The current state of using learning analytics to measure and support K-12 student engagement: A scoping review

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Student engagement has been identified as a critical construct for understanding and predicting educational success. However, research has shown that it can be hard to align data-driven insights of engagement with observed and self-reported levels of engagement. Given the emergence and increasing application of learning analytics (LA) within K-12 education, further research is needed to understand how engagement is being conceptualized and measured within LA research. This scoping review identifies and synthesizes literature published between 2011-2022, focused on LA and student engagement in K-12 contexts, and indexed in five international databases. 27 articles and conference papers from 13 different countries were included for review. We found that most of the research was undertaken in middle school years within STEM subjects. The results show that there is a wide discrepancy in researchers' understanding and operationalization of engagement and little evidence to suggest that LA improves learning outcomes and support. However, the potential to do so remains strong. Guidance is provided for future LA engagement research to better align with these goals.

CCS CONCEPTS • K-12 education • Data analytics • Learning management systems

Additional Keywords and Phrases: Learning Analytics, Student Engagement, Scoping Review, K-12

1 Introduction

Student engagement is significantly related to student retention, grades, and general well-being [1, 2]. Its importance is so high that it has been referred to as a proxy for learning [3, 4], making it a critical consideration for K-12 educators [5] and one of the most important and critical constructs that can be explored in research to inform school development. Engagement shapes and is likewise shaped by context and is affected by internal and external influences, including the complex interplay of relationships, learning activities, and the learning environment; "the more students are engaged and empowered within their learning community, the more likely they are to channel that energy back into their learning" [6, p.3]. The increase in student engagement measures with good psychometric properties has cemented the power and value of student engagement as a useful variable for data-driven decision-making efforts in schools (e.g., [7, 8]), which could benefit from learning analytics (LA).

LA refers to "the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" [9, p.34]. Researchers have suggested that *qualitative* LA is an application of LA that improve learning outcomes, improve teaching and learning, are taken up and used widely (including deployment at scale), and are used in an ethical way [10]. As engagement can be seen as a proxy for learning [4], engagement and disengagement have often been examined by LA researchers, for example by exploring consequences (retention or dropout) (e.g., [11]) and achievement (results and grade) (e.g., [12]), or through specific indicators of engagement and disengagement (i.e., satisfaction, interest, self-regulation, lack of participation) (e.g., [13]). LA research has, however, been more widely undertaken in higher education (HE) than in schools (K-12) [14]. For example, many researchers have explored common input variables from learning management system (LMS) data (e.g., time spent in the LMS, frequency of content access and posting, discussion patterns), and interaction in learning. In fact, frequency has often been used to represent wide-ranged constructs such as attention, engagement and interest (e.g., [15]). These approaches have led to some interesting insights into HE learning.

However, as contextual factors (e.g., teacher support and the mode of instruction), as well as the demands on self-directed and self-regulated learning (SRL) in HE, differ substantially from K-12 settings, one cannot easily transfer HE results to a K-12 setting. In addition, to safeguard our youngest learners, practices in school are to be evidence-based, ethical and well-founded in educational theory and research.

LA research has received some criticism for being poorly informed by theory and lacking ethical rigor [13, 17], with a call from [51] to explore how theory has been used. To address this call, LA scholars have recently shown relevant efforts by mapping out learning theories used by LA researchers [93]. Yet, despite the potential LA has for shining greater light on engagement and allowing engagement theory to develop further [19], insights on how LA research explores K-12 student engagement remains limited [18]. This scoping review, therefore, seeks to provide deeper insight into how LA have been used to understand and support student engagement within K-12 settings with a view to help shape our understanding of engagement, and to provide advice for the undertaking of more robust and theoretically rigorous research in the future [63].

2 Literature Review

2.1 Student engagement

Student engagement has been called a 'meta-construct' or an 'organizing framework' – one that integrates such areas as belonging, behavioral participation, motivation, self-efficacy, and school connectedness [20]. However, engaged students do more than attend or perform academically; they may also persist in the face of challenges, self-regulate their behavior toward goals, strive to fully master a content, and enjoy learning [21].

Engagement is the active verb between the curriculum and actual learning. It depicts the 'proximal processes' that ecological models (e.g., [22]) posit are the primary engines of development. As a result, engagement is the direct pathway to cumulative learning, long-term achievement, and eventual academic success [23]. Thus, it can be viewed as a mediator of learning. This is one of the reasons that more than six million students in the US have undertaken the National Survey of Student Engagement [24]. While the survey demonstrates how using engagement measures is an effective approach to compare schools, evaluate interventions, and develop curricula, having the ability to design engaged learning is also included as a quality standard of online teaching [25]. Engagement scholars have also found that engagement does not just relate to the in-situ benefits for students and schools, but that it provides long-term positive effects on individuals in relation to their societal engagement and the development of higher ability levels [4].

