Bergdahl *et al. Int J Educ Technol High Educ* (2024) 21:63
https://doi.org/10.1186/s41239-024-00493-y

International Journal of Educational Technology in Higher Education

REVIEW ARTICLE

Open Access

# Unpacking student engagement in higher education learning analytics: a systematic review

Nina Bergdahl[1,2], Melissa Bond[3,4,5*], Jeanette Sjöberg[1], Mark Dougherty[1] and Emily Oxley[6]

*Correspondence:
melissa.bond@ucl.ac.uk

[1] Halmstad University, Halmstad, Sweden
[2] Stockholm University, Stockholm, Sweden
[3] EPPI Centre, University College London, London, UK
[4] University of Stavanger, Stavanger, Norway
[5] National Institute of Teaching, London, UK
[6] The School of Social and Environmental Sustainability, University of Glasgow, Glasgow, UK

**Abstract**

Educational outcomes are heavily reliant on student engagement, yet this concept is complex and subject to diverse interpretations. The intricacy of the issue arises from the broad spectrum of interpretations, each contributing to the understanding of student engagement as both complex and multifaceted. Given the emergence and increasing use of Learning Analytics (LA) within higher education to provide enhanced insight into engagement, research is needed to understand how engagement is conceptualised by LA researchers and what dimensions and indicators of engagement are captured by studies that use log data. This systematic review synthesises primary research indexed in the Web of Science, Scopus, ProQuest, A + Education, and SAGE journals or captured through snowballing in OpenAlex. Studies were included if they were published between 2011 and 2023, were journal articles or conference papers and explicitly focused on LA and engagement or disengagement within formal higher education settings. 159 studies were included for data extraction within EPPI Reviewer. The findings reveal that LA research overwhelmingly approaches engagement using observable behavioural engagement measures, such as clicks and task duration, with very few studies exploring multiple dimensions of engagement. Ongoing issues with methodological reporting quality were identified, including a lack of detailed contextual information, and recommendations for future research and practice are provided.

## Introduction

Gaining insight into how students engage within courses is crucial in order to understand how best to improve teaching and learning outcomes and in particular, to identify when interventions are needed for at-risk students (Adnan et al., 2021). Indeed, given the underlying explanatory power of engagement and its relation to student wellbeing, retention, grades, and future careers (Bergdahl et al., 2020; Bond et al., 2020; Fredricks et al., 2004; Henrie et al., 2018), student engagement has been investigated from a number of angles within a wide range of digital learning modalities, often using measures that claim to reflect engagement from learning management systems (LMS) (Beer et al., 2010). The vision of Learning Analytics (LA) is that analytics shall be used to generate data to identify actionable insights and subsequently make informed decisions to improve teaching and learning through monitoring progression, predicting performance, modelling behaviour, and detecting emotions to improve education (Mougiakou et al., 2023), especially given the limited nature of student self-report instruments to accurately identify engagement and realised actions, instead of purely intentions to study (Gašević et al., 2017; Henrie et al., 2018).

However, despite the growth of LA in higher education (Tsai & Gašević, 2017), concerns have been raised about what analytics represent (Gardner et al., 2020). Macfadyen and Dawson (2010), for example, found that time spent on educational resources, as indicated by LA data, did not correlate to academic performance despite the correlation between engagement and academic performance. Furthermore, a systematic review of 38 dashboard studies (Kaliisa et al., 2024) reported that some researchers found a medium to large effect on participation, which shows promise for impact on engagement. Yet, issues were raised with the way that these studies were undertaken, including small sample sizes, a reliance on traditional evaluation methods, and a lack of standardised assessment tools. Concerns have also been raised about whether counting clicks is sufficient to capture engagement (Fincham et al., 2019), and calls have been made for future LA research to explore all dimensions of engagement beyond purely behavioural measures (Johar et al., 2023).

Indicating that there may be a gap between LA research and theory development, Gašević et al. (2019) emphasised that LA must become more rigorous in adopting educational theory. Given the role that LA research could play in informing practitioners and contributing to academic engagement theory enhancement, further insight is therefore first needed into how researchers are currently operationalising and measuring engagement. In addition, engagement researchers recommend the development of new and less commonly known measures to inform theory development, considering different levels and dimensions of engagement (Paulsen & Lindsay, 2024; Salmela-Aro et al., 2021).To that end, a systematic literature review was undertaken to explore the approaches to capturing student engagement in Higher Education Learning Analytics (HELA) research, aligned to a rich, multidimensional student engagement framework, in order to provide more nuanced insights and actionable implications for the field.

## Literature review

### Student engagement theory

Student engagement has been called a 'meta-construct' or 'organising framework' (Christenson et al., 2012; Fredricks et al., 2004). Despite there not being a single theory of engagement, it is consistently understood as critical for learning (e.g., Bergdahl & Bond, 2022; Bond & Bergdahl, 2022; Martin & Borup, 2022; Christenson et al., 2012). Engagement is the mediator between the learning and the content (Reeves, 2012) and being critical for educational success, it is often attributed to the state as a 'proxy for learning' (McClenney et al., 2012). In addition to being a precursor to knowledge and understanding, Kuh (2007) asserts that student engagement is a desired outcome because it leads directly to cumulative learning, long-term achievement, and, ultimately, academic success. Moreover, researchers have found that engagement provides long-term benefits for individuals, notably their societal engagement and higher ability levels,

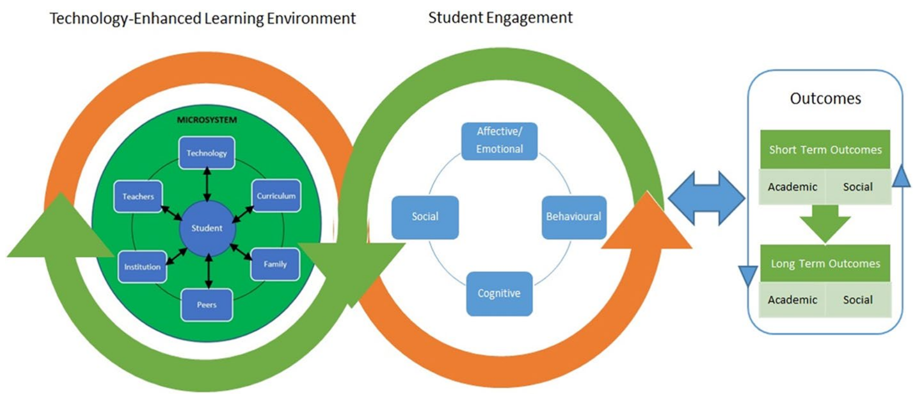


**Fig. 1** Student Engagement in Digital Learning Framework, adapted from Bond and Bedenlier (2019, p. 8)

**Table 1** Example engagement indicators

| Behavioural engagement | Cognitive engagement | Emotional engagement | Social engagement |
|---|---|---|---|
| Participation/involvement | Critical thinking | Enjoyment | Interaction with peers |
| Time on task | Self-regulation | Interest | Interaction with educators |
| Attending live lessons | Focus/concentration | Satisfaction | Interaction with technology |
| Assuming responsibility | Deep learning | Positive attitude towards learning | Asking for help |
| Effort | Self-efficacy | Sense of wellbeing | Turn-taking |

as well as the in-situ benefits for students and institutions (Lawson & Lawson, 2020; Tafelski et al. 2017).

Engagement research has received criticism for not being grounded in theory (e.g., Henrie et al., 2015). When it comes to engagement, one arising problem relates to the emerging and disparate ways to convey what engagement is; for example, researchers may tend to either add variables that are not widely recognised as parts of engagement, supplement theory for research papers, or present vague conceptualisations (e.g., Masiello et al., 2024). Another problem may be that theory is used merely as a window dressing, with vague or shallow connections between theory and research (Salmela-Aro et al., 2021). These instances signal insufficient treatment of the engagement construct, leading to incorrect conclusions and potentially flawed information for educators. This review, therefore, is guided by the Student Engagement in Digital Learning (SEDL) Framework (see Fig. 1; Bergdahl et al., Forthcoming; Bond & Bedenlier, 2019; Bergdahl et al., 2020; Bond et al., 2020) and the definition of engagement in learning as the emotional, behavioural, cognitive, or social energy and effort students direct towards learning (Bond et al., 2023). Each student engagement dimension has many indicators of engagement (see Table 1) and disengagement (see Table 2), which, although related, are two distinctly separate constructs (Wang et al., 2019).

**Table 2** Example disengagement indicators

| Behavioural disengagement | Cognitive disengagement | Emotional disengagement | Social disengagement |
|---|---|---|---|
| Task incompletion | Confusion | Boredom | Decreased interaction |
| Absence | Apathy | Anger | Social isolation/withdrawal |
| Lurking | Unfocussed/inattentive | Dislike | Challenging interactions |
| Time off task | Lack of regulation | Disinterest | Ignoring others |
| Drop out | Distracted | Frustration | Giving up on social inclusion |

### *Student engagement and disengagement*

Student engagement is generally accepted as having two to four dimensions: affective/emotional,[1] behavioural, cognitive and social (e.g., Bergdahl & Bond, 2022; Bond & Bergdahl, 2022; Martin & Borup, 2022; Christenson et al., 2012). Exploring these dimensions, Wang et al (2016) confirmed that these are related yet distinct constructs. Engagement theory suggests that behaviourally engaged learners are those who take actions that support learning and are directly influenced by teaching methods, technologies, and educational modes (Bond & Bergdahl, 2022). Behavioural disengagement may manifest as passive participation or lurking in an online environment, moral disengagement, such as cheating, or simply the absence of expected engagement activities like avoidance, time off task, and procrastination. Outcomes like test results or dropout rates often measure previous engagement or disengagement. Cognitive engagement encompasses cognitive self-regulation, meaning that indicators of cognitive engagement often reflect self-regulatory behaviours. This can include concentration, applying learning strategies, and avoiding failures (Bergdahl et al., 2020; Bond et al., 2020; Bond & Bergdahl, 2022; Viberg et al., 2020), self-efficacy, which concerns an individual's belief in their ability to influence events through their actions (Bandura, 1977), and self-regulation which refers to how individuals participate in learning through planning, monitoring, and evaluating their progress (Pintrich, 2000; Zimmerman, 2000), are critical elements often subsumed under cognitive engagement.

