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A LAK of Direction: Misalignment Between the Goals of Learning Analytics and its Research Scholarship

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Abstract

Learning analytics (LA) defines itself with a focus on data from learners and learning environments, with corresponding goals of understanding and optimizing student learning. LA research, ideally, should make use of data from learners engaged in education systems, should measure student learning, and should improve these learning environments. However, a common concern among members of the LA research community is that these standards are not being met. In two analyses, we reviewed a large, comprehensive sample of research articles from the proceedings of the three most recent Learning Analytics and Knowledge (LAK) conferences and from articles published in the *Journal of Learning Analytics* (JLA) in 2020, 2021, and 2022. We found that 37.4% of articles do not analyze data from learners in an education system, 71.1% do not include any measure of learning outcomes, and 89% do not attempt to intervene in the learning environment. We contrast these findings with the stated definition of LA and infer, like others before us, that LA scholarship presently lacks clear direction toward its stated goals. We invite critical discussion of these findings from the LA community, through open peer commentary.

Notes for Practice

- The defining goal of learning analytics (LA) is to understand and optimize learning.
- In reviewing a comprehensive three-year sample of LA research articles, we find that a small minority of articles measure learning, and even fewer attempt to intervene, optimize, or improve learning.
- We infer that LA research is currently misaligned with the community's defining goal, and we invite critical discussion on these results.

Keywords

Learning analytics, systematic review

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1. Introduction

Since its emergence over 10 years ago, a common question has been this: What is learning analytics? This may be because the learning analytics (LA) research community has unique features. On the one hand, it is interdisciplinary, inclusive of data scientists, psychologists, sociologists, computer scientists, education researchers, and practitioners, among others. On the other hand, the community centres itself on the analysis of data emerging from the digital transformation of education systems, not on a specific theoretical framework or scholarly tradition. Despite its interdisciplinary nature and ideological diversity, the consensus definition of LA has not changed since its original proposal in 2011: *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* (Society for Learning Analytics Research, 2021).

This definition casts a very broad net and could be interpreted to encompass all forms of empirical research on learning and education. But the central criterion is nevertheless quite clear: *Learning analytics is focused on learner data and the context of learner data.* Moreover, the community's stated goal is also quite clear: *Learning analytics aims to understand and optimize learning.* Given the clarity of these standards, it becomes possible to systematically evaluate whether the LA community is achieving these standards in their research. Such a systematic evaluation is the aim of the current study.

We are not the first to inquire whether LA's scholarly literature aligns with its collective aims. When LA was still in its infancy, Clow (2013) described it as "a 'jackdaw' field of inquiry, picking up 'shiny' techniques, tools and methodologies… This eclectic approach is both a strength and a weakness: it facilitates rapid development and the ability to build on established practice and findings, but it — to date — lacks a coherent, articulated epistemology of its own." With this comparison (LA as a scavenger), Clow was suggesting that LA might be methodologically advanced and diverse, but could still lack a research strategy that would enable progress on its own goals.

The focus on techniques, and the absence of a coherent epistemology of LA, has been an ongoing cause of hand-wringing. In 2015, three founders of the LA movement felt compelled to remind the community that LA was, indeed, supposed to be about learning (Gašević et al., 2015). That same year the *Journal of Learning Analytics* (JLA) published a special issue with expert commentary on each contributed article, all advocating for more thoughtful alignment between LA research and learning theory (Wise & Shaffer, 2015). Nevertheless, LA research has continued to favour exploratory studies in niche settings, with little concern for how such work will advance the goals of the field (Dawson et al., 2019).

Even in the absence of a shared trajectory or theoretical focus, one might minimally expect LA to produce evidence of its practical value, but some authors have raised alarms about what they believed to be a paucity of this evidence (Ferguson & Clow, 2017; Larrabee Sønderlund et al., 2019). This may be because, as an interdisciplinary field, agreement on what constitutes evidence for an LA position has yet to emerge. Fields such as medicine and law have evidence hierarchies within which positions can be supported or refuted. One may not agree with a given position about medicine or law, but it is possible to follow evidence and logic to evaluate a claim. In other words, some fields have consensus on how to carry out research for accumulating understanding, but this is not the case for LA (Knight et al., 2014). Since LA combines so many disciplines, each with its own set of evidentiary norms, it is difficult to make a claim that will be generally understood, let alone accepted. The lack of common ground is a barrier to the field's progress (Ferguson et al., 2016).