2.1.1 Issues with engagement conceptualization.

While there is no 'one' engagement theory, there is a scholarly consensus on the fundamentals of engagement and theoretical publications that build on these. For example, there is a consensus that engagement is a multi-dimensional construct with two to four dimensions [20, 26, 27]. Engagement has been conceptualized as a two-dimensional construct with affective/emotional and behavioral dimensions [28], as a three-dimensional construct with affective/emotional, behavioral and cognitive dimensions [20, 29], with various dimension labels, for example cognitive, academic, emotional and behavioral [7], and as four-dimensional with an emotional, a behavioral, a cognitive and a social dimension [30, 31, 32]. Building on [19], we define engagement in learning as the emotional, behavioral, cognitive, or social energy and effort that students direct towards learning.

To talk about engagement theory, is to be oriented in engagement research, and refer to publications that have received acknowledgement in the field, (e.g., [20]), or research that present frameworks and models building further on these insights (e.g., [19, 30]). A problem with engagement research, if theory is not used, is that indicators or dimensions can overlap, or be unclearly connected to theory [36], which may lead to conceptual confusion and thus problems with adequately informing teachers and schools [46, 63]. Operationalizations of engagement may range from including indicators of behavior (a countable measure of real-time interaction) [14, 33], participation and identification with school values [28], earning credit towards graduation [34], to approaching attitudes towards learning that may lead to proactive behavior if disengagement does not occur [35].

SRL measures deal with the individual's (cognitive) manifestation of engagement in planning, monitoring and evaluating one's learning [42]. Within LA research, scholars attempted to better understand SRL activities, based on the measurement of student data originating from online learning platforms as compared to measuring SRL by subjective assessment measures only (e.g., [37]). When SRL is approached with reference to engagement, the relationship between SRL and engagement has often remained unclear. In engagement theory, the cognitive dimension of engagement has been suggested to subsume (cognitive) self-regulation [7, 38], where indicators of cognitive engagement often only rely on variables reflecting self-regulation [31, 39] or also include exerting effort [20, 40], concentration [13], applying learning strategies [7], or avoiding failure [41]. While cognitive self-regulation is the most common approach, there have long been approaches to regulation that connect to the other engagement dimensions, i.e., emotional regulation (e.g., [43]), behavioral regulation (e.g., [44]), and social regulation (e.g., [45]). Given the increasing use of SRL in LA research (e.g., [64]), there is a risk that findings are included as SRL indicators, even though they may have a more natural belonging in the emotional, behavioral, or social dimension of engagement. To not link indicators to its natural dimension risks blurring the conceptual clarity of both SRL and engagement.

2.1.2 Measurements of engagement.

Student engagement has traditionally been explored using self-reports, observations and interviews, with a tendency toward quantitative methods [6, 46]. However other kinds of data, such as online and system data (e.g., messages sent, documents uploaded, chat sessions attended, and presence), have also been used to reflect both engagement [46] and SRL [13]. Research has shown that LMS data alone does not compensate for the loss of theory-informed self-reports when exploring motivational [47] or engagement [33] indicators. LMS data are preferably combined with self-reports or other measures, as LMS data will only reflect a one-dimensional aspect of engagement [14, 32]. The uni-dimensional approach has received some critique, as it has become common in LA research to use easily countable indicators of engagement, rather than considering differences in indicator value and discerning between less and more meaningful measures [48].

2.2 Previous reviews related to LA and engagement

There are many reviews on engagement in technology-mediated learning (e.g., [6, 46]), which challenges LA research to increase considerations or raise the quality in relation to ethics, privacy and theoretical foundation (e.g., [13, 16, 17]). However, reviews on LA and student engagement are scarce, and those focusing on K-12 even more so. One review focused on K-12 multimodal LA research published from 2014-2019 [53] and was limited to exploring the behavior and progression of children under six years of age. Whilst the study acknowledges that engagement is multidimensional, it does not provide further insight into how engagement was used. The study concludes that LA research in K-12 still focuses on technical issues with tracking devices and sensors, risk, and ethical considerations.

