fairness, and JEDI, are considered values of LA rather than goals. This commitment is nominal. In considering a more cohesive epistemology with a comprehensive theoretical framework for describing the field and explicitly including a sociotechnical systems approach, LA can move this commitment from nominal to normative.

Doing so does not need to contradict LA's empirical and computational genealogy. Instead, explicitly stating a normative orientation would enhance LA research practice. Doing so aligns with how philosophers of science approach such questions. Methodological normativity describes the assumptions researchers make when selecting, interpreting, evaluating, and adjusting relevant empirical information (Kaiser, 2019). Right now, methodological normativity is an incidental feature of LA, occurring if researchers focus on questions of openness, fairness, and JEDI, and have access to relevant variables. It should become an intentional feature of LA, wherein these normative dimensions are always considered.

Without broader consideration of the sociotechnical ecosystem in which LA are embedded, even resolving the present LAK of direction (Motz et al., 2023) will not necessarily satisfy the field's aims. Improving the identification of demographic variables and including them in our analyses will be a good step forward. However, if we take as given the construction of the education systems we analyze and the flows of learners into them, more detailed demographic data will merely describe an upstream reality on which the field is dependent. LA can specify its methodological normativity and develop a more cohesive

epistemology by broadening LA research to include more macro, meso, and micro layers and building sociotechnical frameworks that allow these layers to be examined. This can help move LA from a field that, rather than merely describes reality or critiques it, works to uncover the mechanisms influencing reality in order to transform it (Wegerif, 2013; 2018).

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Open Peer Commentary 5

Improving Social Justice Should Be an Objective of Learning Analytics Research

Kimberly Williamson, Valerie A. Guerrero and René Kizilcec

Abstract
To address persistent issues of injustice in education worldwide, we should expand the definition of learning analytics to include promoting social justice beyond understanding and optimizing learning.

Keywords
Social justice, equity, systems, learning analytics

In 2020, the Society for Learning Analytics Research (SoLAR, 2020) issued a Statement of Support and Call for Action that "condemns the murder and treatment of Black people and communities in the U.S. and worldwide" and encourages its global research community "to mobilise our expertise and connections with communities to actively contribute to [...] promoting social justice and dismantling injustices in education." Social justice can be understood as both a goal and a process that cultivates a society mutually shaped to meet individual and group needs, and in which all members are psychologically and physically safe and secure (Adams et al., 2022). SoLAR's Call for Action has stimulated discussion about our field's duty to educate ourselves on the social inequities and external factors embedded into the contexts we study and contribute to developing more just environments. However, while the interdisciplinary nature of learning analytics (LA) lends itself to a broad definition inclusive of all learning environments, the active promotion of social justice is not reflected in SoLAR's definition of LA: "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs."

Motz and colleagues (2023) empirically demonstrate a misalignment between this definition, which emphasizes understanding and optimizing learning, and the emergent LA literature. Building on the authors' findings and SoLAR's Call for Action, we argue that the definition of LA needs to be updated to promote work that addresses objectives beyond understanding and optimizing learning. Specifically, the revised definition should explicitly include a distributed effort to promote social justice in education. This change would signal to the community the importance of work that tackles widespread injustices in education and that advances our understanding of how learning environments impact learner outcomes from a justice, equity, diversity, and inclusion (JEDI) perspective.

A JEDI perspective prioritizes justice and equity to address inequities, and it augments support of diversity and inclusion with accountability for ensuring that these goals are met (Williamson & Kizilcec, 2022). For example, efforts to improve learning with technologies that require Internet access should be matched with efforts to understand how systemic restrictions to Internet access contribute to inequitable learner outcomes by maintaining socially unjust systems or practices. LA researchers should examine how learner outcomes are impacted by institutional, policy, and socio-historic features of their learning environment (Hurtado et al., 2012), and not just features of the immediate classroom environment. By considering the historical contexts and social habitus that have catalyzed in a region and continued to perpetuate systemic inequities, the LA community can (a) more accurately reflect the factors impacting learning optimization, (b) address existing issues of injustice across the globe, and (c) improve alignment between its research and goals to understand and optimize learning.

Inequity and injustice manifest in the context of learning in many ways. For instance, a significant source of inequity throughout the globe is rooted in language differences. Refugees from many places arrive without knowing the local language and struggle to integrate into schools. In France, asylum-seeking children are included in compulsory education until age 16 but are subject to additional evaluations. Schools have no obligation to accept students between ages 16 and 18, and they do not qualify for apprenticeship permits or resources for formal language training, limiting their educational access (Forum Réfugiés, 2023). Such policies and practices create socio-cultural segregation that reinforces educational and workforce gaps; however, the potential to use LA in this context is limited if researchers do not collect and analyze relevant language data. In Australia, secondary school attendance gaps between Indigenous and non-Indigenous students have persisted for decades and impacted educational achievement (Commonwealth of Australia, 2019). LA researchers do not need to be experts in policy, but they ought to consider broader concerns and existing inequities when studying analytics. More purposeful considerations of contextual factors and their impact on equitable learning outcomes will contribute to the field's calls to promote social justice

by encouraging research tackling injustice issues at institutional and political levels.

The LA community is well equipped to investigate the numerous factors contributing to variation in learning processes and outcomes for different groups of learners and across multiple contexts. Because the norms of a given learning environment's institutional, political, and socio-historical contexts can influence the effectiveness of said learning, LA researchers cannot effectively optimize learning for all learners without an in-depth exploration of how inequity and injustice manifest in the environment. When researchers fail to interrogate contextual and external factors, they may inaccurately assume norms that are not universal, which can contribute to inequitable outcomes (Williamson & Kizilcec, 2022). This issue can lead to various interventions, policies, and practices unsupported by contextual research evidence (Hurtado et al., 2012). At a time when the SoLAR community is exploring its identity for the next decade, we hope that improving social justice will be part of that new identity.