Given this ambiguity, what is actually meant by learning analytics' defining purpose "of understanding and optimizing learning"? Superficially, we note that this conjunction uses "and" (rather than "or"), indicating that merely understanding learning is insufficient, and that understanding should not be decoupled from practical improvements in learning (or improvements in the efficiency of learning). Ambition for analytics to produce such improvements, commonly dubbed "actionable insights," is evident from the infancy of LA (Clow, 2012). Nevertheless, the details of what constitute "actionable insights" are not well established (Jørnø & Gynther, 2018). For some, it may be sufficient to present data with the potential to inform decision-making processes among teachers, administrators, and students (Long & Siemens, 2011), but for others, an actionable insight is a direct claim about a causal mechanism that ought to be directly tested through experimentation (Motz et al., 2018). Across this spectrum, data about student learning is the common (necessary) ingredient, and moreover, the same analytical techniques (classification, event mining, statistical modelling) may be employed, but the ways that measurements and analyses achieve the goals of LA (understanding and optimization) have evaded consensus — a likely cause for the lack of evidence of learning analytics' practical value. On this theme, the outgoing JLA editors recently published an editorial urging the community to be more considerate of what questions are being answered with LA, rather than what analytical techniques are being employed (Wise et al., 2021).

Combined, these perspectives reflect a sense of discomfort with the LA community's research focus — specifically, that scholarship within LA concerns itself more with demonstrations of methods than with the *purpose* of the methods. To be clear, methodological refinement and precision is an important element of empirical research. Insofar as this tries to improve measures of learning and its peripheral constructs, it clearly holds status under the definition of LA. But we believe past commentaries on LA suggest an imbalance, where research is more focused on demonstrations of methodology ("Can we do this thing with these data?") and less focused on demonstrations of progress toward goals. We do not discount the merits of these opinions, but the research trends motivating this general discomfort have not been clearly measured.

Despite these key concerns about the substance of LA research, aired openly and prominently by leaders in the community, past reviews of this literature have surveyed the community's analytical choices rather than their research goals (Baek & Dolek, 2021; Baker & Inventado, 2014; Leitner et al., 2017; Papamitsiou & Economides, 2014; Papamitsiou et al., 2020; Cerratto Pargman & McGrath, 2021; Romero & Ventura, 2020; Siemens, 2013). These reviews find, for example, that prediction, classification, and process mining are common in LA. And although useful as reviews of methodological choices employed by a diverse community, they also exemplify the community's focus on techniques (which has been frequently criticized), rather than on the questions being addressed or the advances being made toward understanding and optimizing learning.

One noteworthy exception is the work of Olga Viberg, who, with her colleagues, found that only 9% of LA research studies found evidence of improved student learning in higher education (Viberg et al., 2018). Further, in an examination of LA research specifically on self-regulated learning (SRL), Viberg et al. (2020) found that 70% of papers did not investigate learning outcomes at all. Only 8% of sampled papers discussed the potential of their findings to improve student learning. In interpreting these findings, the authors advanced optimistic perspectives that the field is still maturing (Viberg et al., 2018). Additionally, they suggested that LA investigations of SRL currently prioritize understanding learner experiences; later, this understanding might be exploited to support and improve student learning (Viberg et al., 2020). But if the LA community is expected to self-regulate its research aims, its own research suggests that it could benefit from data-driven feedback (e.g., Pardo et al., 2017). The goal of our study is to provide this feedback.

1.1. The Current Study

In the current study, we ask similar questions about the LA literature to those advanced by Viberg et al., although we shed the restrictions of focusing specifically on LA in *higher education* or regarding *self-regulated learning*. Rather than casting a specific net around a domain of investigation, instead we chose to review a comprehensive sample of all recent articles in the Learning Analytics and Knowledge (LAK) proceedings, the premier conference of the LA community, and the *Journal of Learning Analytics* (JLA). This allows us to ask not only whether LA research is aligned with its original aims, but also to review a representative breadth of LA research so that we can explore what occupies LA if it deviates from its aims.

In full and transparent disclosure, the current review of research topics in the LA literature was not our original intention. Our initial goal was to assess the adoption of open research practices in LA, which involved coding aspects of each article's methodological approach (Motz et al., 2022; this work continues separately). When reading the first set of articles, we were all surprised by the rarity of research studies that dealt directly with learning. In response, we broadened our coding scheme, recoded previously coded articles, and proceeded with the first wave. After completing a preliminary analysis, we then decided to expand our scope and repeat the process in a second wave. Our article lists, assigned codes, secondary codes (for calculating interrater agreement), and analysis scripts for both waves are publicly available at https://osf.io/tzhva/.

2. First Wave: LAK20 & LAK21

2.1. Article Selection

All articles published in the 2020 (Kovanović et al., 2020) and 2021 (Dowell et al., 2021) proceedings of the LAK conference, which were archived in the Association for Computing Machinery (ACM) digital library, were eligible for the first wave of analysis. This included both long and short format peer-reviewed research articles. Non-archived companion proceedings papers, published separately by the Society for Learning Analytics Research (SoLAR) — which included posters, practitioner reports, and workshop papers — were excluded. This sample provided a contemporary snapshot of the state of LA research, including articles written before and after the COVID-19 pandemic (the article submission deadline for LAK20 was October 1, 2019). There were 151 such articles published in LAK20 and LAK21, and all were read and coded without exclusion. During the coding process, we identified five articles that did not analyze data; rather they presented logical, theoretical, or rhetorical positions, and these were excluded from further analysis, leaving 146 articles in the first wave.