In HE, there are LA reviews that have explored varying aspects of learning based on LMS data such as the effectiveness of data analytics [49], the application of LA in online learning [52], and [50] explored visualizations of LA available to teachers and students, concluding that the LA output was not often used as effectively as it could have been. [51] identified that, whilst the aim is often to provide support for teachers and learners, studies often halt at describing the potential of LA. Shahrul and colleagues [18] explored HE student involvement with LMS by exploring LMS design, teacher negotiation, and student engagement strategies, and suggested that teachers could use LA data for a more active approach to students, and that the LMS design, awards, and satisfaction influence engagement. Here, it is important to differentiate engagement with the digital device per se and engagement in learning. While engagement in learning via the LMS inevitably includes engagement with the application, not all application engagement is necessarily engagement in learning. In the same vein, [51] proposed that LA in complex learning environments would benefit from moving from an all-quantitative approach, toward adopting mixed methods, and indicated the possibility of a trend in that direction. Exploring trends in LA research, [51] suggested that the predictive methods that dominated LA research had decreased in favor of striving for a deeper understanding of students' learning experiences. Furthermore, [10] identified a lack of geographical spread in LA research, a lack of attention to how data can optimize learning, limited attention to validity, reliability and generalizability, and limited attention to sample selection.

2.2.1 Research questions.

Against this background, and to respond to a need to analyze the current state and quality of efforts in measuring and supporting student engagement using LA in K-12 settings, this scoping review seeks to answer the following research questions:

1. What are the publication and study characteristics of K-12 LA research exploring student engagement?
2. How does engagement theory inform data analysis in K-12 LA research?
3. What methods and data sources have been used to examine student engagement in K-12?
4. What is the LA evidence to measure and support student engagement in K-12?

3 Method

This scoping review is part of a larger multi-stage evidence synthesis project exploring student engagement and disengagement using LA (see OSF[1] for full project details), undertaken using transparent and explicit methods with pre-defined criteria [54, 55], and following the PRISMA-ScR reporting guidelines as closely as possible [56]. Given the emerging uptake of LA within K-12 settings, and the lack of prior studies synthesizing this evidence, it was decided to focus the present scoping review on only K-12 studies, in order to "map the literature [...] and provide an opportunity to identify key concepts; gaps in the research; and types and sources of evidence to inform practice, policymaking, and research" [65, p.8]. The search strategy detailed here outlines the strategy for the whole project initially, and then explains how the focus narrowed to K-12 engagement.

3.1 Search strategy and selection procedure

3.1.1 Search string development.

Starting from other previously published systematic reviews on student engagement [6, 57], the search string (Table 1) focused on engagement or disengagement, LA and education in formal education settings. Whilst it is recognized that engagement is multifaceted [19], it was decided not to search for each facet separately, but rather to search for explicit phrases or words referencing engagement specifically, in order to better explore how researchers interpret the terms 'engagement' and 'disengagement'. Whilst we did search for both engagement and disengagement as separate constructs [30], it was decided to focus this present review on engagement only. It should also be noted that each database required a slightly different format for the search string (see Appendix A[2]).

The initial search was conducted on 8 February 2022 within the Web of Science, Scopus, ProQuest (including ERIC), A+ Education, and SAGE Journals, followed by a second search on 21 July 2022 to ensure currency in the captured research. These platforms and databases were chosen as they have previously been identified as well-suited to evidence synthesis [58]. The combined search yielded 2,528 items (see Fig. 1), which were imported into evidence synthesis software EPPI-Reviewer [59], along with one item that was found by manual searching.

[1] https://osf.io/8tx6n/
[2] Appendix A - https://osf.io/fs263

Table 1: Search string

Topic	Search string elements
Engagement	"student engagement" OR "engagement" OR "disengagement" OR "learner engagement"
AND	
Learning analytics	"learning analytics"
AND	
education	universit* OR "higher education" OR postgrad* OR undergrad* OR "tertiary education" OR college* OR "K-12" OR kindergarten OR "primary school*" OR "middle school*" OR "secondary school*" OR "elementary school*" OR "middle primary" OR "upper primary" OR "senior school" OR "R-12" OR "high school*"