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JOURNAL OF LEARNING ANALYTICS

Open Peer Commentary 6

Causation and the Interplay Between Learning Outcomes and Learning Interventions

Ben Hicks, Joshua Weidlich, Kirsty Kitto, Simon Buckingham Shum and Hendrik Drachsler

Abstract

Motz et al. (2023) make the point that learning analytics should be more frequently measuring learning outcomes and making interventions in order to better align with its stated goals. These two aspects of their critique are symptomatic of an underlying need for a more formal modelling of causality. We comment on how this might be expected in an emerging field and offer a potential way forward.

Notes for Practice

- Distinguishing between learning and learning outcomes is key for understanding learning interventions
- Graphical causal models provide a way to transparently model causal structure

Keywords

Causal models, theory, learning outcomes

1. Commentary

Motz et al. (2023) lament the misalignment between the stated aim of learning analytics (LA) and the current state of research, questioning how we can "understand and improve learning" if we rarely measure learning outcomes or intervene in learning systems. We are in broad agreement with this stance but wish to interrogate to what degree this might be expected in an emerging, complex field, and how thinking about causal structure offers a possible direction forward.

As an emerging field LA does not yet have well established theoretical frameworks (Kitto et al., 2023). LA is still exploring testable theories of learning, and as such we would not yet expect widespread measurement of a complex phenomenon such as learning, despite the abundance of data. Something is missing between the deluge of data recorded in learning environments and our understanding of the learning processes that leave digital traces. A breadth of research may still be required in order to establish an empirical basis upon which more formal theoretical models and measures of success can be built. The lack of measurement of learning outcomes may be a symptom of the challenges present for an immature field, or indeed any field struggling to theorize and operationalize the complex constructs that we commonly designate as "learning."

Motz et al. (2023) acknowledge this immaturity of the field in reference to the deficiency in active interventions. We think these two challenges for LA in meeting its stated goals — measuring learning outcomes and making interventions — are linked and stem from the informality in how we think about the causal structure of LA systems. Being mindful and precise about how we abstract is critical to modelling learning (Essa, 2019). Improving *learning* is one thing, but improving *learning outcomes* is something entirely different. How we think about and model the causal relationships around this distinction impacts dramatically on how we might use LA to guide interventions. To be clear, here we see learning as the (unseen) cognitive process of understanding more about the world, and the learning outcome as some, possibly measurable, proxy of this process (Mislevy et al., 2019). We take a slightly narrow view of learning outcomes here as data intensive fields such as LA gravitate towards *measurable* outcomes. For instance, learning is what is happening in the student's mind, leading to improved performance in an assessment — the learning outcome. Optimizing purely for a measurable learning outcome could lead to farcical interventions such as simplifying learning content or making assessments easier. Less obvious could be an intervention that improves a student's examination skills, possibly improving learning outcomes without improving learning, a phenomenon known as "teaching to the test" (Jennings & Bearak, 2014).

This is not what we expect LA to do. LA interventions should target student behaviour (learning) as well as student performance (learning outcomes; Larrabee Sønderlund et al., 2019). However, it is easy to slip into modes of thought where we might want to start "privileging the measurement of learning outcomes… to approximate a shared trajectory toward optimizing and improving them" (Motz et al., 2023, p. 9). One way of thinking about consequences of LA interventions is through *consequential validity* (Messick, 1989). In this view, interventions can correctly target the variable of interest (thus being valid in the usual sense) but still produce downstream educational consequences that may be unintended or undesired.

For example, LA-based feedback making use of social comparison information can produce enhanced learning outcomes but, perhaps not immediately visible, also foster undesirable competition and poor learning strategies.

Using directed acyclic graphs (DAGs), we can help ourselves think about these complexities using diagrams to specify an assumed causal structure and to carefully distinguish between what we are intervening on and what we are measuring (Hicks et al., 2022). Figure 1 shows how such a diagram can represent the causal relationships in a learning system.

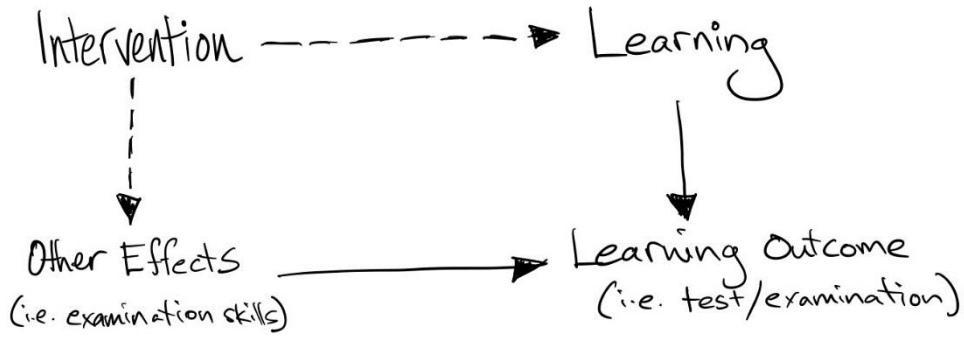

Figure 1. A causal graph showing the relationships between variables of a learning system. An intervention may be affecting the learning or other influences on the learning outcomes (dotted lines).

This presents one way we might formalize how we model causal structure in a learning system. Explicitly modelling causation using such a framework may offer a path forward for developing theory to better align LA with what we mean by learning and what we measure (Kitto et al., 2023). Importantly, causal modelling can be employed in all phases of research, e.g., study planning, analysis, and literature appraisal (Weidlich et al., 2023). In the absence of research contexts amenable to rigorous experimental protocols, DAGs can also provide a principled approach to thinking about and understanding sources of bias in a variety of research designs in LA (Weidlich et al., 2022). For a deeper introduction to causal DAGs and their potential applications in LA see Weidlich et al. (2022) or Hicks et al. (2022).