Emotional engagement relates to students' affective reactions towards learning, such as interest, enjoyment, and curiosity, which are essential as they drive the willingness to engage and persist in learning activities (Fredricks et al., 2004). Emotional disengagement, or disaffection, can include feelings like boredom, indifference, sadness, worry, anxiety, and frustration, affecting student behaviour in distinct ways (Bergdahl & Bond, 2022; Authors, in review). Social engagement involves students' positive attitudes toward collaborating and learning with peers. This includes activities such as spending time with, supporting and assisting classmates (e.g., Bond & Bergdahl, 2022; Fredricks et al., 2016; Wang et al., 2019). Wang et al. (2016) characterised social engagement with behaviours like building on others' ideas and working cooperatively in academic settings, particularly in subjects like science or maths. Negative aspects of social engagement include a lack of interest in others' ideas and an aversion to group work.

[1] This shall be referred to as emotional engagement throughout the article.

### Learning analytics and engagement

Analytics refers to the collection and analysis of learner and context data used to make data-driven decisions and interventions in the learning process. Several categories of methods can be used to analyse learner-generated data and measurements. These include statistical methods, data mining, machine learning, qualitative methods, social network analysis (SNA) and visualisation (Mougiakou et al., 2023). That said, the potential of LA to contribute to engagement theory is substantial. The traditional measures could be combined with LA approaches to gathering a fuller understanding of engagement. Thus, LMS data are preferably combined with self-reports or other measures, as LMS data will only reflect a uni-dimensional aspect of the engagement in situ (e.g., Tempelaar et al., 2020). With better LA metrics quality, learner and learning data will be more valuable and easier to use. In the past, self-reports, observations, and interviews have been the main approaches adopted to study student engagement, with a tendency to use quantitative methods (Henrie et al., 2015). Institutional data is more than attendance and grades; it includes what we can divide into static (Higher Education Commission, 2016) and dynamic data. The former focuses on demographics and other data that are stable over time. Dynamic data describes data generated more frequently, mainly related to the learners' activities during learning (Mougiakou et al., 2023). These trace data may be collected through Learning Management Systems (LMS) or web applications. As there is so much data, LA adoptions must be clear with what data is used and how these are associated with specific measurements related to the object of measure: learning outcomes, achieving goals, performing, changing behaviour, engagement, motivation, cognition, abilities, emotions (e.g., Mougiakou et al., 2023). While the unidimensional approach has potential, it has been criticised for using easy-to-count engagement indicators in LA research rather than considering differences in indicator value and distinguishing between meaningful and less meaningful ones (e.g., Johar et al., 2023).

While using built-in analytics may be tempting to adopt, built-in engagement analytics indicators may not be useful for predicting student online learning outcomes (Iglesias-Pradas et al., 2015; Strang, 2016; Zacharis, 2015). Concurrently, many researchers utilise LMS activity as a representation of student engagement, given its observed correlation with improved final grades (Beer et al., 2010; Blumenstein et al., 2019; Chaka & Nkhobo, 2019; Fritz, 2013; Henrie et al., 2018; Macfadyen & Dawson, 2010). In LA these representations are the indicators considered to measure engagement. However, a recent scoping review on the use of LA in the K-12 setting (Bond et al., 2023) found that while being critical, theory adoption, operationalisation, and measures of engagement could be vague or non-existent in LA research (Henrie et al., 2015).

In addition to monitoring learners' progress and modelling learner behaviour, LA also identify emotional and affective states related to learning; predict learning performance, retention, and drop-out; provide feedback recommendations; inform of adaptations; and support increased self-awareness and reflective behaviour to improve self-regulation (Chatti et al., 2012; Papamitsiou & Economides, 2014). LA are important because they can combine valuable external learner data with information from digital learning environments. Computational methods can isolate, identify, and classify actions in meaningful patterns in such environments. Behavioural schemes can be developed to code every interaction then decode them into interpretable guidance for decision-making. A recent review focusing on LA methods (Charitopoulos et al., 2020) identified the most frequently used methods and common connections between certain methods and analysis: (regression analysis was the most commonly combined with Decision Trees, Bayesian analysis, SVM and Random Forests, and emotion/sentiment analysis were found to use Bayesian/Probabilistic reasoning, SVM and ANN).

### Prior reviews on HELA

The interest in LA in higher education has led to a substantial increase in reviews aiming to understand its impact on teaching and learning (see Appendix A). However, whilst reviews have found moderate evidence to support LA's role in improving teaching and learning support (e.g., Viberg et al., 2018), they have noted significant lags in applying these insights effectively (e.g., Ifenthaler & Yau, 2020; Masiello et al., 2024) and a general lack of consideration of ethics (Braunack-Mayer et al., 2020; Stojanov & Daniel, 2023). Guzmán-Valenzuela et al. (2021) explored 385 papers from 2013 to 2019. They critiqued the prevailing focus on analytics over substantive learning improvements, advocating for a balanced approach that equally values pedagogical effectiveness alongside technological advancements (Drugova et al., 2024).

Previous reviews have also criticised LA interventions for lack of methodological quality (e.g., Larrabee Sønderlund et al., 2019), such as tending to be small in scale (e.g., Braunack-Mayer et al., 2020), lacking longitudinal designs (e.g., Algayres & Triantafyllou, 2019), and being over-reliant on one type of methodology (e.g., Foster & Francis, 2020; Kaliisa et al., 2024). A lack of theoretical grounding has also been raised (e.g., Guzmán-Valenzuela et al., 2021; Masiello et al., 2024), including the framing of research questions (Drugova et al., 2024) and underdeveloped theories of change (Foster & Francis, 2020). While Foster and Francis (2020) found evidence to suggest that outcomes can be predicted by LA, inconsistency across terms and definitions led to difficulties in the overall interpretation of results. This has also been the case with reviews focused on LA's impact on student engagement specifically, with Johar et al. (2023) emphasising the need for studies that consider all dimensions of student engagement more robustly rather than purely focusing on one in isolation, echoing calls from wider engagement literature (e.g., Henrie et al., 2015). However, that review only focused on research published between 2011 and 2021 and was limited to online learning in higher education studies indexed in Scopus or within four publisher repositories.

### Research questions

Against this background, this review seeks to answer the following research questions:

1. When, where and about whom has HELA student engagement research been undertaken between 2011 and 2023?
2. What are the prevalent data collection and research methods when exploring student engagement in LA research?
3. How are theories or frameworks of student engagement applied to guide data analysis in LA research?
4. What indicators have been used to measure engagement in HELA research?
5. What are the overall findings of HELA student engagement research?

**Table 3** Search string

| Topic | Search string elements |
|---|---|
| Engagement | "student engagement" OR "engagement" OR "disengagement" OR "learner engagement" |
| AND | |
| Learning analytics | "learning analytics" |
| AND | |
| Education | university* 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*" |

## Method

To explore how LA research has attempted to capture and understand student engagement in higher education, a systematic review was conducted using explicit and transparent methods (Bond et al., 2024; Gough et al., 2012; Zawacki-Richter et al., 2020), following reporting guidelines according to the Preferred Reporting Items for Systematic Review and Meta-Analyses (PRISMA, see Appendix B; Page et al., 2021) as closely as possible, and checked against the Quality of Evidence Synthesis Tool.[2] This review is the second output from a larger project (see OSF[3] for full project details), with the first publication being a scoping review focused on K-12 LA engagement literature (Bond et al., 2023). The search strategy initially outlines the larger project strategy and then details how the focus is narrowed to higher education engagement.

### Search strategy and study selection

#### *Search string*

The search string was developed based on previous student engagement reviews (Bergdahl et al., 2020; Bond et al., 2020) and focused on engagement or disengagement, LA and educational settings (see Table 3). Although the authors recognise that engagement is multifaceted (e.g., Bond & Bergdahl, 2022), the decision was made not to search for each indicator or facet separately but rather to search for explicit phrases or words to support an exploration of how researchers are interpreting the understanding and measurement of 'engagement' and 'disengagement'. A slightly different version of the search string was required for each database owing to their varying functionality (see Appendix C).

The first search was conducted on 8 February 2022, with further searches in July 2022, February 2023, and October 2023 to ensure that recent pertinent literature was included. The platforms searched were the Web of Science, Scopus (including the LAK conference proceedings), ProQuest (including ERIC), A + Education and SAGE Journals, which were chosen as well-suited to evidence synthesis (Gusenbauer & Haddaway, 2020). The combined search yielded 3,914 items (see Fig. 2), which were imported into evidence synthesis software EPPI Reviewer (Thomas et al., 2023), along with one item that was