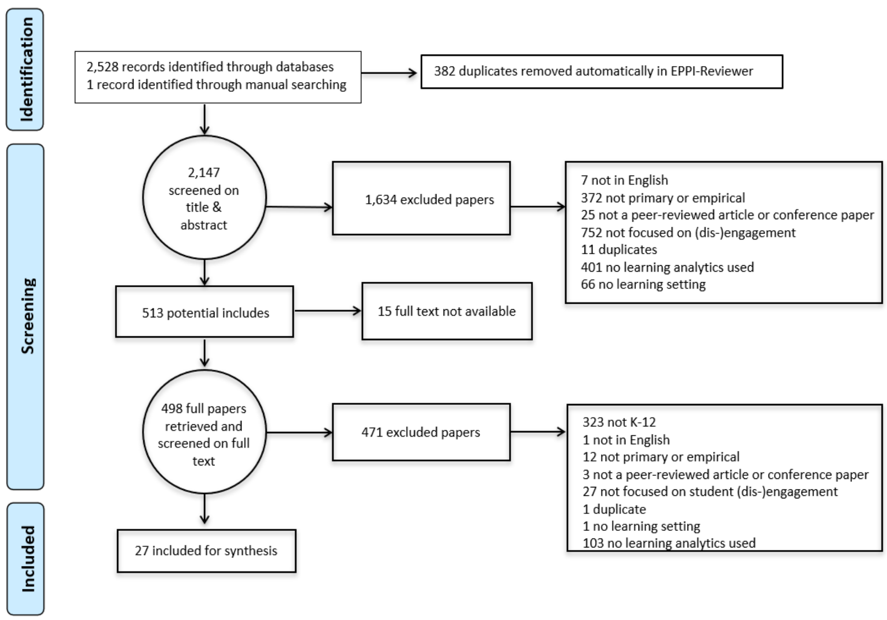

Figure 1: PRISMA Diagram

3.1.2 Inclusion/Exclusion Criteria.

Following the automatic removal of 382 duplicates, 2,147 items were screened on title and abstract by the review team, applying the inclusion/exclusion criteria. Studies were included if they were primary, empirical studies conducted in formal education settings, published after 2011, explicitly focused on LA and mentioned engagement or disengagement in the title, abstract or keywords. Included studies also needed to be either peer-reviewed journal articles or conference papers.

The authors screened the data separately and, following the coding of titles and abstracts for 100 randomly selected articles, inter-rater reliability was calculated using Cohen's Kappa [60] as 0.86-0.90 between the three coders, which is considered almost perfect agreement. To align coding further, the authors engaged in in-depth dialogue. Data was also checked for inconsistency and controlled for overlap.

513 studies were included on title and abstract, however 15 items could not be located, leaving 498 to screen on full text, applying the inclusion/exclusion criteria. 27 studies were then identified as K-12 and progressed to the data extraction and synthesis stage.

3.2 Data extraction, analysis and synthesis

The coding system used by [6] was adapted for this review and data was extracted within EPPI-Reviewer [59] (see Appendix B[3]). As a guiding principle, it should be noted, studies were included based on what they reported doing. For example, if a study stated that it explored engagement, it was included and analyzed accordingly. Data extraction codes included publication year and type (journal article or conference paper), theoretical framework, methodology (i.e., data sources, methods for data collection and analysis), setting (e.g., participant country) and the LA evidence. Specific examples of student engagement that could be identified were coded using indicators of behavioral, social, cognitive, or emotional engagement [19] and research approach was coded using the adapted method in [51].

In a call to the LA community, [10] suggested that LA research should further develop qualitative aspects and be classified using the following propositions: 1. LA improve learning outcomes. 2. LA improve learning support and teaching, including retention, completion, and progression. 3. LA are taken up and used widely, including deployment at scale. 4. LA are used in an ethical way. Therefore, when assessing evidence of LA research to measure and support student engagement, we adopted these four validated propositions to structure the evidence, using the approach by [51] to class studies as 'yes', 'no', or 'potentially' for the first two propositions. Studies were coded as 'potentially' if the authors had argued that their results could lead to future improvements, despite their results not identifying evidence of the proposition. The evidence for the last two propositions were coded as 'yes' or 'no' only.

To extract data relating to how studies conducted data analysis, items were coded as to whether they used a single analysis method or mixed methods (i.e., when quantitative and qualitative methods are combined), and the computational methods for data analysis categories were then adapted from [61]. A narrative synthesis of the data was then undertaken [62], including a tabulation of the studies and their characteristics (see Appendix C[4]), alongside tables summarizing the review findings, accompanied by narrative descriptions.

An openly accessible web database of all included studies and associated coding decisions was also created[5]. This allows users to view the data in an interactive way, such as study design, engagement dimensions, and the nature of LA evidence, through frequency and crosstabulation charts, with direct links to the included studies. This database also allows users to view interactive evidence gap maps (including methods and data sources, LA evidence by discipline and education level, and publication by country and type), as well as to save and export the data.