While Motz et al. (2023) are correct that LA currently does little to measure the effectiveness of its interventions, we would caution the field against a simple response that involves more intervention or measurement without a better understanding of causality in learning systems. Sound measurement requires a strong theoretical basis grounded in our scientific understanding of learning itself. This will take time and investment for a field to achieve as it gradually matures. Causal models provide one avenue for achieving this more robust measurement of meaningful learning outcomes. LA has investigated many pieces of this complex puzzle over the past 15 years. Perhaps it is now time to attempt more formal abstractions of what we know in order to join these pieces together.

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Open Peer Commentary 7

Rethinking How We Measure Learning

Lars van Rijn, Michael Hanses and Ioana Jivet

Abstract
This commentary challenges the operationalization of the goals of the learning analytics research field (i.e., "understanding and optimising learning and the environments in which it occurs") into the coding scheme used by the authors to analyze recent literature from the Learning Analytics and Knowledge Conference and the *Journal of Learning Analytics*. We will use the proposed code for learning outcome as a starting point to reflect on the concept of learning and learning outcomes from an educational science perspective. We reiterate the idea that the definition of learning outcome disregards process-oriented measurement of learning. In closing, we emphasize the need for discourse to refine what the field understands as learning, how to impact it, and how to evaluate the community's goals.

Keywords
Educational science, evidence of learning, learning outcome, learning process, measuring learning

1. What Constitutes Learning?

In this commentary, we challenge the conceptualization of learning used by Motz and colleagues (2023) to assess the alignment between learning analytics (LA) goals and its research scholarship. In particular, we object to the result that 71% of the analyzed papers do not include any measure of learning. Central to this argument is the way in which learning is understood, which in turn determines how evidence of learning is measured.

Although learning has multiple definitions across research contexts (e.g., neuroscience, biology) (Barron et al., 2015), we want to outline an educational science perspective of the concept, relying on Ludwig's (2020) synthesis of definitions within the field. Here, learning is a mostly cognitive process that leads to changes in what one might be able to do (dispositional potential), which cannot be explained by natural development through aging (maturation) (Ludwig, 2020). More specifically, learning means changing behaviour or dispositions while reflecting on experiences. Consequently, learning is not the change in one's capability, but rather the processes bringing about the change. We rely on this simplified description to analyze how Motz and colleagues (2023) perceive learning and to highlight the complexity of measuring learning.

2. Measurements of Learning

To derive whether learning was measured, Motz and colleagues (2023) used the code "Is It Outcome Learning?" indicating "…whether any of the study outcomes measure evidence of learning" (p. 4). Evidence of learning was conceptualized as "performance measures" (p. 8) of aspects to be learned, for example, assessment of student artifacts, grades, scores, and expressing expertise, skills, and competencies. We would agree that measuring learning via performance is a valid indication that learning has taken place. However, this conceptualization disregards insights into or measurements of the process itself as evidence of learning, instead looking at changes in learners' performance at the end of the process (i.e., the "delta"). Interventions thereby can only be summative, informing upcoming but not current learning processes. We argue that understanding and measuring the learning processes enables the LA community to build tools supporting students while learning occurs. Such interventions can be preventive, guiding learners toward productive habits or supporting self-learning. To elaborate on this, we discuss two negatively coded papers under "Is It Outcome Learning?" that measure evidence of learning according to the described educational perspective on learning.

3. Reflections on Coded Articles

Saint and colleagues (2020) investigate learning via temporal patterns in digital traces of learners' activities. Sequences of context-specific student events (e.g., (in)correctly solving assessment items or loading the course index page) are mapped to micro-level self-regulated learning (SRL) processes (e.g., goal setting, working on a task, evaluation). Inferring these learning processes from possible activity patterns would already qualify this paper as measuring learning, thereby adhering to the LA community's goals. Saint and colleagues (2020) also show that the SRL patterns are qualitatively different for high- and

low-performing students, measured by exam scores. The latter gives evidence that differences in performance co-occur with different identified patterns. We would therefore argue that investigating students' SRL by triangulating trace data with context and SRL theory to uncover seamless ways of measuring learning processes is well within the community's goals.

Poquet and Jovanovic (2019) used forum data to identify network structures between learners and analyzed implications on the interaction between learners over time. They argue that intergroup and interpersonal connections imply collaborative activities, relating their measurements to collaborative learning (CL) contexts (Jeong et al., 2019). Not measuring learning outcomes (e.g., changes in learners' knowledge or collaboration skills) but rather investigating student interactions provides insights that could inform interventions facilitating CL, for example, prompting participation, eventually leading to better learning outcomes. However, the forum's context could offer additional insights into the learning process. For example, in a discussion (forum) on specific learning content, interconnections between learners could represent engagement with the content or peer perspectives on it (Engeness & Edwards, 2017). Our argument is that depending on context, certain measurable steps in CL coincide with critical moments in learning processes, allowing for their indirect measurement.

Both examples show that observing and contextualizing learner behaviour makes it possible to infer whether learning is taking place. This way LA can further educational research through new ways of collecting data and computational methods of educational data analysis, generating new findings or expanding possibilities for intervention throughout the learning process.

4. Conclusion

This commentary shows that learning, from an educational perspective, is a process rather than its outcome. While we agree that LA interventions should eventually show improved learning outcomes, there is considerable value in understanding the inner workings of learning processes and devising new ways to analyze learning. These insights enable interventions that support learners throughout learning processes leading to higher achievement. Applying this to Motz and colleagues (2023), measurements that might not appear as evidence of learning at first glance can contain critical information about the learning process. While the discussion around more strongly integrating educational and learning science into LA (Gašević et al., 2015) has led to new ways of analyzing and interpreting learner data, it might be sensible to involve more interdisciplinary discourse on the community's goals (Viberg et al., 2018). This includes debating the understanding of what learning is and what constitutes evidence of learning, re-evaluating current measurements of learning, and refining the methods we apply to derive richer interpretations from educational data.