2.2. Measured Variables

For each of the selected articles, we recorded two factual details: the country (or countries) of data collection and the sample size, categorized as the number of students (or learners, depending on the study's context), teachers, classes, or researchers providing study data, as relevant. In rare instances where some information about the size of the sample was provided, but the sample size was not directly stated, we estimated a likely sample size based on information provided. We also summarized the article's general methodology and findings in our own words prior to coding the following four binary variables:

1. *Is it Qualitative?* (yes/no) Defined by whether the research employed qualitative research methods. For mixed methods research (both qualitative and quantitative), this value would be "yes."
2. *Is the Data from Students During Learning?* (yes/no) Defined by whether the data were from authentic students learning in an education system (online or in-person). Learning studies conducted in laboratories do measure data from student learning, but this variable would be "no," because the learning would be independent from the student's participation in an education system. However, data from students engaged in supplemental instruction (e.g., using an intelligent tutor), would have a "yes" value because the learning is directly related to the student's education experience. Similarly, articles reporting data from students enrolled in MOOCs and badged open courses would also have a value of "yes." Thus, we refrain from referring to this variable as measuring whether a study used data from only "formal" education systems.
3. *Is it Outcome Learning?* (yes/no) Defined by whether any of the study outcomes measure evidence of learning. We adopted a liberal definition of learning outcomes. Any qualitative or quantitative measurement that provided evidence that learning had occurred would be coded as "yes." These might include assessments of student performance or student artifacts, or any measure of grades or scores. In this regard, whether a student passes or fails the course also counts as evidence of learning. However, if they were ambiguous about whether learning had actually occurred, incidental measurements of student behaviours during learning (e.g., time on task, whether students accessed a resource, etc.), were coded as "no." Furthermore, we did not include student self-reports as providing this evidence of learning (Nisbett & Wilson, 1977; Zhou & Winne, 2012). An article that only measured self-reported learning would be marked "no."
4. *Did the Study Intervene in Learning?* (yes/no) Defined by whether the research systematically intervened during the learning process. It did not need to be a randomized controlled experiment; the intervention might apply to the whole sample. However, for a "yes" value, the study should introduce a novel intervention that would not otherwise be present.

2.3. Coding

Seven authors of the current study self-selected between nine and 48 articles from the complete set of 151 articles (mean = 18.9 articles per coder), and then read and coded them according to the variables defined above. During this initial coding phase, each article was handled by a single coder, and we discussed and resolved questions while assigning codes. Afterward, collaborative spot-checking revealed three articles where the originally assigned codes did not match definitions established during the coding phase, and these were revised. The purpose of this revision was to ensure that the assigned codes aligned accurately with our measurement intentions.

Two raters then recoded a sample of 30 articles (19.8%), 15 each, blind to the assigned codes. This set was randomly sampled from the whole article set, under the constraints that each rater (a) did not recode articles that they had previously coded; (b) did not overlap in their recoding between the two raters; and (c) recoded at least one article from each previous coder. Only the four binary variables were recoded (qualitative methods, data from student learning, whether student learning was an outcome variable, and intervention in the learning process). Comparing the original ratings from the initial coding phase with these secondary ratings, we calculated interrater agreement as the number of exact coding matches (n=108) divided by the number of coding opportunities (n=120). This agreement was high at 90% (*kappa* = 0.80). There was no evidence of systematicity in disagreement between coded variables, between coders, or in the direction of disagreement.

3. Second Wave: LAK 2022 & JLA 2020–2022

After collecting data and conducting our preliminary analysis, we were sensitive that our first wave did not include articles published in the JLA, which limited our ability to make generalizable claims about LA scholarship. Furthermore, as we concluded the first wave, another LAK conference was held (LAK22), and a corresponding set of articles published in its proceedings. We decided to repeat our systematic review, aiming to replicate and extend our observations from the first wave.

3.1. Article Selection

All articles published in the LAK22 proceedings (Wise et al., 2022), and all articles published in the JLA from volume 7 issue 1 through volume 9 issue 1, were eligible for this second wave. This JLA issue range was chosen to overlap with the publication period of LAK articles in the first and second waves of the current study, March 2020 through March 2022. As with the first wave, we accessed LAK articles (both long and short format, excluding companion proceedings) through the ACM digital library and JLA articles directly from its open access web archive. In the JLA sample, we excluded articles explicitly labelled as "editorial" or "extended conference papers" (likely already included in LAK samples). There were 62 eligible articles from

LAK22 and 48 from the JLA (110 total), all of which were read and coded. During the coding process, we identified 10 articles that did not analyze data, which were excluded from further analysis, leaving 100 articles in the second wave.