4 Results

4.1 Publication and study characteristics of the included studies

The majority of studies were published as journal articles (n = 20, see Appendix C[4]), with STEM settings by far the most researched (n = 20), alongside two studies from the Arts, Humanities & Languages [66, 67] and one featuring students from STEM and Social Sciences [68]. Years 5 and 6 were the most frequently studied grade levels (n = 7), followed by Year 9 (n = 6). However, in five studies the exact year level under focus could not be determined. One quarter of the studies did not specify the country where the research was undertaken, but of those that did, the most prominent countries were the US (n = 6), followed by two studies in Germany and two in China.

[3] Appendix B - https://osf.io/x64zw
[4] Appendix C - https://osf.io/4xdwa
[5] https://eppi.ioe.ac.uk/eppi-vis/login/open?webdbid=286

4.2 How does engagement theory inform data analysis in K-12 LA research?

As with previous engagement research in educational technology (EdTech, e.g., [63]), a common issue here was the conceptualization and operationalization of engagement. The studies in this review conceptualized engagement in many different ways (see Appendix C[4] and D[6]), with most (n = 6) approaching engagement through two dimensions (e.g., cognitive and emotional [69]) or by only one dimension (n = 4, e.g., cognitive [70]). One study [71] referred to all four dimensions, three studies conceptualized engagement through the three dimensions of behavioral, affective/emotional and cognitive [77, 81, 90], and one study [87] included the three dimensions as well as SRL. Whilst such conceptualizations were detailed and well-referenced, there were some studies that only referred to engagement after the introduction and background (e.g., [72, 73]), leaving it up to the reader to infer how engagement was understood, or that cited a few articles that had explored engagement within their introduction but did not then provide any insight into the conceptualization that was used in in their studies (e.g., [74]).

Engagement was approached as a secondary aim in four studies. [75] undertook their study within the context of computational thinking (CT) and explored how learners engage through persistence in the acquisition of CT concepts. Another study [76] explored indirect effects on engagement, such as how embodied engagement (operationalized as movement) influences cognition, and [77] explored online collaboration through learners' speech, actions, gaze and emotions. Even though the term 'engagement' was repeatedly mentioned, collaboration was the explicit aim, with links to engagement remaining unclear. Similarly, [78] focused on SRL and social cognition, with engagement approached from a meta-level.

Commonly, LA researchers operationalized and analyzed engagement through one (n = 6) or two (n = 6) dimensions, with behavioral engagement the most prominent (n = 9), followed by emotional/affective (n = 7), cognitive (n = 7) and social (n = 4). There were also cases where specific indicators of engagement were attributed to dimensions that they would not usually be (e.g., confusion and engaged concentration being attributed to affective engagement rather than cognitive [80]), and where two dimensions of engagement were subsumed into one (e.g., behavioral engagement into cognitive engagement [70]), as well as examples where a few indicators were explicitly linked to engagement dimensions and others were left on their own (e.g., [68]).

4.3 LA methods and data sources used to analyze student engagement

4.3.1 Research approach.

The majority of studies (n = 22) undertook an interpretative or exploratory approach (see Appendix C[4]), followed by experimental studies (n = 5), two studies that used surveys, as well as a study in which a clear methodological approach could not be identified. In some cases, it was clear that more than one approach had been used (e.g., [66, 81]). Studies that employed the interpretative approach frequently aimed to assess and understand learners' state of engagement, including its different aspects and dimensions, as a better indicator of learning compared to performance (e.g., [72, 77]). In two studies, surveys were used to subjectively assess student engagement. For example, [82] using a multi-case approach, examined students' behavior patterns when interacting with a serious game environment; two types of surveys were used to measure students' game engagement and fantasy proneness. In another study [73], scholars used a survey instrument to measure the expected impact of the proposed visualizations.

4.2.2. Data sources.

Just over half of the corpus (n = 15) used multiple data collection methods (see Appendix C[4]), with many of the data sources (>20 studies) used to measure K-12 student engagement frequently scrutinizing system log data (see Fig. 2), either separately or in combination with other data sources. Such log data frequently originated from various LMS used by schools (e.g., [68]), digital game-based environments (e.g. [75, 83, 84, 85]), as well as specially employed or designed systems that have been integrated into educational practice (e.g., [78, 86]). Researchers also

[6] Appendix D - https://osf.io/4r5hs

used various multimodal data sources, including speech emotions observations [69, 81], video data [81], computer screen recording data [72], heart rate data [87], and eye gaze and eye blinking data [70]. Measuring student performance assessment data (e.g., test scores and grades) was used in 10 studies (e.g., [76]), and data originating from subjective assessment sources such as surveys (e.g., [82]), interviews [76] and focus groups (e.g., [81]) were harvested by a few studies to offer additional insights into students' engagement.