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Open Peer Commentary 8

A Structural Realist Defence of Learning Analytics

Max van Haastrecht, Matthieu Brinkhuis, Anouschka van Leeuwen and Marco Spruit

Abstract
We reflect favourably on the methodological choices made by Motz et al. (2023). Therefore, our commentary will not focus on the methodology and results presented in the article, but rather on the conclusion that there is misalignment in the learning analytics (LA) field. We critically discuss the two suggested causes for this misalignment: either the LA definition does not accurately reflect the field's research or the field's research is not living up to the high standards of its definition. We argue that a structural realist appraisal of LA, combined with an appreciation for research projects over single publications, could offer a perspective highlighting that LA is not as misaligned as it may seem.

Keywords
Learning analytics, structural realism, research projects, epistemology

1. Cause 1: The LA Definition is Not an Accurate Reflection of the LA Field

One possibility presented by the authors is that the LA definition is at fault. LA focuses on analyzing educational data "for purposes of understanding and optimizing learning and the environments in which it occurs" (SoLAR, 2021). Since the results of Motz et al. (2023) suggest that researchers mostly do not intervene in learning environments, it is natural to wonder whether the original LA definition should be altered to form a more attainable beacon for the field.

As Clow (2013, p. 686) pointed out early on, LA "lacks a coherent, articulated epistemology of its own." This epistemological diversity was recently reaffirmed in our own work (van Haastrecht et al., 2023), where we delineated how different epistemological views lead to distinct strategies for validating LA solutions. Without epistemological consensus, we can expect that researchers will interpret a single definition in a multitude of ways. In other words, we do not require a new definition, but a consensus interpretation of our existing definition. Structural realism could offer the lens that facilitates such an interpretation.

Structural realism (Worrall, 1989) strikes a balance between scientific realism and anti-realism by positing that an external reality exists, but that we can only lay bare its structure, not its true nature. According to Motz et al. (2023, p. 2), "practical improvements in learning" are a demand for a successful LA solution. A structural realist would counter that optimization can only be achieved through the discovery of models that are increasingly informative about the structures present in educational contexts.

Within this frame, a study aiming to minimize student dropout might switch its approach from predicting dropout directly to modelling and understanding common dropout patterns. Intervening becomes a desideratum rather than a demand, meaning that LA research would not be as misaligned with its definition as it may seem. The structural realist view highlights that generating new hypotheses about educational contexts can be just as valuable in the long run as direct improvements are in the short run. Just as there are no absolute truths in educational contexts, there are no instant truths either. The absence of instant truth is our starting premise to address the second suggested cause for misalignment.

2. Cause 2: LA Research Is Not Living Up to the High Standards of the LA Definition

The second cause posited by the authors is that LA research is not living up to the high standards of the LA definition. Since "89% of articles do not attempt to intervene in the learning environment" it follows that "LA is very rarely introducing *any* improvements into the learning environment" (Motz et al., 2023, p. 7). While this argument seems convincing, it glosses over the fact that many interventions are the result of complex research projects spanning several years.

Although single publications regularly fail to integrate learning interventions and outcomes, research projects are more likely to succeed in doing so. Projects commonly consist of sub-studies that are published separately, often years apart. For example, we examined self-regulation processes in MOOCs (Jansen et al., 2022), followed by an intervention aimed at improving self-regulated learning (Jansen et al., 2020). The unpredictable nature of the publishing process caused the reversal of the study publishing dates. Motz et al. (2023) choose to include method evaluations and short papers in their analyzed set.

It should not be surprising that these individual papers, often a part of larger research projects, do not all describe extensive interventions in learning environments.

We agree that it is desirable for LA projects to close the loop (Wise et al., 2021). However, research will always be ahead of practice. Due to persistent technical, organizational, and ethical concerns, LA applications are rarely adopted without resistance. Even mature LA systems require active experimentation and evaluation to ensure that stakeholders continue to see their value (Brinkhuis et al., 2018). The disconnect between research and intervention may speak to the careful considerations institutes make, rather than being a deficiency of research projects.

3. Conclusion

Motz et al. (2023) insightfully delineate the challenges we currently face within the LA field. We should be mindful of the broadcasted signal when many LA articles do not intervene in the learning environment, and we should recognize that novel analytical techniques are the vessel taking us to our destination, not the destination itself. However, neither a new LA definition nor a renewed focus on interventions will solve our issues while we lack some common ground. A structural realist appraisal of LA, combined with an appreciation for research projects over single publications, could offer a solution.

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Open Peer Commentary 9

The Complexity of Inferring Long-term, Generalizable Learning from Immediate Behavioural Indicators

Brendan A. Schuetze and Veronica X. Yan

Abstract

We discuss the implications of Motz et al.'s (2023) relatively expansive definition of learning and draw attention to two features from cognitive psychology literature that have important implications should LA focus on measurement and intervention in learning environments: 1) short-term performance is a poor proxy for long-term learning, and 2) aptitude-by-treatment interactions require a focus on cognitive processes to ensure proper cross-study generalizations.

Keywords

Learning-performance distinction, aptitude-by-treatment interaction, treatment effect heterogeneity

1. Introduction

Motz et al. (2023) suggest that learning analytics (LA) researchers must increase their focus on measuring and intervening upon learning. Motz and colleagues define learning broadly, focusing on whether the reviewed studies have tried to measure learning in any way beyond student self-report. We argue that meaningful definitions of learning should also contain some kind of durability; learning is not useful unless it lasts. Furthermore, we argue that LA research must build upon theories of cognition and learning with attention to learning contexts guiding the broader application of findings.