[2] QuEST appraisal form available here: https://doi.org/10.17605/OSF.IO/8TX6N

[3] https://osf.io/8tx6n/?view_only=cb07fea5cbb3491a99f25f9b2470dff6

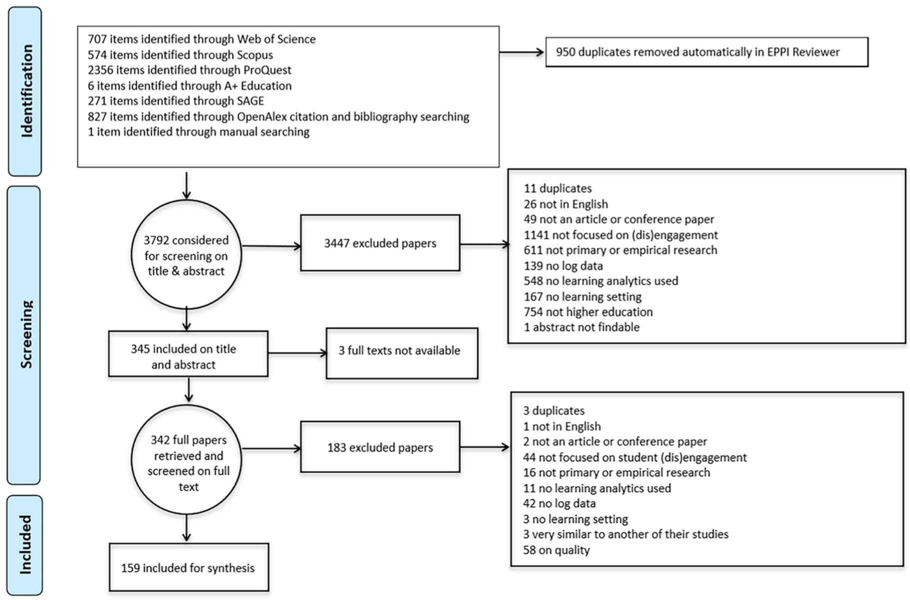


**Fig. 2** PRISMA diagram

**Table 4** Inclusion and exclusion criteria

| Inclusion criteria | Exclusion criteria |
|---|---|
| Published between 2011–2023 | Published before 2011 |
| A primary, empirical study | Reviews, conceptual papers, editorials |
| Application of learning analytics | No learning analytics or log data used |
| Formal higher education learning setting | Not focused on (dis-)engagement |
| Focus on student (dis-) engagement | K-12, MOOCs, professional learning |
| Log data used | No formal learning setting |

found through manual searching. A further 827 items were identified through OpenAlex forward and backward snowball searching and imported directly into EPPI Reviewer.

Although this review focuses on higher education, the search string included terms related to K-12 education. This inclusion was intentional and part of a broader research strategy for a larger project examining student engagement across all educational levels. By incorporating K-12 terms, we aimed to ensure comprehensive coverage and avoid missing any studies that might span multiple educational settings or use overlapping terminology. For this particular analysis, however, we focused exclusively on higher education settings. During the screening process, we applied our inclusion and exclusion criteria rigorously (see Table 4) to filter out articles that were not pertinent to higher education, thereby ensuring that only relevant studies were included in the final synthesis.

### *Inclusion/exclusion criteria*

Following the automatic removal of 950 duplicates within EPPI Reviewer, 3,792 items remained to screen on title and abstract by a team of four reviewers (see Fig. 2). Most of these had previously been screened in 2022 as part of the larger project (see Bond et al., 2023). However, to achieve inter-rater reliability between the reviewers with the items identified in 2023, two rounds of screening 50 items were conducted, applying the inclusion/exclusion criteria (see Table 2), achieving a substantial Fleiss kappa of 0.63 (Cohen, 1960). To align coding further, the reviewers engaged in multiple in-depth conversations and resolved disagreements together. Items were included if they were a journal article or conference paper published after 2011, focused on LA in higher education, included log data as one of the data collection methods, and mentioned engagement or disengagement in the title, abstract or keywords. Studies were excluded if they were secondary research (e.g., systematic reviews) or conceptual, focused on participants outside of formal higher education learning settings, or did not focus specifically on engagement or disengagement.

345 studies were included after screening titles and abstracts. However, three papers could not be located, leaving 342 to screen on full text. In order to ensure ongoing reliability between coders, three rounds of 50 items and one round of 25 items were screened by all four reviewers on full text, with reconciliation discussions held between each round to achieve greater consistency. A Fleiss kappa of 0.84 was achieved, which is considered an almost perfect inter-rater agreement (Cohen, 1960). After screening the remaining items, 243 studies were included for quality appraisal.

#### Quality assessment

Given the heterogeneity of the included studies, the Mixed Methods Appraisal Tool (MMAT; Hong et al., 2018) was selected to assess their quality and suitability. Two screening questions were answered for all studies (Are there clear research questions? Do the collected data allow us to address the research questions?), alongside five method-specific questions (see Appendix D). Two reviewers screened 10 items using the MMAT in EPPI Reviewer and reconciled any discrepancies, to ensure a consistent approach, before screening the remaining 233 items. 58 items were excluded on quality, seven were not focused enough on engagement, three had no log data, and one was not a primary study. The remaining 159 items were then included for data extraction.

#### Data extraction

The data extraction coding tool (see Appendix E) was adapted from Bergdahl et al. (2020; Bond et al., 2020) It included publication characteristics (year, type and discipline of first author), study characteristics (continent, discipline, study level), methodology (method, data collection, data analysis), theoretical framework, engagement operationalisation, and findings. The engagement operationalisation and the findings were coded against the four dimensions of engagement (emotional, behavioural, cognitive, and social) and their indicators (Bond & Bergdahl, 2022), as per the approach taken by Bergdahl et al. (2020; Bond et al., 2020). All data were extracted manually and input into EPPI Reviewer (Thomas et al., 2023).

#### Data synthesis

A narrative synthesis of the data was undertaken (Petticrew & Roberts, 2006), including a tabulation of the included studies (see Appendix F). Tables are also provided throughout the text or included as appendices and accompanied by narrative descriptions, created using Word and Excel. An openly accessible web database of all included studies and associated coding decisions was also created[4] using EPPI Visualiser, to provide researchers with the opportunity to produce their own frequency and crosstabulation charts, download a.ris file of the included studies, or explore the coding in a more nuanced way.

### Limitations

Although every attempt was made to conduct this systematic review as transparently and rigorously as possible, according to previously established quality criteria (Bond et al., 2024), there are some limitations that must be acknowledged. Firstly, a protocol was not registered prior to undertaking the review. Only English language research was included, which limits our understanding of research that has been undertaken in other languages. Individual journals could also have been manually searched, such as *Computers & Education: Artificial Intelligence*, although it was reasoned that the snowball searching done with OpenAlex would pick up further pertinent literature. It should also be acknowledged that this review chose to use the presence of system log data as an inclusion criterion, thereby excluding any HELA study that might also shed light on engagement through other methods. We adopted this as a principle guiding inclusion/exclusion, as this is the focus and scope of the project and as it has been argued that system log data can provide a more authentic and less-biased understanding of student engagement with their learning (see Walsh & Rísquez, 2020).

In addition, our search strategy focused on studies that explicitly used 'engagement' and 'disengagement' in the title, abstract, or keywords, as our aim was to explore the use of these terms in HELA research. Studies exploring the sub-constructs of engagement, but not mentioning those terms, have been excluded. As a result, key studies with strong theoretical foundations might have been disregarded. Future reviews may benefit from including related constructs in their search strategies. Furthermore, we acknowledge that research undertaken in 2012 and research undertaken in 2023 are quite different, and therefore collating them into one aggregate category might miss the development of the field and its conceptualisation of engagement over time. Whilst beyond the scope of this current review, exploring the evolution of engagement conceptualization and methodologies longitudinally could offer valuable insights in future work.

## Findings

### RQ1: When, where and about whom has HELA student engagement research been undertaken?

Of the 159 studies in this corpus (see Appendix F), the majority were published as journal articles ($n=124$, 78%), as opposed to conference papers ($n=35$, 22%). Publications were rising slowly before the COVID-19 pandemic (see Fig. 3), after which there was a distinct increase, likely owing to the heightened need to understand how students were reacting to the shift to emergency remote education on the one hand, and the increased availability of log data on the other (Bond et al., 2021).