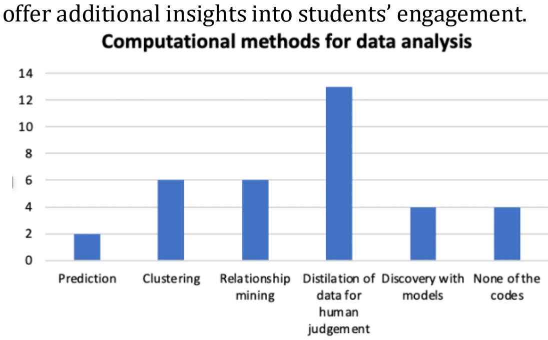

Figure 2: Data sources used

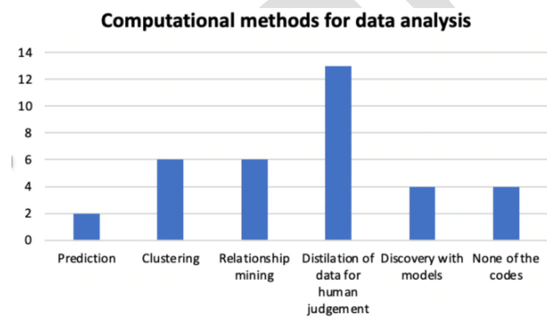

Figure 3: Computational methods for data analysis[7]

4.3.2 Data analysis methods.

In order to gain further understanding of how student engagement has been analyzed, study approaches were examined, revealing that 63% of the reviewed sample (n = 17) employed single methods of data analysis, with 10 studies using a mixed-method approach. As most of the sample applied computational methods (n = 23), in line with most LA research [51], the categorization of [61] was then used to examine them further. The most frequently used methods in the corpus were those in the 'distillation of data for human judgement' category (n = 13, see Fig. 3). These methods include different types of visualizations of student engagement (e.g., [66, 74]) and statistical methods of data analysis [72, 75, 82], which have been used either separately or in combination. Six studies employed various types of relationship mining methods (e.g., [70, 80, 87], and six employed clustering techniques to better understand different patterns of student engagement (e.g., [77, 85, 89]). In four studies, researchers employed modelling techniques to understand and predict student behaviors, including a prediction model for college attendance [80], an early warning model, based on deep learning and machine learning mechanisms [15], a

[7] In several papers, methods that fall into more than one category were used

model that distinguishes a learner's guessing behavior from solution behavior [83], and an unsupervised deep learning model to model students' SRL patterns [68]. Finally, prediction methods were used in two studies [15, 90].

4.4 What is the evidence of LA to support student engagement?

4.4.1 Learning outcomes.

Overall, the findings of this study exhibit very little evidence in terms of students' improved learning outcomes (see Fig. 4), with only three studies showing evidence that the application of LA to support student engagement improves their learning outcomes [66, 74, 76]. Most studies (*n* = 24) did not attempt to assess any improvements in learning outcomes, although three studies did explicitly discuss the potential to improve learning outcomes [67, 75, 81].

Among the studies that showed improvements in learning outcomes, [66] offered and evaluated a LA dashboard visualizing secondary school students' (*n* =101) latest data against their self-referenced data from previous weeks. The results exhibited the effectiveness of the theory-informed dashboard, as shown by the statistically significant pre- to post-trial improvements in students' (i) critical reading fluency scores, and self-reported (ii) cognitive reading engagement, and (iii) English language/reading self-efficacy and critical reading ability. [78] implemented an embodied learning approach to promote children's (*n* = 52) active engagement in the classroom. Based on the standardized pre-post testing for children's cognitive and academic performance, general LA from games' (Kinems games) usage, interviews, and observations from the teachers involved, significant effects both on children's cognitive abilities (i.e., short-memory skills) and academic performance (i.e., expressive vocabulary) were identified. Finally, [74] examined the engagement and performance of students (*n* = 27) in a classroom using the Cognitive Learning Companion, a tool designed to keep track of the relationship between the student, content interaction and learning progression. The results revealed a strong correlation between performance and engagement, with students exhibiting higher levels of engagement performing better on average.