2. A Critical Distinction between Long-term Learning and Immediate Performance

Motz et al. (2023) took a generous, pluralistic approach to defining learning, but we caution that not all measures of learning are equal. For instance, performance data (correct responses in tutor, log activity, length of engagement, completion rates) are often used to infer student learning. The intuitive, *but often misleading*, assumption is that such in-the-moment assessments and artifacts are good proxies for long-term retention, and that learning environments that promote rapid immediate improvement or completion during training are effective learning environments. However, cognitive science has established a critical distinction between immediate performance and longer-term learning (see Soderstrom & Bjork, 2015). Indeed, short-term performance can be inflated in ways that circumvent the deeper cognitive processing that supports true learning. In each section of Figure 1, the strategy that creates the appearance of learning in the short-term leads to worse long-term retention (Rawson & Kintsch, 2005; Yan & Schuetze, 2022; Yeo & Fazio, 2019). LA research that focuses on optimizing in-the-moment performance might ultimately lead to recommendations that hinder learning. We have all been in situations where we have written an essay, participated in a debate, or won a board game — showing strong performance in the moment — but could not draw upon the skills or knowledge in a different time or place. Delayed outcomes — that are *appropriately* aligned with learning objectives — are needed to infer learning. Concretely, this means evaluating interventions via a post-test and ideally a post-test that occurs a day or more after the manipulation.

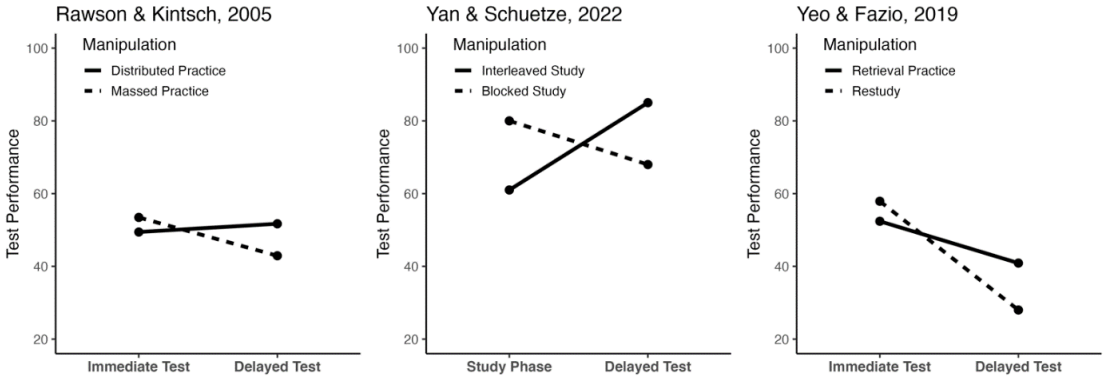

Figure 1. Conditions that support immediate performance do not always support longer-term retention.

3. Aptitude-by-Treatment Interactions

Motz et al. (2023) call upon LA researchers to conduct more experimental interventions as these provide "*the strongest and most compelling evidence for understanding causal relationships*" (p. 7). Adding to this, we draw attention to the many aptitude-by-treatment interactions found in education (Cronbach, 1975) — features or technology that benefit some learners might not benefit others (also known as *treatment effect heterogeneity*). Researchers should focus on the cognitive processes that learning features engage and consider whether learners are prepared to engage those processes (e.g., dependent on developmental capacities, expertise, and prior knowledge). Without a theory of learning, it is difficult to predict the contexts to which an intervention or a model will successfully generalize.

For example, there is a long-standing debate concerning the use of problem-based or discovery learning in science education. We believe part of this debate could be better understood as miscommunication related to how learners of different expertise levels best learn (expertise-reversal effects; Kühl, 2021). While a physics PhD candidate at the boundary of human knowledge may learn best through self-guided discovery learning, this does not necessitate that the same strategies will benefit high-schoolers in introductory physics. Figure 2 illustrates several such examples of expertise-reversal aptitude-by-treatment interactions (Blayney et al., 2016; Kühl, 2021; Roelle & Berthold, 2013). Throughout these three panels, the common theme is that more advanced learners often thrive in — or at least manage — complexity, but novices tend to be overwhelmed by it (as measured by a post-test). Expertise is one source of heterogeneity, but there are many more: Who are the students? What knowledge do they bring? What other learning activities are occurring? The answers to these questions have important implications for the type of intervention or technology that would be most useful.

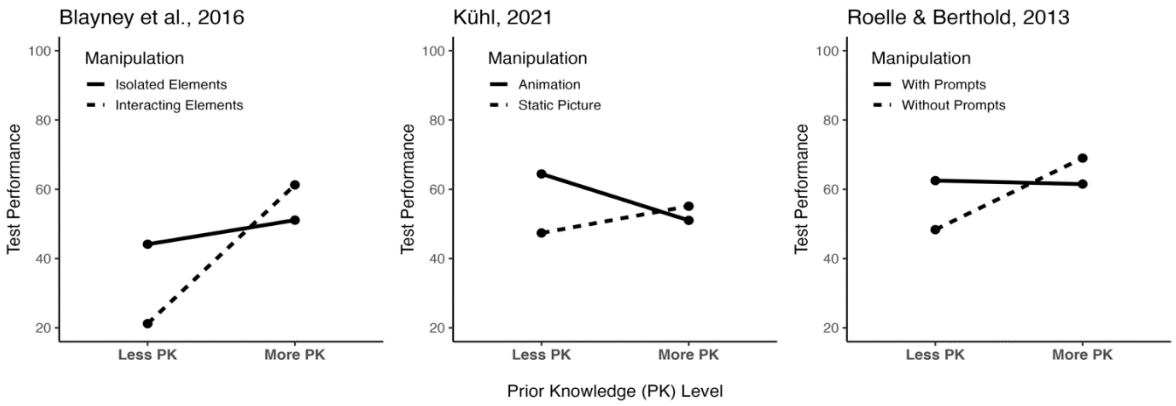

Figure 2. Examples of aptitude-by-treatment interactions.

4. Conclusion

We focus on potential threats to the validity of making inferences from the type of data commonly used in LA research. Understanding the complex cognitive dynamics between performance and learning and how they may vary across learners is particularly important for the development and analysis of (experimental) data collected from intelligent tutors, game-based learning, and other LA applications.