[4] https://eppi.ioe.ac.uk/eppi-vis/login/open?webdbid=572

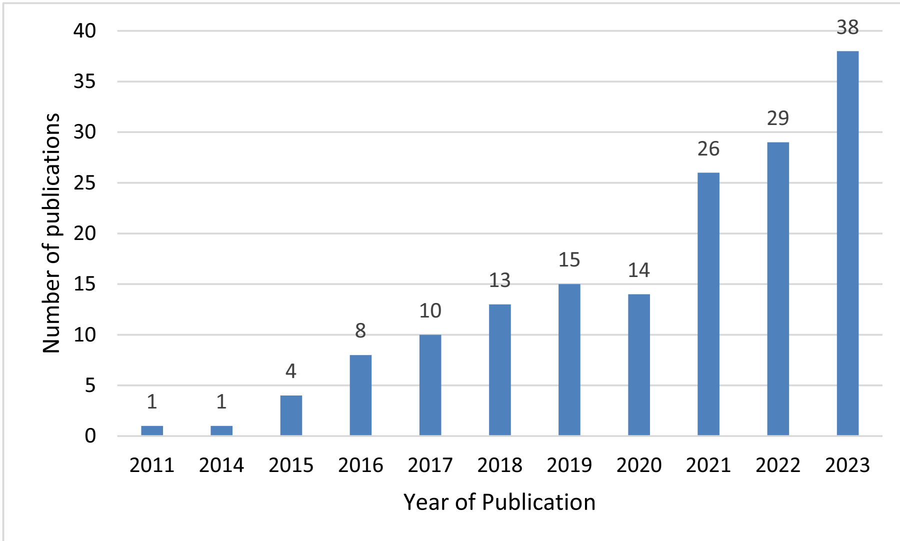


**Fig. 3** Number of HELA student engagement studies published by year

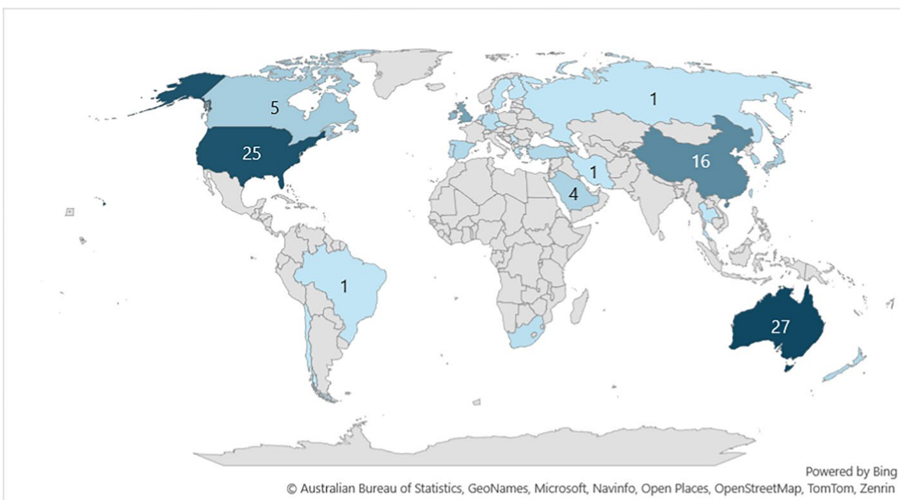


**Fig. 4** Distribution of HELA student engagement studies across countries

The research synthesised in this review was undertaken across all continents (see Appendix G), with most research occurring in Europe (24.5%, $n=39$), Asia (23.9%, $n=38$), North America (20.1%, $n=32$) and Oceania (18.9%, $n=30$), although Australia was the most represented (see Fig. 4; $n=27$), followed closely by the United States ($n=25$). Notably, only two studies were conducted in Africa (Chaka & Nkhobo, 2019; Kritzinger et al., 2018) and two in Central and South America (González et al., 2022; Oliveira et al., 2021), echoing many previous review findings within the wider educational technology field (e.g., Bond & Bedenlier, 2019; Bergdahl et al., 2020; Bond et al., 2020). A noteworthy finding is that 16 studies (10.1%) did not identify at all which continent their research had been conducted in, and 22 studies (13.8%) did not identify the specific country or countries of research. Likewise, 14 studies (8.8%) did not specify whether participants were undergraduates or postgraduates. However, again in line with prior EdTech literature (e.g., Bond et al., 2021), postgraduate data was only included in 13.2% of studies (5 both undergraduate and postgraduate data, and 16 postgraduate data only), and 5.0% of studies ($n=8$) did not mention the discipline of participants.

Whilst 15.7% of studies included students from multiple disciplines ($n=25$), the majority of participants were studying in the fields of Natural Sciences, Maths & Statistics (25.8%, $n=41$) and Engineering, Manufacturing & Construction (19.5%, $n=31$), with STEM disciplines representing 60.4% of participants across the review corpus (see Table 1, Appendix H). It is interesting, then, that 34.0% of first authors come from Computer Science ($n=54$; see Table 2, Appendix H), and 30.8% of authors from Education disciplines ($n=49$). This is further confirmed when exploring which disciplinary data is being used by researchers across faculties (see Table 3, Appendix H), which reveals that most authors are predominantly using participant data from within their own faculty, except for Education and Computer Science and to a lesser extent, Social Sciences.

#### RQ2: What are the prevalent data collection and research methods in studies of student engagement within LA?

A diversity of research methods was identified, reflecting the interdisciplinary nature and complexity of the field. While 14 studies did not clearly specify their methodological approach, experimental designs emerged as the predominant method ($n=138$). In contrast, surveys ($n=32$) and interpretative or exploratory studies were notably less frequent ($n=11$).

##### *Data collection*

Log data was used as a single data source in 34 studies (21.4%; e.g., Elliott & Luo, 2022; Fan et al., 2021). Student assessments, such as semester grades, were used alongside log data in 81 studies (50.9%; see Appendix I), followed by surveys ($n=53$, 33.3%). Qualitative data types were less commonly reported, such as interviews ($n=8$; e.g., González et al., 2022), focus groups ($n=4$; e.g., Lewis et al., 2021), respondent diaries ($n=3$; e.g., Ouyang et al., 2023), and observations ($n=2$; e.g., Kannan et al., 2020). When combining multiple sources of data, system log data, surveys and assessment data were combined in 25 studies (15.7%; e.g., Bourguet, 2022; Yildirim & Gülbahar, 2022), indicating that this combination is far more prevalent than combining system log data, with qualitative measures, such as interviews (e.g., Burke & Fanshawe, 2021) or respondent diaries (e.g., Allen et al., 2016).

##### *Sample sizes*

An analysis of sample sizes across the included studies (see Fig. 5) revealed that the majority (65.4%, $n=104$) included data from less than 500 students. However, the number of studies with samples over 1000, and particularly over 3000, have been steadily increasing in the past 5 years, which is particularly notable as studies in education and the wider educational technology field often have much smaller sample sizes (e.g., Forsström et al., 2024). The utilisation of large datasets contributes

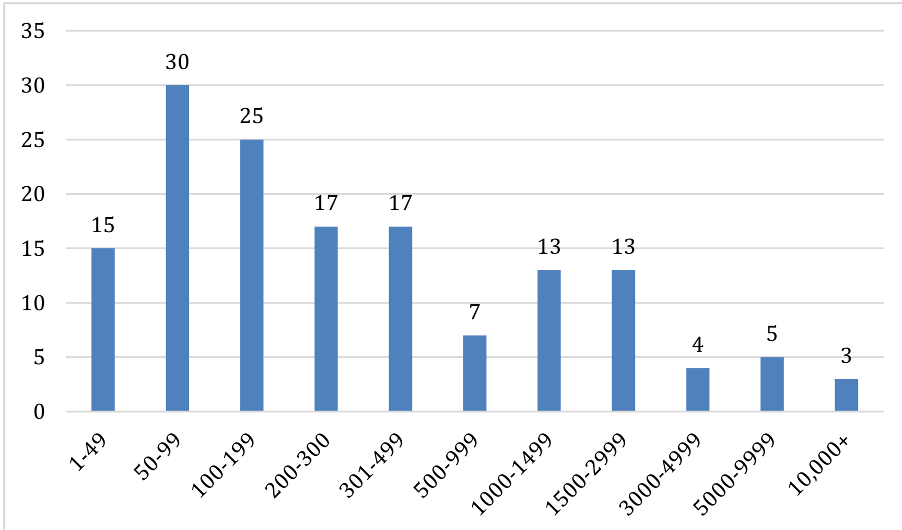


**Fig. 5** Student sample sizes per study

significantly to advancing our understanding of student engagement, as they allow researchers to identify patterns and trends that might not be apparent in smaller samples, thereby providing deeper insights into various aspects of engagement across diverse populations. For example, Tempelaar et al. (2018) analysed data from over 1600 undergraduate students to explore the interplay between learning cognition, behaviour, and regulation, and Saqr et al. (2023) conducted a large-scale analysis to compare retention and engagement data across different cohorts.

### *Data analysis*

All studies adopted descriptive or inferential statistics, often combined with computational methods. Following the emerging trends highlighted by Merceron (2015), relationship mining was the most frequently used computational method ($n = 105$; e.g., Aida, 2023), including Epistemic Network Analysis (e.g., Huang et al., 2021) and Social Network Analysis (e.g., Chaka & Nkhobo, 2019). This was followed by discovery with models ($n = 48$; e.g., Abdi et al., 2020), prediction ($n = 48$; e.g., Argyriou et al., 2022), clustering ($n = 38$; e.g., Azcona & Smeaton, 2017) and distillation of data for human judgement ($n = 18$; e.g., Alam et al., 2023). Despite a recent call for qualitative methods to improve the understanding of system data (e.g., Saqr & López-Pernas, 2021), only 27 papers adopted content or thematic analysis, either alongside other methods or as the sole method of analysis ($n = 7$; e.g., Seo et al., 2021). Content analysis was often combined with computational techniques such as relationship mining ($n = 16$; e.g., Kim et al., 2016; Nguyen, 2022). Other approaches to text analysis included using QADQAS (e.g., Strang, 2016) and lexical analysis (e.g., Chen et al., 2018). Such mixed methods provided the opportunity for numerical data to be enhanced by more nuanced insights.

#### RQ3: How are theories or frameworks of student engagement applied to guide data analysis in LA research?

The term 'engagement' was sometimes used with inferred knowledge, lacking a clear definition of how it was conceptualised by the authors. However, understanding how researchers analyse data, informed by theory, is critical to exploring student engagement. Thus, we categorised theory adoption across studies as follows:

1. The paper used an engagement framework or theory to inform the analysis of LMS data.
2. The paper used engagement research to describe their view on engagement.
3. The study did not use any engagement research, theories or frameworks.

HELA studies have mostly (44.7%, $n = 71$) used previous research on engagement in their introduction or background and linked this to their engagement analysis (e.g., Tempelaar et al., 2018; Wong & Chong, 2018). This has included using psychometric scales to analyse survey data, e.g. the Engagement Scale (Reeve & Tseng, 2011), or as part of their overall data collection and analysis (e.g., Banihashem et al., 2022). Only 42 studies (26.4%) used an engagement framework to inform their data analysis. This included the Community of Inquiry (Garrison et al., 1999), the Online Engagement Framework (Redmond et al., 2018), Constructivist Learning Design and Learning Analytics (Banihashem, 2020), Achievement Goal Theory (Daumiller et al., 2023), or a combination of approaches (e.g., Henrie et al., 2018). The remaining 46 studies (28.9%) stated that they explored engagement, yet the link between data analysis and engagement theories or frameworks was either unclear or they relied upon 'student engagement' only as an LMS output. New engagement-related terms were also identified, such as 'LMS engagement' (e.g., Kalaitzopoulou et al., 2023) and 'Learner Engagement Analytics (LEA)' (e.g., Naeem & Bosman, 2023).

#### RQ4: What indicators have been used to measure engagement in HELA research?

In order to deepen the work by Johar et al. (2023) and to further explore how HELA researchers have operationalised student engagement, studies were coded against the dimensions of student engagement or disengagement as per the SEDL framework (emotional, behavioural, cognitive, social), and further coded using the indicators within each dimension (see Appendix K). This analysis revealed an overwhelming focus on behavioural engagement (see Table 3), with 95.0% of studies measuring engagement through active and observable activities, such as time on task or number of clicks, as opposed to measuring deeper processing and understanding through cognitive engagement (25.8%, $n = 41$), emotional investment in learning (16.4%, $n = 26$), or collaborative and communicative interactions (16.4%, $n = 26$). More than half (56.0%, $n = 89$) of the studies in the corpus operationalised engagement as behavioural engagement only, including 74% of conference papers. Only three studies used behavioural, cognitive, emotional and social engagement (Hisey et al., 2024; Lin et al., 2023; Sherifi et al., 2023), and only two studies considered both engagement and disengagement for behavioural, cognitive and emotional dimensions (Tempelaar et al., 2018, 2021).