3.2. Coding

We used the same variables and definitions from the first analysis wave. A trained coder, not previously been exposed to LA research (and not involved in the first wave), assigned preliminary codes during this second wave. Training involved first studying the variable definitions and reading examples of LA articles. Subsequently we held a norming round where five of the current authors (including the coder) assigned codes for 10 randomly sampled articles in this second wave (blind to each other's codes). We then met to discuss our individually assigned codes, examine disagreements, reach consensus, and clarify the variable definitions. Coding then commenced on the full set in weekly batches (10 to 20 articles per week) where the coder also summarized each article's methodology and findings in their own words, with intervening check-ins to answer questions and discuss assigned codes from the most recent batch. In the instances where incorrect codes were identified, the coder reviewed all previously coded articles to ensure consistency following the correction. Once all 110 articles had been coded, the other eight authors reviewed all codes (13.75 articles each), and revised any coding errors.

In parallel, one author coded a random selection of 30 articles from the second wave (27.3%), excluding the 10 identified articles, enabling us to calculate agreement. We calculated interrater agreement as the number of exact coding matches (n=98) divided by the number of coding opportunities (n=120). This agreement was modest at 82% (*kappa* = 0.63). Much of this disagreement pertained to the *Is it Qualitative?* variable (only 73.3% agreement), indicating that the second wave codes, in general, used a more liberal definition of qualitative research than the recoded subsample. As such, we adopted (and recommend that readers similarly adopt) a cautious stance when considering codes for this variable.

4. Results

Of the 246 selected articles (146 in the first wave, 100 in the second wave), 184 describe a sample of students (74.8%) and 99 describe a sample of courses (40.2%). These values are not equal because 95 articles described a student sample but did not specify the quantity of courses in which the students were enrolled (e.g., analysis of survey data, or student use of a learning tool outside the scope of a specific course). Ten articles described courses but did not specify the quantity of students enrolled (e.g., analysis of course activities and curriculum structures). Additionally, 47 articles describe a sample of teachers (19.1%), and six describe a sample of researchers (2.4%). The 24 studies that analyzed data but did not describe a sample were typically systematic reviews or method evaluations.

Considering only articles where such quantities were specified, selected articles had a median sample size of 283 students, one course, 19 teachers, or 14 researchers. There was a large positive skew in the reported sample sizes of students, as 47 articles reported samples of more than 1,000 students (25.5% of those reporting student sample quantity). However, the number of courses under analysis was less skewed, with 77 articles reporting samples of five or fewer courses (77.8% of those reporting course quantity).

The location of data collection had a wide geographical distribution. Our codes included locations distributed across North America (90 articles; 36.6%), Europe (41 articles; 16.7%), Australia and New Zealand (33 articles; 13.4%), Asia (16 articles; 6.5%), South America (10 articles; 4%), and the Middle East (7 articles; 2.9%). Additionally, 10 articles (4.1%) described data samples collected online (e.g., open online courses), and 39 articles (15.9%) were either multinational or did not specify the location of data collection. The median quantity of students under analysis (when reported) was roughly equivalent across geographical regions (between 100 and 300 for most regions). Despite this impressive breadth, a noteworthy gap across this three-year sample is the absence of any data collected specifically in Africa.[1]

4.1. Use of Qualitative Methods

Fifty of the 246 articles (20.3%) described qualitative research methods. Understandably, these articles had markedly smaller samples (median = 94 students). Moreover, these articles were far more likely to sample non-students; for example, 52% sampled teachers (compared to 10.7% of non-qualitative articles), and 6% sampled researchers (compared to 1.5%).

4.2. Use of Data from Students During Learning

We found that 154 articles used data from authentic students learning in an education system (62.6% of the 246 articles that analyzed some form of data), and 92 articles did not (37.4%). Of those 154 articles, 16 employed qualitative methods (10%).

[1] Notably, a new SoLAR special interest group is currently being formed: the African Network for Learning Analytics Research (ANLAR).

Among the 184 articles that described a student sample, 43 of them (23.4%) did not include data from students' authentic experiences in an education setting. Instead, they used data collected in a laboratory, used enrollment data, used data collected by an application unrelated to the formal learning environment, or used data from elsewhere. Importantly, we do not claim that these 43 articles do not measure *learning* per se, but rather, that these articles do not describe the learning environments in which it formally occurs.