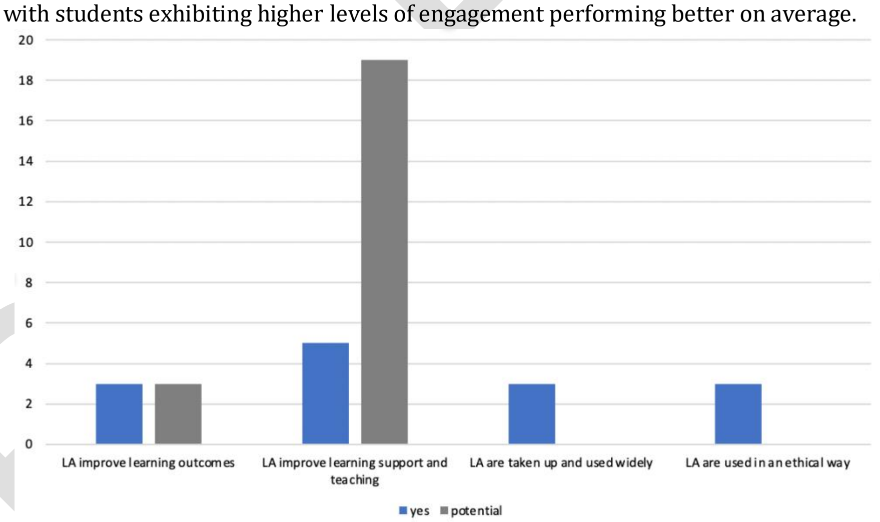

Figure 4: LA evidence to support student engagement

4.4.2 Learning support and teaching.

Little evidence was found in terms of improved learning support and teaching (see Fig. 4), with only five studies demonstrating related improvements [66, 73, 74, 81, 86]. For example, [86] offered a LA dashboard for supporting students' collaborative work, which the students (*n* = 22) found useful in regard to their improved collaborative learning experience. [81] demonstrated that the user engagement analytics tool (SEAT) enabled teachers to better identify which students needed help, to facilitate timely support. [74] offered an engagement tool (the Cognitive Learning Companion), designed to keep track of the relationship between the student, content interaction and learning progression, with the sensor-rich instrumented learning environment providing actionable insights to the teacher on learners' cognitive and affective states. The evidence of supporting teachers by increasing their awareness of students' progress, possible misconceptions, and task difficulty, was shown by [73] through the use of visualizations. Despite this limited evidence for supporting learning and teaching, many studies in the sample (n = 19) did explicitly exhibit the potential of improved learning and/or teaching (see Appendix C[4]).

4.4.3 LA deployment at scale.

The third proposition by [10] pertains to the level of LA usage and is concerned with institutional and policy perspectives [37], which was met by only three studies in the present corpus. [80] used LA and data mining measures of middle school student (*n* = 7636) behavior, emotions and knowledge, to develop a prediction model of college attendance, evaluating their relationships to intermediate outcome on the path to college attendance, and to develop an overall path model between middle school and high school educational experiences, and eventual college attendance. A middle school informatics tutoring system (ASSISTments) was used across one year. In the exploratory study by [15], a large data set from 12,869 students from a virtual K-12 school in the US offered an effective early warning deep learning model to identify at-risk students, and in another study [78], the SRL behavior of 468 junior high school graduates from across many regions in China was examined in an online resource platform with an integrated (self-selecting) social network. All in all, the results of this review show a general current lack of the institutional uptake of LA.

4.4.4. Ethical uses of LA.

Finally, considering the importance of performing LA research in an ethical way, including the careful protection of children's privacy (e.g., [91]) in the increased datafication of K-12 education worldwide (e.g., [92]), this proposition is about the 'should we' questions, rather than 'can we' ones. The results of this study show that very few studies [76, 87, 90] reported the related ethical efforts that have been undertaken in this regard.

5 Discussion

This scoping review was a first step in exploring LA research approaches to examining and supporting student engagement in K-12, by exploring publication and study characteristics, researcher conceptualizations, operationalizations and analysis of engagement, methods and data sources used, as well as the evidence of LA research for learning and teaching, following the validated propositions by [10] as a framework.

A lack of geographical spread in LA research was previously identified by [10], however this review included studies from all continents except South America; a disappointingly common occurrence in English language K-12 EdTech research (e.g., [57]). In line with previous K-12 student engagement research (e.g., [57]), the middle years (Year 5, 6 and 9 in particular) and STEM subjects (74%, *n* = 20) were by far the most researched, although interestingly only 65% of STEM studies were undertaken by first authors who identified as researching in STEM (including Computer Science) or Maths education. This raises the question of whether LA researchers are choosing to undertake studies within disciplines similar to their own, whether STEM subjects produce data that is more easily analyzable than other learning areas, or whether STEM subjects are a natural go to in EdTech research in general. Either way, this represents opportunities for further LA research to be undertaken within other disciplines.