It should also be noted that engagement was sometimes approached at a general level; for example, Wu et al. (2023) suggested that engagement can be understood and measured within broader dimensions, implying a holistic approach to assessing behavioural engagement without pinpointing specific activities or behaviours, and Burke and Fanshawe (2021) did not specify exactly how engagement was operationalised. There were also examples where studies specifically referred to measuring behavioural, cognitive and emotional engagement but used indicators of behavioural engagement for all three dimensions (e.g., Doherty, 2023). Disengagement was far less specifically operationalised despite the focus of many studies on at-risk students and dropout prediction (e.g., Poellhuber et al., 2023).

#### *Operationalisation of behavioural engagement and disengagement*

*Participation* was the most frequently measured form of engagement across the corpus (86.2%, $n=137$; see Appendix J, Table 1), followed by *time on task* (45.9%, $n=73$), *homework completion* (17.0%, $n=27$), *attendance* (7.5%, $n=12$), and *effort* (6.3%, $n=10$) as the top five most frequent. *Participation* was approached as participating in formative activities such as lessons and quizzes (e.g., Rajabalee et al., 2020; Smith et al., 2022), the number of LMS logins (e.g., Guo & Lee, 2023), contributing to forums (e.g., Strang, 2016), and active viewing behaviours such as pausing and re-watching videos (e.g., Wang et al., 2021). Participation was also framed as the frequency of accessing learning materials (e.g., Lewis et al., 2021) and the number of resources viewed (e.g., Nkomo & Nat, 2021), including the number of course notifications read (e.g., Ma et al., 2015). *Time on task* was measured in almost half of the studies (45.9%, $n=73$), with some studies approaching it as time spent accessing learning materials (e.g., Abdi et al., 2020) or watching video content (e.g., Zhu et al., 2022). Rienties et al. (2018) used the weekly time students spent on the LMS, observing fluctuations and finding that time spent was directly influenced by the learning design of courses, especially during weeks with substantial assessments. Su et al. (2017) segmented students into 'intensive use', 'regular use', and 'short use' clusters based on their engagement time with various learning activities. They found that the 'intensive use' and 'regular use' clusters had better learning effectiveness due to more time and effort invested in the activities (Table 5).

Behavioural disengagement was formally operationalised in 10 studies, with *task incompletion* the most frequent (1.9%, $n=3$; see Appendix J, Table 1). Linden et al. (2023)

**Table 5** Student engagement operationalisation by dimension

| Rank | (Dis)Engagement dimension | *n* | % |
|---|---|---|---|
| 1 | Behavioural engagement | 151 | 95.0 |
| 2 | Cognitive engagement | 41 | 25.8 |
| 3 | Emotional engagement | 26 | 16.4 |
| = | Social engagement | 26 | 16.4 |
| 4 | Emotional disengagement | 10 | 6.3 |
| 5 | Behavioural disengagement | 9 | 5.7 |
| 6 | Cognitive disengagement | 7 | 4.4 |
| 7 | Social disengagement | 2 | 1.3 |

identified disengaged students through their non-submission of a low-stakes assessment item or by low LMS activity, Liu et al. (2015) analysed the total risk rating assigned to students based on low activity, and Veerasamy et al. (2021) defined students as at-risk by not submitting formative assessments. It should also be noted, however, that a number of studies specifically investigating student dropout did this by exploring measures of behavioural *engagement* rather than *disengagement*. For example, in order to use machine learning to predict students at risk, Poellhuber et al. (2023) used the number of courses and discussion views, clicks, discussions and posts created, and quiz completion to represent levels of behavioural engagement, which they used as "a continuum of participation" as "dropout was conceptualised as a process of disengagement" (p. 593).

#### ***Operationalisation of cognitive engagement and disengagement***

*Self-regulation* was the most frequently measured indicator of cognitive engagement (10.1%, $n=16$; see Appendix J, Table 2), followed by *critical thinking and focus/concentration* (both 5.0%, $n=8$), *synthesis/connecting ideas* and *self-efficacy* (4.4%, $n=7$), and *deep learning* (3.8%, $n=6$) as the most frequent. *Self-regulation* was approached through, for example, pre-test and post-test mean scores (e.g., Suraworachet et al., 2023), quiz scores and frequency of viewing teaching materials as indirect indicators (e.g., Dobashi et al., 2022), and preparation (e.g., Tempelaar et al., 2018). Dobashi et al.'s (2022) research shed light on the variability of learning strategies among students, revealing that higher quiz scores were not necessarily linked to more frequent reviews of teaching materials. This observation suggests that effective cognitive self-regulation may stem from prior knowledge or the ability to grasp concepts during live demonstrations, underscoring the diverse ways students navigate learning processes.

Cognitive disengagement was most frequently operationalised through *confusion* (1.9%, $n=3$; see Appendix J, Table 2), followed by *anxiety* and *lack of regulation* (1.3%, $n=2$ each), and *distracted* (0.6%, $n=1$). Several studies (e.g., Rienties et al., 2019; Tempelaar et al., 2018, 2021) used the Epistemic Emotion Scales (see Pekrun et al., 2017) to explore how learning cognition and behaviour impacted learning regulation in three different cohorts of undergraduate Business and Economics students, measuring *confusion, anxiety, frustration, enjoyment, boredom, surprise* and *curiosity.* Even though *anxiety* would usually be an indicator of emotional disengagement, Tempelaar et al. (2018, 2021) used 'Anxiety motive' from the Motivation and Engagement Wheel (Martin, 2007) as a maladaptive, cognitive factor, and 'Anxiety' from the Achievement Emotions Questionnaire (Pekrun et al., 2011) as a negative activating emotion. Wang (2022) used log data to explore the affective learning states of 269 undergraduate students majoring in educational technology, to determine whether students were in a state of *confusion*, engagement, *frustration* or *distraction.*

#### ***Operationalisation of emotional engagement and disengagement***

Emotional engagement was most frequently operationalised through *enjoyment* (5.7%, $n=9$; see Appendix J, Table 3), followed by *satisfaction* (3.1%, $n=5$), *interest* and *positive attitude towards learning* (2.5%, $n=4$), *confidence, joy* and *sense of wellbeing* (0.6%, $n=1$ each). Guided by Redmond et al.'s (2018) engagement framework, Hisey et al. (2024) explored how interactive storytelling lecture trailers affected students' behavioural, cognitive, emotional, and student–instructor (social) engagement. Emotional and social engagement were evaluated through surveys and semi-structured interviews; behavioural engagement through online participation (quizzes, assignments, discussion boards, page views, polls, etc.) and attendance in Zoom calls; and cognitive engagement through the survey by measuring cognitive effort and mastery. Emerson et al. (2020) used the Interest and Enjoyment subscale of the Intrinsic Motivation Inventory (Ryan, 1982), alongside multimodal LA to explore undergraduate students' engagement with game-based learning, measuring *enjoyment*, *interest*, *boredom* and *disinterest*.

*Boredom* (4.4%, $n=7$) was the most frequent measure of emotional disengagement (see Appendix J, Table 3), followed by *frustration* (2.5%, n=4), *worry/anxiety* (1.9%, $n=3$), *anger* and *hopelessness* (1.3%, $n=2$ each), *disgust*, *disinterest*, *fear* and *sadness* 0.6%, $n=1$ each). Allen et al. (2016) explored *boredom* and engagement during undergraduate writing by logging keystrokes, capturing participants' faces on video, and providing self-reports of affective states. Yilmaz and Yilmaz (2022) used the student engagement scale (Sun & Rueda, 2012) to measure undergraduate students' behavioural, cognitive and emotional engagement within an online Computing course. The survey has eight emotional items, including 'I feel bored by the online class', which are all classified as 'engagement', rather than a mixture of 'engagement' and 'disengagement' indicators.

#### ***Operationalisation of social engagement and disengagement***

Social engagement and disengagement were the least measured of all the engagement dimensions (see Appendix J, Table 4). However, *interaction with peers* was explored in 24 studies (15.1%), indicating that communication and collaboration with fellow learners are considered critical components of the social aspect of learning, followed by *interaction with educators* (5.0%, $n=8$). *Interaction with peers* was approached by identifying patterns in peer interaction (e.g., Huang et al., 2021; Jan, 2018), where some used network analysis to compare connectedness and network centralisation (e.g., Chen et al., 2018). Kannan et al. (2020) considered "talking to peers on topic, listening to peers, asking questions about the topic, group discussion, [and] responding to teacher's questions…as 'actively engaged'" (p. 12), and Wang et al. (2023) collected two types of data to measure *interaction with peers*; the number of messages posted, replied to and total words as captured by log data, and the discourse data whilst undertaking a problem-solving process. Studies exploring *interaction with educators* analysed communication patterns (e.g., Karapiperis et al., 2023), feedback (e.g., Lee & Recker, 2021), uploading materials (e.g., Ma et al., 2015), or student feedback using data from focus groups and interviews (e.g., Lewis et al., 2021).

Social disengagement was only explicitly measured in two studies, which both used *egocentric elaboration.* Lee and Recker (2021) explored the effect of online discussion strategies on participation and performance in 72 online Mathematics and Statistics courses between 2011 and 2015, using a combination of log data, discussion posts and students' final grades. Among the many variables used, *egocentric elaboration* related to the percentage of posts elaborating on one's own arguments, as opposed to *allocentric elaboration*, where students compare or synthesise that of their peers. Lee and Recker (2022) then explored the same dataset further to further understand which instructor discussion strategies influence course performance, in order to build multilevel models to predict students' course performance.