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Open Peer Commentary 10

Building the Future of Learning Analytics Research

Ashish Aggarwal

Abstract
This commentary interprets and situates the findings presented by Motz and colleagues in the article "A LAK of direction: Misalignment between the goals of learning analytics and its research scholarship" and offers actionable suggestions to address the identified gaps. Analyzing the study against the backdrop of limited applied interventions for enhancing learning outcomes, the commentary advocates incentivizing and prioritizing action research within the learning analytics (LA) community. It suggests collaborative efforts between LA researchers as well as higher-ed instructional faculties for tangible on-the-ground impact. Additionally, it recommends tackling significant research challenges collectively to catalyze broader advancements. With the LA field at an inflection point, these proposals aim to bolster its practical relevance.

Keywords
Learning analytics research, impact, incentives, action research, collaboration

Motz and colleagues (2023) provide a timely contemplation and a snapshot of the current landscape of research in learning analytics (LA), aiming to contextualize it within the community's intended objectives. Their discoveries indicate a notable lack of emphasis on the assessment, intervention, optimization, and enhancement of the learning process. While legitimate discussions and deliberations can arise concerning the feasibility of translating the community's broader objectives into precise quantitative metrics and addressing specific nuances of analysis, the essential point remains: the LA research community offers limited tangible outcomes in terms of actionable research for end users such as teachers in schools or instructional faculty in higher-ed institutions (Gašević et al., 2015; Viberg et al., 2018; Dawson et al., 2019). This scarcity underscores the significance of acknowledging the findings as presented and utilizing them as a foundation for future advancements.

Any research community allows its researchers a very wide spectrum to think, work, and innovate independently. And a relatively young community like LA has had a lot of ground to cover in terms of establishing itself as a research discipline with its sense of epistemological perspective and ways to analyze the complex phenomena of learning (Dawson et al., 2019; Baker, 2019; Du et al., 2021). LA researchers have come up with innovative ways of using and inferring from different types of data (Nistor & Hernández-Garcıa, 2018; Ranjeeth et al., 2020; Sghir et al., 2022). Thus, it's important to acknowledge the value inherent in the output of LA researchers. Their contributions signify arduous efforts aimed at constructing a solid foundation. However, a pivotal inquiry emerges: is this progress transformative? In other words: **Is the realm of LA evolving and pushing the boundaries of learning? Moreover, is the research conducted in LA driving tangible changes?** These are demanding queries that warrant contemplation within the LA research community. This article's timeliness underscores the necessity for such introspection, making this discourse both pertinent and indispensable.

One could contend that all research inherently carries an exploratory essence. Consequently, the following question arises: should research bear the predominant responsibility for end-user applications, interventions, and products? This is not a matter of one choice over another. In the end, the significance of any research and its corresponding community hinges on the value it bestows upon society. Given that the subject of study for the LA community is a process as crucial as learning—a process of immense societal importance—there exists an amplified duty and prospect for this community to fulfill its obligations through diligent research endeavours (Prinsloo & Slade, 2017; Buckingham Shum, 2018). Hence, as efforts to discover new methods for data analysis and idiosyncratic correlations continue to rise, it's equally imperative to focus on enhancing the development of innovative interventions and measuring effective learning (Gašević et al., 2015; Dawson et al., 2019). This involves integrating a greater amount of learner data from in-situ real-time situations into analyses and actively exploring the intricacies of learning outcomes.

So, what steps could be taken to cultivate an environment that fills this gap?

Charlie Munger's famous quote, "Show me the incentive, and I'll show you the outcome" (Phillips, n.d.) encapsulates a profound truth. If the LA community finds alignment with the conclusions of the article, a proactive approach to addressing this disparity could commence by establishing incentives for researchers. Several avenues present themselves, such as **introducing**

specific awards honouring impact-oriented research and its researchers; initiating challenges and competitions designed to engage early researchers in tackling intervention-based challenges; creating a distinct conference track dedicated to synthesizing papers founded on in-situ learner data, thus affording them a platform; and spotlighting enduring research or impactful accomplishments. Each of these proposals boasts cost-effectiveness and feasibility in implementation. As well, their potential to recalibrate the landscape is formidable, particularly for fledgling researchers nurturing ambitions of effecting meaningful change.

Here are some long-term suggestions that could address the sources of the gap in research:

- **Foster collaborations between LA researchers and higher-ed instructors:** With the increase in instructional faculty recruitment at universities, particularly for extensively attended courses, an opportunity emerges. These educators, along with counterparts in analogous roles, amass real-time learner data and preside over a continuous data flow. This repository serves as not only a data source but also a sphere for substantial influence. Partnering with these ground-level professionals could yield valuable research of considerable consequence (Gašević et al., 2015). Encouraging such liaisons stands as a communal duty for LA, involving the innovation of incentives to spotlight and publish such efforts.

- **Foster collaboration among LA researchers on innovating and assessing novel interventions:** To come up with interventions that can have a meaningful impact, one needs ideas that could be tested and assessed at scale over time. This needs not only resources but also intentional collaboration among researchers. Much of the research can be siloed, which limits the generalizability of findings (Baker, 2019). While this is a broader problem, LA, as a platform, can encourage collaborations that identify and assess specific interventions. Yet again, the infusion of appropriate incentives becomes paramount to nurturing these research initiatives.

Motz and colleagues (2023) have initiated a meaningful dialogue and a process of introspection. While ample time remains for deliberation and discourse on these findings, if we intend to address the identified gaps, a collective effort within our community is imperative. Alongside the suggestions provided here, a plethora of additional ideas can potentially emerge when a consensus forms around proactive measures. I believe that the trajectory of LA research holds promise, yet this promise could shine even brighter if, as a community, we regularly consciously assess our efforts and take necessary action.

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JOURNAL OF LEARNING ANALYTICS

Open Peer Commentary 11

Intervention Studies at LAK: Why So Few, What Are They, and What Could We Learn from Them?

Lujie Karen Chen

Abstract
This commentary focuses on one specific finding of the paper by Motz and colleagues (2023), that only 27 (11%) of the 246 reviewed articles "attempt to intervene in the learning environment." It provides a detailed analysis of those intervention papers concerning the three-stage pipeline of educational research and explores the plausible reason for such a low frequency. Furthermore, the papers are categorized along dimensions of "driver of change" and "research stage," providing insights into patterns of intervention studies and revealing less explored areas that may inspire future research. The commentary concludes by highlighting three papers exemplifying robust methodologies and case studies for intervention-oriented research, which could benefit learning analytics researchers planning intervention studies.