4.3. Use of Learning Outcome Measures

As described above, our coding scheme adopted a liberal definition of "learning," inclusive of any qualitative or quantitative measurement of grades, scores, or performance outcomes, as long as it is not self-reported by the learners themselves. A study could meet this criterion even if the learning occurred outside the scope of a formal education setting (e.g., in a laboratory).

Even with this liberal definition of learning, we found that only 71 articles included some measure of learning outcomes. Thus, 71.1% of empirical articles across three years of LAK proceedings and JLA articles do not measure learning (175 out of the 246 articles that analyzed some form of data). It is noteworthy how closely this observation mirrors findings from Viberg et al. (2020), who examined a different set of LA research articles pre-dating the current sample, and also found that 70% of LA research on self-regulated learning does not measure learning outcomes.

This finding begs the following question: *If not learning, what do learning analytics studies measure instead?* Our systematic review did not include discrete codes for each article's measured variables, but we did summarize the methods and findings of each selected article. Only two articles had learners self-report their own learning outcomes, so our decision to exclude these from our definition of learning had negligible influence on the current findings. Of the remaining articles, a coarse thematic analysis identified several research themes among articles that did not measure learning. Among these, we saw repeated efforts to train models to automatically classify human-labelled text, to relate activity within learning tools with learning strategies or predispositions, to create valid unsupervised classifications of such activity, to create informative descriptions of the network structure of student interactions, and to conduct systematic reviews of the LA literature. As mentioned previously, insofar as this work refines the community's analytical treatment of constructs related to learning, it has value. But if efforts to refine these analyses overwhelm the community's research, a consequence, as we observe presently, is the deprioritization of insights more directly about learning.

Of the 71 articles that did measure learning outcomes, a coarse examination indicated that these studies used a variety of different outcome measures. These mostly included formal summative exams, narrowly scoped quizzes, assignment scores, or even particular item responses to particular elements of assessments. Additionally, some studies used qualitative measures of learning, measuring aspects of student collaboration, written work, and task performance, for example. A minority of these measured students' final grades or whether students successfully completed the course.

4.4. Use of an Intervention

Across all 246 selected articles, 27 introduced an intervention into a learning environment (11%) with seven of those employing qualitative research methods. Roughly half of the 27 studies (n=15; 55.6%) measured the effect of the intervention on some measure of learning; the remainder measured the effect on survey responses or on student behaviour.

The interventions introduced in these studies included nudges or prompts for improving student engagement (n=9), feedback on student work (n=7), recommendations for courses or resources (n=7), and dashboards or alerts summarizing learning data to teachers or students (n=4).

These topics of inquiry (alerts, dashboards, prompts, feedback) are not unique to these 27 articles. However, other studies on these topics did not examine the introduction of novel features into a learning environment. Indeed, 89% of the selected articles do not make any direct attempt to optimize or improve a learning environment.

4.5. Difference Between LAK and the JLA

Our sample included 206 articles from LAK proceedings (83.7%) and 40 articles from the JLA (16.3%). Given that these two sources differ substantially in their frequency, it is worth considering whether the aggregate findings are similarly representative of LAK and the JLA (see Figure 1).

We compared the mean number of students included in the JLA and LAK samples using a t-test (after log-transforming the data to correct for positive skew). There was no difference in the number of students under analysis between these two venues. We analyzed the remaining binary variables using a multivariate linear model. There was a significant difference in the number of articles coded as using qualitative research methods, with more qualitative research in the JLA than in LAK ($F(1,244) = 4.415$, $p = 0.037$). However, this may be because we adopted a more liberal definition of qualitative research during the second wave (see Section 3.2), and we recommend against making inferences from this difference. There were no significant differences between LAK and the JLA in the use of data from students (p = 0.47), the measurement of learning outcomes (p = 0.58), or the use of an intervention (p = 0.19).