**RQ 5: What are the overall findings of HELA student engagement research?**

The included studies were coded on indicators of behavioural, emotional, cognitive and social engagement and disengagement (see Table 4). Overall, 84.9% provided evidence of behavioural engagement, 35.2% behavioural disengagement, 25.8% cognitive engagement, 20.8% social engagement, and 13.8% identified emotional engagement, with other disengagement dimensions found far less. However, whilst some studies operationalised engagement through various dimensions and distinct variables, they aggregated the findings under the same category, treating engagement as a unified construct rather than presenting the individual aspects measured independently (e.g., Banihashem et al., 2022). Therefore, studies that gave an overall 'engagement' finding but did not specify which indicators and/or dimensions this referred to were coded separately. There were also some studies that measured individual indicators of engagement but then subsumed them under the umbrella dimension. For example, Yoon et al. (2021) operationalised behavioural engagement through two indicators (*attention* and *participation*) but then combined these results under 'behavioural engagement'. In this case, a code of 'behavioural engagement' was assigned to the study, but not any individual indicators (e.g., attention) (Table 6).

***Behavioural engagement and disengagement findings***

Evidence of behavioural engagement was captured across nine separate indicators (see Appendix L, Table 1), with positive *participation* found in 66.7% of studies ($n = 106$); by far the most frequent indicator of engagement, well ahead of the next indicator *time on task* (21.4%, $n = 34$). Nadeem and Blumenstein (2021) conducted a study that established a moderate correlation between the percentage of activities completed by students and their performance in end-project assessments ($r = 0.42$, $p < 0.05$) as well as in final exams ($r = 0.34$, $p < 0.05$), providing evidence that students who complete a higher percentage of activities tend to perform better academically. Likewise, Naeem and Bosman (2023) reported findings from an analysis indicating a strong positive correlation ($r = 0.71$) between the rate of engagement with the activities and resources provided on the LMS and the grades students achieved in their modules. This high correlation suggests

**Table 6** Student engagement findings by dimension

| Rank | (Dis)Engagement dimension | *n* | % |
|---|---|---|---|
| 1 | Behavioural engagement | 135 | 84.9 |
| 2 | Behavioural disengagement | 56 | 35.2 |
| 3 | Cognitive engagement | 41 | 25.8 |
| 4 | Social engagement | 33 | 20.8 |
| 5 | Emotional engagement | 22 | 13.8 |
| 6 | Emotional disengagement | 19 | 11.9 |
| 7 | Cognitive disengagement | 13 | 8.2 |
| 8 | Social disengagement | 10 | 6.3 |

a significant relationship where increased engagement is likely to result in better academic performance. O'Brien and Verma (2019) categorised student behaviours, revealing a spectrum of engagement from active participation, such as attending lectures and accessing recordings, to more passive forms, such as downloading lecture notes, suggesting a diversity of engagement approaches among students, and results from Oliveira et al. (2021) indicated high student interaction levels with a smart learning environment that was intertwined with social media, reflecting an engagement pattern that permeated informal and formal learning contexts.

Behavioural disengagement manifested itself across 12 indicators (see Appendix L, Table 1), although most of them were not found in many studies. *Avoidance* was the most frequently found (15.7%, $n=25$) and included students ignoring badges (e.g., Hakulinen et al., 2015), having reduced participation (e.g., Burke & Fanshawe, 2021), not logging in to the LMS (e.g., Linden et al., 2023), or having lower rates of engagement with the LMS (e.g., Matz et al., 2021). For example, Alam et al. (2023) measured avoidance in terms of the infrequent use of a gamified LA dashboard. This was quantified by survey responses indicating limited use and supported by actual dashboard access data. Students' avoidance was attributed to preferences for traditional tools, quicker access to resources outside the dashboard, and a lack of awareness of its benefits. Karapiperis et al. (2023) identified avoidance in the form of low active participation in forum discussions despite high levels of forum views among students with the highest grades. The measure here is the contrast between the number of forum views and the actual posts made by students, suggesting a form of passive engagement or avoidance of active participation in discussions. Similarly, Nguyen et al. (2018) assessed avoidance by comparing the intended learning design with actual student behaviour. Substantial discrepancies were found, with students spending significantly less time on assigned materials than recommended by instructors.

#### *Cognitive engagement and disengagement findings*

Cognitive engagement was identified across 14 different indicators (see Appendix L, Table 2), with *cognitive self-regulation* the most frequent (6.9%, $n=11$), followed by *deep learning, reflection* and *focus/concentration* (3.1%, $n=5$ each). Banihashem et al. (2022) found a statistically significant increase in students' self-regulation scores following the intervention. This elevation from a mean pre-test score of 37.88 to a post-test score of 40.16, both with a standard deviation of 1.90, suggests the positive impact of tailored learning environments on cognitive self-regulation abilities. Tempelaar et al.'s (2018) research delved into the timing of learning activities, distinguishing between self-regulated and externally regulated learners. The study found that self-regulated learners chose their learning timings autonomously, leading to more effective out-of-time preparation. In contrast, externally regulated learners adhered strictly to prescribed schedules, highlighting the influence of regulatory strategies on learning efficiency. Li et al. (2023) focused on the role of adaptive scaffolding in promoting metacognitive engagement among learners. By comparing conditions of adaptive, fixed, and no scaffolding, they found that adaptive scaffolding significantly encouraged students to be more task-oriented and strategically engaged in reading and writing activities. This finding highlights the critical role of tailored educational support in enhancing cognitive self-regulation and metacognitive strategies.

Indicators of cognitive disengagement were found far less frequently, with only five studies (3.1%) identifying *unfocussed/inattentive* behaviour, *confusion* in four studies (2.5%), followed by *apathy* (1.3%, $n=2$), *distracted* and *pressured/stressed* (0.6%, $n=1$). Findings demonstrated that the use of clickstream data (e.g., Dobashi et al., 2022) provided a metric of engagement, yet it revealed that not all interactions with materials represent focused attention. Some students demonstrated a pattern of opening materials but did not fully comprehend them, characterising a superficial form of engagement. Papamitsiou et al. (2020) found that low performance correlated with low cognitive load indicators, suggesting that these students may not have focused effectively on understanding the content. Although they showed high attention, this might have been directed towards irrelevant aspects of the task, signifying inattention towards essential elements of the learning material. Saqr et al. (2023) identified a 'light state' group's low activity across various learning indicators, which could reflect a slight behavioural engagement but a significant cognitive disengagement. Such students may be present in the learning environment but not mentally engaged with the content, which is indicative of inattentiveness.

#### *Emotional engagement and disengagement findings*

Both emotional engagement and disengagement were not identified very frequently, with the most frequent for both appearing in six studies each (3.8%): *interest* and *worry/anxiety* (see Appendix L, Table 3). Emerson et al. (2020) utilised multimodal predictive models to classify performance and interest groups in a game-based learning setting. The study found that models incorporating facial expression and gameplay data were preferred for real-time scaffolding due to their high accuracy in explaining student performance and interest. However, the addition of facial expression data to the predictive models decreased their performance, indicating the complexity of accurately capturing and interpreting students' emotional engagement. Lin et al. (2023) showed that giving students the autonomy to choose assessment topics significantly impacted their level of interest. The Free Selection & Invitation group experienced a higher average flow ($M=3.98$) compared to the Assigned Partners (AP) group ($M=3.64$), with effect sizes ranging from small to medium across various engagement dimensions, including interest ($F=-2.87$, $p=0.005<0.05$, $\eta^2=0.08$). This indicates that student autonomy in learning activities can profoundly influence their engagement and interest levels. Yousuf and Conlan's (2018) study on the impact of exploratory visual narratives showed that presenting learning progress in this format was both engaging and interesting to students.

*Worry/anxiety* was expressed about a range of LA interventions, despite there being evidence of increased engagement overall. For example, Abdi et al. (2020) found that students were worried about trying challenging practice questions in an open learner model and having it affect their overall rating. Likewise, the use of a thermometer starting off at 0 points in a gamified LA dashboard was a concern for some students, with the amount of extended time moving from F to D level leading to mixed emotions (Alam et al., 2023). The use of nudges in online Education and Regional/Town Planning courses (Brown et al., 2023) also led to students feeling anxious when they were considered non-encouraging, overly persuasive, sent too frequently, or being sent across a range of platforms simultaneously.

#### *Social engagement and disengagement findings*

*Interaction with peers* was the third most frequent engagement indicator across the corpus (16.4%, $n=26$), with several studies finding that it had a positive influence on students (see Appendix L, Table 4). Chen et al. (2018) found that some students, even without access to a social LA tool, exhibited higher levels of social engagement through broader interactions among themselves. This was demonstrated by higher connectedness and more evenly distributed network interactions, suggesting a natural propensity towards collaborative engagement within this group. Jan (2018) identified that the presence of closely-knit groups within the learning community, characterised by high mutual exchange and transitivity, indicates an open and interactive network. Huang et al. (2021) discovered that social–emotional interactions, particularly those involving humour (joking-positive and joking-negative sentiments), played a crucial role in alleviating the confusion and frustration often associated with learning activities. Other studies focused more on the impact of social engagement on academic success and engagement. For example, Serembus and Riccio (2019) reported that interactions and submissions significantly impacted the final course grade, reinforcing the theory that active engagement with faculty and peers correlates with academic success. Kannan et al.'s (2020) use of observation protocol data and student perceptions during peer instructional activities revealed that a combination of active discussion, listening, and group discussions led to most students being classified as 'actively engaged', and Garbers et al. (2023) observed that engagement significantly increased during weeks when students participated in live sessions with teachers and classmates. This indicates that live interactions foster a more engaged learning community compared to periods without such sessions.