Keywords
Intervention

1. Why So Few? The Three-Stage Pipeline of Educational Research

First, let us examine the pipeline of educational research. As an example, the Institute of Education Sciences (United States Department of Education) and the National Science Foundation (IES/NSF, 2013) proposed a three-stage framework that includes the following elements:

1. **Foundational and Early-Stage or Exploratory Research** to generate fundamental knowledge and explore relations among crucial constructs
2. **Design and Development Research** for developing and piloting potential solutions
3. **Efficacy, Effectiveness, and Scale-up Research** (i.e., impact studies) for testing interventions in various circumstances and at various scales

Learning analytics–driven interventions, as a form of educational intervention, can be analyzed within this framework. To qualify as an "intervention attempt," a study must be at least in stage 2 or 3. However, many learning analytics studies remain foundational or exploratory due to the nascent state of the field and the emergence of new data sources. On the other hand, research is inherently risky. Even the most promising early-stage studies face funding hurdles, leading to many projects being discontinued. If these projects are not easily built upon (e.g., via open-source platforms), it complicates further research, resulting in few progressing to later stages, thus limiting intervention studies.

2. What Are They? Mapping the Intervention Studies

Assuming these 27 intervention studies serve as valuable examples, it would be beneficial to identify any recurring themes or lessons that could shape future research. To facilitate this analysis, I have sorted each study into categories along those two main dimensions, as illustrated in Figure 1.

Dimension #1 – Driver of Change: What is the primary mechanism implied in the intervention to enhance learning? When categorizing the studies, I considered the degree of agency available to the learners.

1. **System:** Interventions that involve altering specific aspects of the learning system with which students engage
2. **Teacher:** Interventions that involve making changes to the teaching practices via active engagement with the teacher-facing LA system (e.g., dashboard)
3. **Student:** Interventions that aim to change student behaviours; for example, through systems that gently nudge students to become more self-regulated learners

Dimension #2 – Research Stage: Where do the studies stand along the previously described research pipeline definition? I placed the studies according to my subjective assessment of their maturity level. For instance, a design and development study that explains an algorithm without conducting a pilot study to test it would be rated as less mature than those with pilot studies.

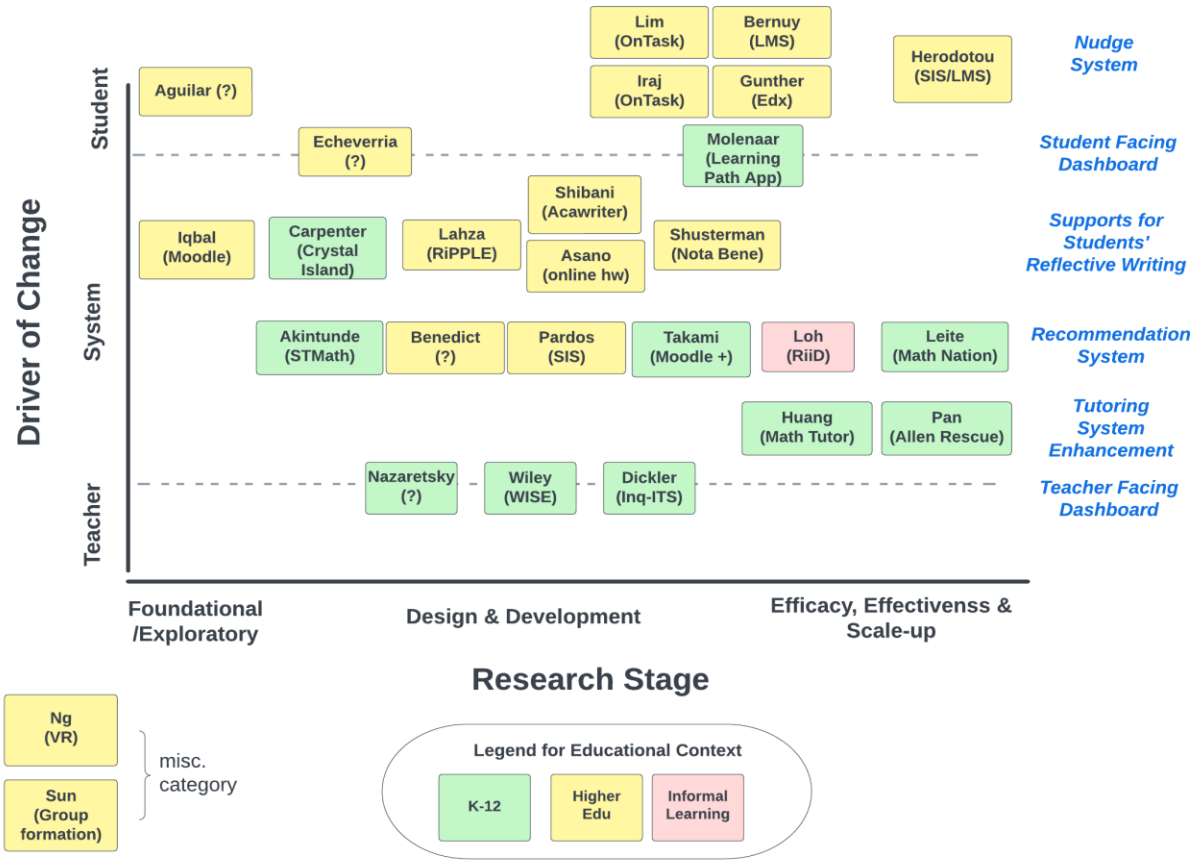

Figure 1. Mapping of 27 intervention studies along the two dimensions — "driver of change" and "research stage" — colour-coded by educational context.