The analysis revealed that student engagement research in K-12 LA suffers from ongoing problems experienced in wider EdTech research; a lack of rigor and transparency in study design (e.g., [57]) and issues with theoretical conceptualization and operationalization (e.g., [6, 46]). One quarter of the studies in this review (*n* = 7) did not specify the country in which the research had been undertaken, five studies did not specify the exact year levels involved, four studies did not provide the number of participants, and seven studies did not indicate which subjects (e.g., Science, English) were being investigated. It is vital that researchers provide explicit study design information, irrespective of whether the publication is a journal article or a conference paper, to enable better comprehension of research context, and for interpretation and potential application of methods and recommendations to other contexts [10]. The operationalizations of engagement seem to rely heavily on the researchers' own understanding, interpretation and classification of online input data and underlying theory. This may explain why there is no consistency in the adoption of engagement theory (or related theories) across the analyzed studies (e.g., [70, 79, 80]). In order to move the field forward, studies must be explicit in how they understand engagement and then be transparent and logical in how engagement is measured and analyzed [33, 57, 63]. As such, this scoping review proposes these aspects to ensure quality when focusing on engagement into LA research:

- There are links to theory to support the conceptualization of engagement,
- The measures are linked to theory,
- The terminology is consistent, and
- Indicators are clearly linked to the engagement dimension explored.

56% of studies in the corpus (*n* = 15) used multiple data sources, and ten studies used mixed methods, which supports [51]'s assertion that there is a trend towards the use of mixed-method approaches. Also, most studies used computational methods that fall under the category of the 'Distillation of data for human judgement'; this shows a tendency towards a greater understanding (as compared to a focus on prediction) of student engagement or learning activities. Only two studies in this corpus (7%) used predictive methods of analysis, which could also confirm that LA research is seeking to gain deeper understandings of students' engagement experiences in the learning process.

This review also revealed that there is very little evidence of LA improving learning outcomes or learning support and teaching, although there were a high number of studies that showed the potential to support learning and teaching. This is in line with earlier LA research results in other contexts (e.g., [36, 51]). Overall, this finding suggests that there is still a critical need for LA scholars to show how the potential of LA could be realized in practice to improve student learning, learning support and teaching. Here, it is important to highlight that scholars need to consider that the contextual nature of LA efforts undertaken in the context of K-12 is rather different from HE settings. For example, the number of stakeholders involved could differ, i.e., be higher (e.g., parents and school principals) in the K-12 context as compared to HE, as well as the purposes of LA could vary considerably depending on the needs and interests of different stakeholders.

There is also a continued lack of institutional uptake of LA, which is in line with the findings of another review focusing on the use of LA in high school settings [88], and which requires further conversation. This slow uptake of LA in K-12 settings could be explained by several reasons including challenges with: 1. the understanding among stakeholders of what LA are, 2. what LA can contribute to different stakeholders, 3. data interoperability and 4. ethical issues, including stakeholders' privacy concerns, security and transparency. The findings of this review highlight that enhanced transparency is needed on ethical issues in K-12 LA use. We found, in particular, that only a few studies reflected on ethical issues; this, however, does not mean that the studies in this corpus were performed in an unethical way, rather that more transparency is expected regarding this proposition.

5.1 Limitations

Whilst this review was undertaken using replicable and transparent methods [54, 55], guided by PRISMA-ScR [56], there are limitations that need to be acknowledged. The databases searched have been shown to be well-suited to synthesis [58], capturing a range of global research, however it is possible that pertinent literature was missed, especially given the inclusion of English language only research. To this end, the authors recommend that further research be undertaken in languages and databases other than English, particularly given the high number of US studies in this corpus. In addition to the presented findings, the search string included terms related to disengagement and higher education, however the authors decided to limit the scope of this particular review to K-12 and engagement.

6 Conclusion

This scoping review synthesized 27 studies published between 2011-2022, focused on LA and student engagement in K-12 contexts. The studies reflect that LA is gaining momentum in the care and education of young learners. This review emphasizes the pertinence of key aspects in this regard: that is, it is critical to understand the foundations from which engagement research is being undertaken, that research should reflect how different stakeholders (e.g., school leadership, teachers and students) benefit from using LA, and that LA can be used to further drive insights into the development of engagement theory. However, to do so, LA researchers should strive to align their view of how the engagement construct should be conceptualized and operationalized. Pointing to ways forward, the review proposes four key aspects to consider for LA scholars who seek to explore the engagement construct in education settings. Further research is particularly welcome that explicitly links engagement indicators to engagement dimensions, supported by engagement theory (e.g., [19]), as well as research on LA to improve emotional and social engagement, with a focus on critical ethical uses.

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