Social disengagement manifested through *decreased interaction* (5.0%, $n=8$), *social isolation/withdrawal* (0.6%, $n=1$), and *challenging interactions* (0.6%, $n=1$). Summers et al. (2021) found a rise in asynchronous interactions during the pandemic, such as watching recorded lectures and accessing online materials, whilst synchronous activities decreased, including attending live lectures and tutorials. However, Mohammadhassan and Mitrovic (2022) found that the lack of interaction with both videos and humans, as well as the lack of feedback and personalisation, can turn video-based learning into a passive form of learning, with learners simply watching the videos and not engaging deeply. Furthermore, Guo and Lee (2023) identified that, even though there was a rise in increased peer interaction in LMS discussion forums during the pandemic among undergraduate Chemistry students, it has since dropped back to pre-pandemic levels. In a study exploring collaborative concept mapping (Ouyang & Xu, 2022), students preferred to answer the educator's questions and write directly onto the map rather than initiate conversations with peers. One of the main reasons given for this was the difference in power dynamics, where the educator was trying to scaffold the activity. Still, the students felt they did not have enough agency and knowledge to be able to contribute satisfactorily. These studies indicate a heightened need to ensure that authentic peer learning opportunities are available to students, tailored in a way that empowers students to collaborate in both synchronous and asynchronous activities.

## Discussion

This systematic review appraised and synthesised 159 studies exploring how student engagement has been conceptualised and manifested in HELA research. Studies approached engagement from a wide range of perspectives, including using LA to predict student engagement (e.g., Flanagan et al., 2022), to assess whether log data could be used as a proxy for engagement (e.g., Henrie et al., 2018), to investigate whether there is a correlation between LMS engagement and achievement (e.g., Naeem & Bosman, 2023), and to compare retention and engagement data (e.g., Saqr et al., 2023). The findings echo that of previous LA and broader educational technology reviews in several ways, including methodological quality issues, a lack of diverse research contexts and approaches, and a disconnect between theory, research and practice. However, encouragingly, a number of studies have begun to adopt multi-dimensional frameworks of engagement, integrating behavioural, cognitive, emotional, and social dimensions into their analyses (e.g., Hisey et al., 2024; Lin et al., 2023). These studies illustrate a move towards a more holistic understanding of student engagement in HELA research.

### Advancements in the field

Over the past decade, significant progress has been made in terms of methodological rigor, scale, and theoretical integration in HELA research. A substantial number of studies demonstrated strong theoretical grounding by integrating established engagement frameworks into their analyses (e.g., Tempelaar et al., 2018; Wong & Chong, 2018). These studies have successfully combined large-scale datasets with robust analytical methods to provide nuanced insights into student engagement. For instance, Tempelaar et al. (2018) utilised the Epistemic Emotion Scales and Achievement Emotions Questionnaire to explore the interplay between learning cognition, behaviour, and regulation among undergraduate students. Their work exemplifies how integrating theoretical frameworks can enrich the interpretation of LA data, leading to more meaningful conclusions about student engagement. Similarly, Banihashem et al. (2022) employed a combination of LMS data, surveys, and psychometric scales to measure different dimensions of engagement, including behavioural, cognitive, and emotional aspects. Their study not only highlights the importance of multi-dimensional engagement analysis but also demonstrates the effective integration of theory and empirical data. Recent studies have also showcased improvements in methodological rigor and scalability. Large-scale analyses leveraging big data have become more prevalent, allowing for more generalisable findings. For example, Naeem and Bosman (2023) analysed engagement data across multiple modules and found strong correlations between LMS engagement and student grades, reinforcing the predictive power of LA at scale. Moreover, advancements in computational methods have enabled researchers to handle complex datasets more effectively. The adoption of techniques such as machine learning, network analysis, and multimodal analytics has enriched the analytical capabilities within the field (e.g., Huang et al., 2021; Wang et al., 2023).

### Areas for improvement

While acknowledging these advancements, it is also important to address areas where improvements can be made.

#### *Issues with methodological quality*

LA research has previously been criticised for its lack of methodological rigour and ability for small studies to be scalable (e.g., Larrabee Sønderlund et al., 2019; Viberg et al., 2018). This review found that, despite having used the MMAT quality appraisal tool, certain information about study design details was still lacking. For example, 16 papers did not mention in which continent their study had been undertaken, and 22 did not specify the country, 5% of papers did not mention which discipline the participants were from, and 14 did not specify whether students were undergraduates or postgraduates. While most studies provided comprehensive demographic information, some studies lacked full contextual information, which not only enhances the generalisability and applicability of findings, it enables their research to be located by others. Therefore, all LA researchers are encouraged to consistently report detailed demographic data to facilitate comparisons and replication across different settings (Bergdahl et al., 2020; Bond et al., 2020, 2024).

#### *Lack of diversity*

At times, papers embraced both traditional and innovative approaches, including experiments, surveys, ethnography, and design-oriented research, alongside emerging computational methods, for example, combining survey, LMS data, and multimodal data (e.g., Wang et al., 2023) or longitudinal studies combining a design intervention, a survey, test results and LMS data (e.g., Zhou et al., 2023). However, these were rare, with relatively few studies using qualitative data collection and analysis methods (Banihashem et al., 2022; Foster & Francis, 2020). As previous LA and educational technology reviews have found (e.g., Bergdahl et al., 2020; Bond et al., 2020; Banihashem et al., 2022), there is an underrepresentation of African and South and Central American research, although this might be due in some part to the search strategy employed for this review. HELA research also focused heavily on undergraduate students, with only a small percentage of studies exploring postgraduate student engagement (Bergdahl et al., 2020; Bond et al., 2020), and a large proportion of participants (60%) were from a STEM discipline, which raises questions of wider study generalisability (Kaliisa et al., 2024).

#### *Disconnect with theory*

Engagement is inherently a complex and multifaceted concept in educational research. It encompasses various dimensions, including emotional, behavioural, and cognitive engagement. However, a predominant reliance on LMS data for operationalising engagement often results in a narrowed conceptualisation. Studies frequently equated engagement with observable online behaviours, such as the number of clicks or time logged in, which predominantly captures only the behavioural aspect (Algayres & Triantafyllou, 2019; Paulsen & Lindsay, 2024). This approach can significantly narrow the definition of engagement, omitting crucial emotional and cognitive dimensions. Another critical issue is the lack of standardisation in measuring engagement through LMS data, leading to inconsistencies across studies. For example, what one study might classify as 'high engagement' based on click frequency or login duration could be interpreted differently in another context. This disparity poses significant challenges in comparing and synthesising findings across different research works, potentially leading to conflicting conclusions or an incomplete understanding of student engagement. Moreover, there appears to be an over-reliance on LMS's built-in analytics and reports to define engagement. While these metrics provide a convenient means to quantify certain aspects of student interaction, they might not comprehensively capture the full spectrum of student engagement. This approach can lead to a simplistic understanding of engagement that fails to account for qualitative aspects such as student motivation, satisfaction, or depth of cognitive involvement. This complexity emphasises the need for a more comprehensive and nuanced approach to engagement in research and practice and for understanding and measuring student engagement beyond the confines of LMS data and simplistic metrics (Johar et al., 2023).

Researchers like Halverson and Graham (2019) suggest that online traces can reflect behavioural and cognitive engagement. Yet, they acknowledge the limited capacity of these traces to provide insights into emotional engagement. In contrast, Martin and Borup (2022) propose that behavioural engagement, which is more tangibly traced online, could be a physical manifestation of cognitive and emotional engagement. Thus, the main problem lies in the ambiguity of trace data interpretation. There needs to be a consensus on mapping these data to specific engagement dimensions, especially for cognitive and emotional engagement, which are less tangible than behavioural indicators. This presents a significant challenge in LA, as reliance on trace data might provide an incomplete picture of student engagement. Encouragingly, more studies integrate insights from established engagement theories and frameworks into their analyses. However, a considerable challenge remains in the comparability of these studies. This is because the same trace data is often interpreted differently across studies, with claims varying on whether it represents various aspects of engagement or disengagement. This divergence in interpretation complicates the ability to compare findings across different research works directly.

#### Implications for practice

The findings from this systematic review underscore several key areas for enhancing student engagement in higher education through the use of LA, such as comprehensive engagement measurement, the integration of multimodal data, customised interventions, educator training, ethical considerations, and continuous improvement and adaptive learning. For example, the review shows that many studies focus primarily on behavioural indicators, such as clicks and the time spent on tasks, while cognitive, emotional, and social dimensions are less frequently measured (Henrie et al., 2018). This suggests that adopting a more holistic engagement framework could provide a fuller understanding of student engagement. Combining system log data with qualitative data has yielded richer insights into student engagement. For instance, studies that integrated LMS data with surveys and interviews uncovered deeper patterns and underlying causes of student behaviours (Dobashi et al., 2022; Ouyang et al., 2023). Evidence also indicates that LA can inform tailored interventions to support specific student needs. For example, Abdi et al. (2020) found that using LA to identify at-risk students allowed for timely and customised support, improving student outcomes. Similarly, interventions based on emotional and cognitive engagement data enhanced self-regulation and motivation

(Banihashem et al., 2022). However, the effectiveness of LA in enhancing student engagement often depends on the ability of educators to interpret and apply the data. Studies suggest that professional development and training in LA can improve educators' capacity to use data-driven insights to support student learning (Bergdahl et al., 2020; Bond et al., 2020; Gašević et al., 2019). Likewise, students also need to understand how to use the digital tools available to them and why they are being used, as some LA interventions caused anxiety (e.g., Abdi et al., 2020; Alam et al., 2023), including the frequency and tone of nudges (Brown et al., 2023). Furthermore, quizzes are useful in identifying at-risk students, however they are more helpful when they are deemed relevant and useful for learning by students (e.g., Kohnke et al., 2022).

The review highlights that iterative and adaptive use of LA can lead to sustained improvements in student engagement. For instance, iterative reviews of LA data and subsequent adjustments in teaching strategies were shown to enhance learning outcomes over time (Rienties et al., 2018; Saqr et al., 2023). This suggests that a continuous improvement approach, where data is regularly analysed, and interventions are refined based on effectiveness, can be beneficial. Furthermore, the utilisation of large-scale datasets in HELA research has provided educators and institutions with robust evidence to inform practice. The findings from these studies can guide the development of interventions and policies that are more likely to be effective across diverse student populations due to their generalisability. Practitioners should consider leveraging large datasets available within their institutions to monitor student engagement and identify areas for improvement.