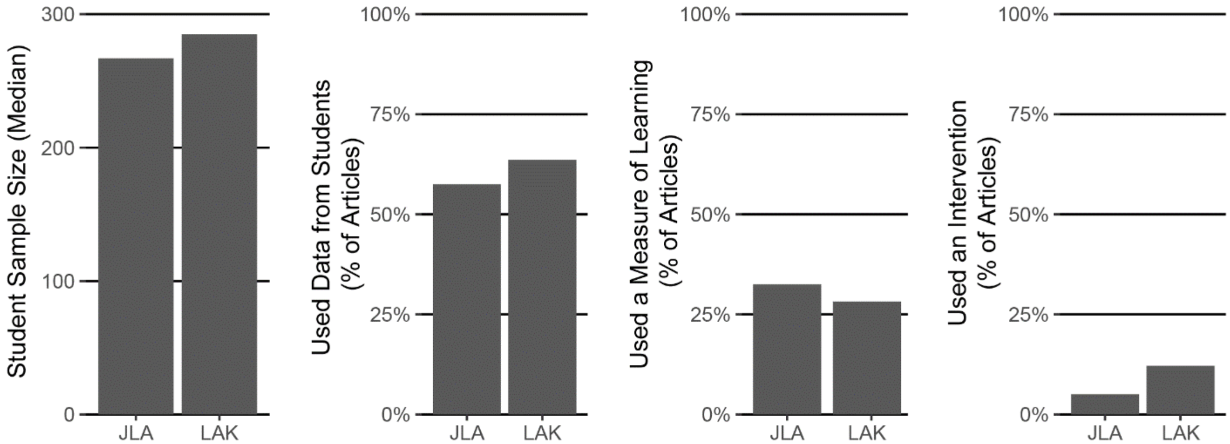

Figure 1. Summary statistics for coded variables for articles in the JLA and LAK.

5. General Discussion

By its consensus definition, LA research should focus on learner data, and the context of learner data, in order to understand and optimize learning environments. The goal of the current study was to systematically evaluate the LA literature against these defining standards. Specifically, we measured whether articles used data from existing learning environments, whether articles measured learning outcomes, and whether articles attempted to intervene in the learning environment (among other variables) for a complete, recent, three-year sample of articles published in LAK conference proceedings and the JLA.

Our most striking finding is that 71.1% of articles do not measure learning outcomes. This figure closely matches Viberg et al.'s (2020) findings on a distinct, broad, subsequent sample from the LA literature. Combined, these findings might appear to conflict with Papamitsiou et al. (2020), whose subjective gloss of author-provided key terms in LA articles suggested that "performance" was one of the most frequent topics under analysis. But reading further into Papamitsiou et al.'s (2020) methods, their "performance" label is broadly inclusive of any analyses of activity logs and motivation (among others), which do not directly measure learning. While these are relevant when describing the behaviour of students engaged in learning activities, these measures describe constructs that are inadequate as a meaningful account of learning (Gray & Bergner, 2022).

Additionally, we find that 37.4% of articles did not analyze data from existing education environments. Among those that did, the typical sample was one course and 283 students, which we speculate to commonly be a researcher's own course. This opportunistic sampling provides supporting evidence for Clow's (2013) characterization of LA as a jackdaw-like discipline, implementing analyses where it is convenient to do so, rather than addressing generalizable theoretical questions at the possible population scale of current digital records.

Finally, we observe that 89% of articles do not attempt to intervene in the learning environment. The scarcity of interventions aligns with past reviews of LA, such as Si Na and Tasir (2017) who found only six articles attempting an intervention between 2012 and 2016, and Wong and Li (2020), who found only 24 articles between 2011 and 2018. This is particularly problematic for LA's goal of understanding and optimizing learning environments. An experimental intervention, particularly when using random assignment, provides the strongest and most compelling evidence for understanding causal relationships, because researchers can directly examine whether a change in behaviour or learning can be directly attributed to an antecedent intervention (Motz et al., 2018) rather than other covariates (Reinhart et al., 2013). Our coding was inclusive of experiments using random assignment (e.g., randomized controlled trials, or RCTs), but it was also inclusive of any study that introduced a candidate improvement into a learning environment and assessed what happened. For example, Shibani et al. (2022) had students complete a pen-and-paper exercise in order to facilitate engagement with automated writing feedback; all students did the exercise, and we categorized this among the few studies that introduced an intervention. It is true that LA uses RCTs very rarely, but it is also true that LA is very rarely introducing *any* improvements into the learning environment. Given the scarcity of such efforts, even when an "intervention" is defined under broad and pluralistic terms, LA research is not currently making progress on its goal to optimize student learning environments. To be fair, descriptive and correlational

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studies might be viewed as steps in the sequence of understanding that precedes the step of developing testable, causal theories. Adopting such a view, evidence of the field's maturation is lacking (Larrabee Sønderlund et al., 2019).

Perhaps LAK proceedings and JLA articles mischaracterize the LA community's research activities. For example, perhaps LA researchers use the LAK conference as a testbed for exploratory research and use the JLA as a forum for critical reflection, but then subsequently target other venues when publishing research that focuses more directly on understanding and optimizing learning. We believe this is unlikely for several reasons. One prominent reason is that our findings are consistent with past reviews of LA research that were not limited by publication venue. And there are additional reasons to think that LAK, in particular, is quintessentially representative of LA research. First, LAK is highly selective, with an average acceptance rate of roughly 30%. It is unlikely that LA researchers are reserving high quality work for other venues. Second, LAK proceedings also have substantial impact on scholarship, with a current h5-index of 46 (as measured by Google Scholar at the time of writing this article), higher than related journals (e.g., *IEEE Transactions on Learning Technology* or the *International Journal of Artificial Intelligence in Education*). Third, the LA community has commonly used the LAK conference as a bellwether of the community's interests, interaction patterns, and research topics (e.g., Chen et al., 2015; Ionita et al., 2021; Ochoa & Merceron, 2018; Dawson et al., 2019). So while LAK is certainly not the only publication venue for the LA research community, it is selective and impactful, and the community itself views it as a representative reflection of research activity. Indeed, the overarching theme of LAK21 was "The Impact We Make: The Contributions of LA to Learning" (Dowell et al., 2021), so it is unlikely that our sample is inappropriate for evaluating these standards.