Figure 1 maps the 27 intervention studies organized along two axes: Y = driver of change; X = research stage. The colours correspond to the educational context. Each study is identified by the first author's last name, with the system used in the intervention (when information is available) included in parentheses. Two studies — Ng on virtual reality (VR) and Sun on group formation — did not align with the established categories and are thus listed separately (bottom left-hand corner of Figure 1). A complete list of papers and codes can be found at this link: https://osf.io/97vur/.

Figure 1 highlights a few patterns:

1. The system is the primary driver for change. These studies primarily operate by recommending optimal resources (e.g., video, next practices) or providing support to enhance students' reflective writing or through tutoring system improvements.
2. Most studies are at the design and development stage, with only a handful advancing to the third stage — evaluating interventions across large student populations.
3. There is an unexpectedly high representation of K–12 intervention studies, considering the generally low representation of K–12 work within the LAK community. Most of these studies use mature learning systems that have been developing for a long time, often with a robust user base and school partnerships.
4. There is a relatively low presence of teacher- and student-facing learning analytics. While all of the teacher-facing learning analytics are found in K–12, most student-facing learning analytics appear in higher education, primarily using nudging/feedback systems to improve students' self-regulated learning skills.

3. What Could We Learn from Them?

Translating data insights into promising educational interventions can be a complex process. This mini-analysis may help LA researchers to identify areas needing more attention, such as impact studies in higher education and intervention-focused student-facing and teacher-facing learning analytics. Moreover, the community could benefit from rigorous intervention-oriented methodology frameworks and case studies. I recommend three studies:

1. Huang et al., 2021, presenting a learning engineering framework using learning analytics as part of the data-loop for tutoring system redesign
2. Wiley et al., 2020, proposing a design-based research framework (T-GLADE) that grounds the development and evaluation of learning analytics in learning design theory
3. Leite et al., 2022, offering an excellent reference for rigorous impact studies

4. Conclusion

In summary, the low frequency of intervention papers likely reflects the nature of the educational research staged pipeline. A few interventions often build upon a large amount of both successful and unsuccessful exploratory work. Mapping the intervention studies reveals patterns, opportunities, and a few noteworthy exemplary intervention studies that we could learn from.

Declaration of Conflicting Interest

The author declares no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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JOURNAL OF LEARNING ANALYTICS

Open Peer Commentary 12

(Novel) Interventions Not Required

Rebecca L. Matz and Caitlin Hayward

Abstract
Commenting on "A LAK of Direction" (Motz et al., 2023), we argue that (novel) interventions are not always required for valuable learning analytics research. First, we critique the guidelines for the measured variable related to intervention and contend that studies of large-scale, long-standing platforms that aim to support student learning do constitute systematic intervention in learning environments. Second, we advocate for space within the learning analytics community for research on curricular analytics and student pathways, which do not require intervention in the learning environment in order to produce valuable insights.

Keywords
Curricular analytics, intervention, learning analytics

1. Commentary

We are research staff in a central unit at our university that, among other endeavors, develops and stewards educational technology tools used by students on our campus and beyond — a coaching tool, a writing tool, a teamwork tool, and so on. As such, we bring an applied research perspective to this conversation that might be characterized as "in-between" practitioner instructors and faculty doing basic research. In the spirit of speaking to one another (Bruyat & Julien, 2001), we offer two arguments under the main point that (novel) interventions aren't always required for useful learning analytics research.

Our first argument presses on the Motz et al. (2023) variable related to novel intervention: did the study intervene in learning? To describe an article as having intervened in learning, the authors stated that "the study should introduce a novel intervention that would not otherwise be present" (p. 4). For transparency's sake, our curiosity about this variable was piqued after reviewing how the authors coded our own LAK publications; incidentally, we applaud the authors' open data practice. One paper in question (Matz et al., 2021) evaluates the efficacy of ECoach, a coaching tool for student success that has been in use and under active iteration on our campus for a decade. The tool is used by students in large, lower-division courses and focuses on tailored messaging and resources for exam preparation.

This paper was not coded with the criterion for having intervened in learning, we speculate based on the interpretation of the words "introduce" or "novel." However, we purport that studies of large-scale, long-standing platforms that aim to support student learning (in our case, the outcome measure was final course grades) do constitute systematic intervention. In alignment with design-based implementation research (Fishman et al., 2013), we argue that these platforms and the research done on them, including Matz et al. (2021), do make a "direct attempt to optimize or improve a learning environment" (Motz et al., 2023, p. 6). The intervention need not be introduced afresh within the timeline of the study for the results to be informative.

Notwithstanding the possibility that this paper was miscoded, it is also true that the common definition of learning analytics (Siemens & Gašević, 2012) does not address the *novel* aspect of interventions. While we agree that studying the efficacy of novel interventions, whether new to a particular context or new altogether, is valuable for advancing learning analytics, we hope the community will maintain space for the evaluation of actively used, widely adopted tools that support learning at scale. Excluding research on efforts to replicate and scale the use of learning analytics technology undermines our collective ability to establish generalized understanding of impact.

Second, we offer a more general argument that is aligned with the conclusion of Motz et al. (2023) that "LA scholarship presently lacks clear direction toward its stated goals" (p. 1). However, we believe not so much that the scholarship lacks clear direction, but that our community's goals, insofar as we are part of the community, are broader than what is framed in the consensus definition (Siemens & Gašević, 2012). These broader goals should be accepted in and central to the field of learning analytics.

In particular, we have been researching curricular analytics and student pathways on our campus. In Evrard et al. (2021), which is included in the Motz et al. (2023) sample, we explore the relationship between institutional selectivity and grade inflation. This paper contributes to the learning analytics field by building understanding of learner contexts — no intervention was required.

We contend that the interests of colleagues in and around our community are aligned (e.g., Kizilcec et al., 2023) and thus advocate for space within the learning analytics community — at conferences and in journals, for example — for conversation

about grading practices, grade outcomes, and student choices. Student curricular experiences and trajectories are keystone elements that provide context for their learning experiences.

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