Or perhaps it is the case that LA is achieving its standards *and also* conducting complementary research peripheral to these standards. In such a scenario, a smaller percentage of LA articles might be expected to examine data from education systems, to measure learning, or to intervene, even while making strong progress. However, we also believe that this is unlikely. Past assessments of the quality of LA research for improving learning has found that evidence of this efficacy is weak (Ferguson & Clow, 2017; Larrabee Sønderlund et al., 2019). Given this, our findings suggest that LA research lacks clear direction toward addressing questions about learning, preferring instead to examine analytical approaches (see also Liu et al., 2022). This focus on examining "things that we can do" instead of "problems that we can solve" has been a chronic obstacle in the nearby field of educational technology research for the past 40 years (Clark, 1983; Reeves & Lin, 2020). In LA, there is a similar lure: the much easier path to publication of analyzing found data, at a limited scope, collected by technology not designed to support research or measure latent constructs of learning (Kitto et al., 2020; Gray & Bergner, 2022). It would be unfortunate if LA perpetuated this misstep (Wise et al., 2021).

In keeping with the definition of LA (and the name itself), we adopt the stance that *measuring learning* is an essential aspect of LA. In the current study, we use a liberal definition of "learning," which included any measure of grades, scores, performance, or completion. Exam scores were the most common form, but our definition also included other measures such as reading fluency (Klebanov et al., 2020) and the depth of student reflections as rated on an established rubric (Carpenter et al., 2021); thus we emphasize that studies using noncognitive learning outcomes (Joksimović et al., 2020) were coded as *measuring learning*, to the extent that these outcomes were directly and deliberately assessed. These, and any other measures of learning, involve a set of assumptions about knowledge and meaning (Knight et al., 2014); our approach is intended to be pluralistic across such assumptions.

Nevertheless, some readers will remain skeptical that our definition of learning outcomes was sufficiently inclusive to make meaningful claims about whether LA is achieving its own standards. Perhaps such readers would advocate for the following to be coded as *measuring learning*: participating constructively in a disciplinary practice, communicating in a way that demonstrates expertise, expressing skills and competencies during interactions with complex situations, and so on. *We would agree!* These performance measures, and many more, had they been observed, would have been coded as measuring learning. A study that examined different methods for assessing middle school students' use of evidence and systems thinking was coded as measuring learning (Ahn et al., 2021). Two studies that examined children's dialogue during collaborative problem solving were both coded as measuring learning (Emara et al., 2021; Ma et al., 2022). For readers who are skeptical of our findings, rather than presume that we've mischaracterized a learning-oriented literature, we recommend reviewing the article list, and our associated codes, and drawing your own conclusions from the data, which we've made public at https://osf.io/tzhva/. As was the case when we first began coding articles, we suspect that the rarity of studies measuring learning outcomes will become apparent, even for those who adopt more expansive views of learning outcomes than grades and scores. The issue is *not* that 71.1% of LA studies don't measure grades; the issue is that 71.1% of LA studies don't measure learning outcomes at all. We acknowledge that learning is a complex temporal process, and any single measure is likely to be incomplete and possibly confounded by other sources of variance. But, to echo Gray and Bergner (2022, p. 25), "Do we give up on Measurement? No," and we similarly affirm that the measurement of learning outcomes is fundamental to advancing the field and establishing impact, inclusive of many possible measurement and methodological traditions. We are disturbed by our finding that most LA articles fall short of this standard.

Why measure learning outcomes? There are many reasons (Gašević et al., 2015). Among these, by measuring learning outcomes, a study can situate its findings within robust theories of learning, gauge the educational context under analysis and the aptitude of its student sample, and build evidence of and make inferences about possible relationships with student achievement. The latter, in our view, holds principal importance, and possibly also stands as an ethical imperative. We should not just assume that LA will benefit the learner, or that a student's self-regulated use of a resource provides evidence of that resource's efficacy. When students have autonomy to choose their own learning strategies, long-standing evidence shows that student choices are often suboptimal (e.g., Kornell & Bjork, 2007; Pressley et al., 1989). There are plenty of examples of well-intentioned educational programs that appeared to be effective on the surface, but in reality, were causing harm (e.g., DARE, Werch & Owen, 2002; Scared Straight, Petrosino et al., 2013). Personalized interventions are not without risk (e.g., Canning et al., 2019). As researchers who might expose students to alerts, recommendations, automated feedback, and more, we should be measuring authentic learning outcomes if for no other reason than to monitor our innovations. However, we additionally believe that by privileging the measurement of learning outcomes (even with a diversity of different measurement traditions), the LA community might begin to approximate a shared trajectory toward optimizing and improving them.

We also anticipate that some readers will be skeptical that a research community's direction can be assessed by simply counting articles against coded variables. Rather than defend the utility of systematic review methodology, we simply affirm that *representation matters*. In any social setting, people interpret numerical representation as a social cue, providing information about what is valued by the group. If the LA community minoritizes research on student learning and experimental interventions (for example), the community signals that such research has less value. For interdisciplinary communities in particular, bias in the relative weight of contributions to the community's products can create serious concerns about its viability as an interdisciplinary forum (for example, see Núñez et al., 2019). As much as the LA-faithful might desire to be inclusive of all data-driven efforts to understand and optimize learning, alternative communities may be more welcoming of this work if it is deprioritized in LA (for a sprawling informal online discussion on this topic, see Siemens, 2020).

At this point it bears mentioning that we, the authors of this current review, are not merely spectators of LA research. Most of us have published in the JLA or LAK during the selected years and our articles do not categorically achieve the standards we established for this review. We openly admit that we have materially contributed to the misalignment presently observed in this study. Of course, we do not believe that our research is without merit (or that LA research itself is without merit), but we must also admit that our studies' merits are pursuant to conventional LA research themes within the community, and not those idealized in the consensus definition of LA. For example, we believe that our work, like others in the published LA literature, contributes to an improved understanding of how one might interpret activity data from learning environments, or how stakeholders could constructively participate in the design of LA tools and systems. These are areas of inquiry currently valued by LA researchers (as evidenced by their relative weight in the community's products). But, like Newell (1973), we might ponder: Suppose we extrapolated a lifetime of research comprehensively examining these areas, *where will learning analytics then be*? We might garner insights into the full range of correlates of student clicks, and sophisticated models of how to effectively engage diverse stakeholders during design tasks; but we acknowledge that these accomplishments, on their own, will have no effect on learners nor on their learning environments.

Like the vast majority of articles we reviewed in the LA literature, the specific ways that our research contributes to advancing the stated goals of LA (rather than making fractal progress within niches of common interest) were not well articulated — but they should be. We believe that the community needs to reflect on and discuss the standards for LA research (Bergner et al., 2018), and identify ways to hold ourselves responsible for achieving them. By authoring this review, and opening our work to peer commentary, we hope to catalyze this reflection. In the absence of such reflection, "Researchers tend to speak after one another, rather than to one another … and knowledge cannot be accumulated" (Bruyat & Julien, 2001). Our present review does not measure learner data or learning, nor does it assess an intervention in the learning environment, but we hope it causes researchers to reflect on their collective aims and discuss how such aims might be addressed.

But while we invite and advocate for reflection and discussion, it is also likely that policy action is needed for LA to become better aligned with its own goals. This is because publishing in LA, like many other conference proceedings and journals, is undermined by a cyclical process: authors of accepted articles are invited to become reviewers for subsequent article submissions. This feedback loop may present an obstacle to change, particularly in situations where current scholarship is out of alignment with intended goals. Given that reviewers have an incentive to maintain the status quo (because it reflects their own research contributions and strengths), it might be unreasonable to expect improvements in LA research to occur bottom-up alone. As Dawson et al. (2019) firmly assert, "Research directions and priorities can be influenced" (p. 454), and after engaging in collaborative reflection and discussion, we encourage those in positions of influence in the community to advance structural reforms.

What our findings reveal most clearly is the misalignment between the stated goals of LA and the research activities that LA is currently pursuing, as evidenced in LAK proceedings and JLA articles. The definition of LA aspires to do one thing, but actually, it mostly does not. In this way, the current findings provide compelling empirical support for the perennially enduring discomforts expressed within the LA community. This misalignment could be corrected in at least two ways. First, obviously, the LA community could adapt its research to focus more commonly on understanding and optimizing learning (as suggested by Viberg et al., 2018, 2020; Ferguson & Clow, 2017; Dawson et al., 2019). Alternatively, the LA community could modify the definition of "learning analytics" to reflect the research activities actually pursued by the community. Concisely, LA is dominated by research studies that ask, "Can we do this thing with these data?" Based on the current review, we induce that LA explores various ways one might analyze the data made available by technology-enriched learning environments, but lacks direction on how these analyses might be relevant for learning.

Open Research Practices

Study data, materials, and analysis scripts are available at https://osf.io/tzhva.

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