### Implications for future research

This review has revealed a number of avenues for further research. Firstly, more robust, theoretically oriented research needs to be undertaken using established frameworks and a wider range of metrics. The influence of social engagement on academic engagement, student well-being and learning outcomes, in particular, requires further research. All study design information should be clearly stated, including participant country, number of participants (and the number of log data events), discipline, study length, and operationalisation of student engagement. More longitudinal, cross-modal and mixed methods studies should be conducted in order to provide further insight into helping at-risk students and preventing dropout. Future research should therefore continue to embrace large-scale studies to enhance the reliability and applicability of findings, including more diverse participants from a wider range of disciplines, especially those outside of STEM and in underrepresented regions. While large datasets offer breadth, integrating qualitative approaches can provide depth, capturing contextual factors and student perspectives that quantitative data alone may miss. As the field progresses, it is crucial to uphold rigorous methodological practices in data collection, analysis, and interpretation, especially when dealing with complex, large-scale data. Researchers must continue to prioritise ethical practices in data handling, ensuring student privacy and data security, particularly in large-scale studies. By building on the strengths of existing large-scale research and addressing its challenges, the field can advance towards a more comprehensive and inclusive understanding of student engagement.

## Conclusion

This review reveals that over the past decade, progress has been made in the field. Researchers have increasingly adopted rigorous methodologies, utilised large-scale datasets, and integrated educational theories into their analyses, leading to more nuanced and comprehensive insights into student engagement. However, challenges remain. While many studies have focused on behavioural engagement, further exploration of cognitive, emotional, and social dimensions is essential for a holistic understanding. In addition, inconsistencies in defining and measuring engagement persist, and there is a need for greater standardisation and clarity. Consequently, researchers often forego the guidance of theoretical frameworks, opting instead to rely on existing research findings. While this approach may provide some insights, it often lacks the methodological rigour and clarity offered by a solid theoretical foundation. Addressing these challenges will be crucial for developing a more comprehensive understanding of student engagement in online learning environments and their educational implications. By acknowledging both the advancements and the areas for improvement, this review contributes to a deeper understanding of student engagement in HELA research. Future research should continue to build on these strengths while addressing existing gaps, fostering a more robust and inclusive field of study.

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41239-024-00493-y.

Additional file 1.
Additional file 2.
Additional file 3.
Additional file 4.
Additional file 5.
Additional file 6.
Additional file 7.
Additional file 8.
Additional file 9.
Additional file 10.
Additional file 11.
Additional file 12.

**Acknowledgements**
The authors would like to thank Olga Viberg for their integral role in the first part of this project.

**Author contributions**
NB and MB conceptualised the review and MB managed the software. NB, MB, JS & MD all contributed to screening and data extraction. All authors contributed to synthesis, writing up, and editorial revisions.

**Funding**
This work received no funding.

**Availability of data and material**
All data is available on the OSF (https://osf.io/8tx6n/?view_only=cb07fea5cbb3491a99f25f9b2470dff6), as well as via the openly accessible web database (https://eppi.ioe.ac.uk/eppi-vis/login/open?webdbid=572).

## Declarations

**Competing interests**
The authors declare no competing interests.

Received: 11 June 2024 Accepted: 8 November 2024
Published online: 20 December 2024

**References**

***Indicates inclusion in the review corpus**

* Abdi, S., Khosravi, H., Sadiq, S., & Gasevic, D. (2020). Complementing educational recommender systems with open learner models. In C. Rensing & H. Drachsler (Eds.), *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 360–365). ACM. https://doi.org/10.1145/3375462.3375520

Adnan, M., Habib, A., Ashraf, J., Mussadiq, S., Raza, A. A., Abid, M., Bashir, M., & Khan, S. U. (2021). Predicting at-risk students at different percentages of course length for early intervention using machine learning models. *IEEE Access, 9*, 7519–7539. https://doi.org/10.1109/ACCESS.2021.3049446

* Aida, S. (2023). Impact of e-learning orientation, moodle usage, and learning planning on learning outcomes in on-demand lectures. *Education Sciences*, *13*(10), 1005. https://doi.org/10.3390/educsci13101005

* Alam, M. I., Malone, L., Nadolny, L., Brown, M., & Cervato, C. (2023). Investigating the impact of a gamified learning analytics dashboard: Student experiences and academic achievement. *Journal of Computer Assisted Learning*, *39*(5), 1436–1449. https://doi.org/10.1111/jcal.12853

Algayres, M., & Triantafyllou, E. (2019). Online Environments for supporting learning analytics in the flipped classroom: A scoping review. In *Proceedings of the 18th European Conference on e-Learning* (p. 8). ACPI. https://doi.org/10.34190/EEL.19.063

* Allen, L. K., Mills, C., Jacovina, M. E., Crossley, S., D'Mello, S., & McNamara, D. S. (2016). Investigating boredom and engagement during writing using multiple sources of information. In D. Gašević, G. Lynch, S. Dawson, H. Drachsler, & C. Penstein Rosé (Eds.), *Proceedings of the sixth international conference on learning analytics & knowledge* (pp. 114–123). ACM. https://doi.org/10.1145/2883851.2883939

* Argyriou, P., Benamar, K., & Nikolajeva, M. (2022). What to blend? Exploring the relationship between student engagement and academic achievement via a blended learning approach. *Psychology Learning & Teaching*, *21*(2), 126–137. https://doi.org/10.1177/14757257221091512

* Azcona, D., & Smeaton, A. F. (2017). Targeting at-risk students using engagement and effort predictors in an introductory computer programming course. In É. Lavoué, H. Drachsler, K. Verbert, J. Broisin, & M. Pérez-Sanagustín (Eds.), *Lecture notes in computer science. data driven approaches in digital education* (Vol. 10474, pp. 361–366). Springer International Publishing. https://doi.org/10.1007/978-3-319-66610-5_27

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review, 84*(2), 191–215.

Banihashem, S. K. (2020). Development and validation of learning environment design model based on the constructivism theory in higher education with a focus on learning analytics [Unpublished doctoral dissertation]. Allameh Tabataba'i University.

* Banihashem, S. K., Farrokhnia, M., Badali, M., & Noroozi, O. (2022). The impacts of constructivist learning design and learning analytics on students' engagement and self-regulation. *Innovations in Education and Teaching International*, *59*(4), 442–452. https://doi.org/10.1080/14703297.2021.1890634

Beer, C., Clark, K., & Jones, D. (2010). Indicators of engagement. Curriculum, technology & transformation for an unknown future. Proceedings ASCILITE Sydney, 75–86. Retrieved from http://www.ascilite.org/conferences/sydney10/procs/Beer-full.pdf

Bergdahl, N., & Bond, M. (2022). Negotiating (dis-)engagement in K-12 blended learning. *Education and Information Technologies, 27*(2), 2635–2660. https://doi.org/10.1007/s10639-021-10714-w

Bergdahl, N., Bond, M., & Brown, A. (Forthcoming). Cracking the engagement enigma: Decoding the multifaceted sociocultural influences on student engagement in digital learning. In G. Liem, J. Fredricks, & Z. Y. Wong (Eds.), Sociocultural perspectives on student engagement: Theory, research, and practice. Information Age Publishing.

Bergdahl, N., Nouri, J., Karunaratne, T., Afzaal, M., & Saqr, M. (2020). Learning analytics in blended learning - a systematic review of theory, methodology, and ethical considerations. *International Journal of Learning Analytics and Artificial Intelligence for Education (iJAI), 2*(2), 46. https://doi.org/10.3991/ijai.v2i2.17887

Blumenstein, M., Liu, D. Y. T., Richards, D., et al. (2019). Data-informed nudges for student engagement and success. In J. M. Lodge, J. C. Horvath, & L. Corrin (Eds.), *Learning analytics in the classroom: Translating learning analytics research for teachers* (pp. 185–207). Routledge.

Bond, M., & Bedenlier, S. (2019). Facilitating student engagement through educational technology: Towards a conceptual framework. *Journal of Interactive Media in Education, 2019*(1), 1–14. https://doi.org/10.5334/jime.528

Bond, M., Bedenlier, S., Marín, V. I., & Händel, M. (2021). Emergency remote teaching in higher education: Mapping the first global online semester. *International Journal of Educational Technology in Higher Education, 18*(1), 50. https://doi.org/10.1186/s41239-021-00282-x

Bond, M., & Bergdahl, N. (2022). Student engagement in open, distance, and digital education. In *Handbook of Open, Distance and Digital Education* (pp. 1–16). Springer Nature Singapore. https://doi.org/10.1007/978-981-19-0351-9_79-1

Bond, M., Buntins, K., Bedenlier, S., Zawacki-Richter, O., & Kerres, M. (2020). Mapping research in student engagement and educational technology in higher education: A systematic evidence map. *International Journal of Educational Technology in Higher Education, 17*(1), 1–30. https://doi.org/10.1186/s41239-019-0176-8

Bond, M., Khosravi, H., de Laat, M., Bergdahl, N., Negrea, V., Oxley, E., Pham, P., Chong, S. W., & Siemens, G. (2024). A meta systematic review of artificial intelligence in higher education: a call for increased ethics, collaboration, and rigour. *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-023-00436-z

Bond., M., Viberg, O., & Bergdahl, N. (2023). The current state of using learning analytics to measure and support K-12 student engagement: A scoping review of engagement in K-12 learning analytics. *The 13th International Conference of Learning Analytics Research, LAK23*. March 13–17. Texas, USA.

* Bourguet, M.-L. (2022). Measuring learners' self-regulated learning skills from their digital traces and learning pathways. In I. Hilliger, P. J. Muñoz-Merino, T. de Laet, A. Ortega-Arranz, & T. Farrell (Eds.), *Lecture notes in computer science. Educating for a new future: making sense of technology-enhanced learning adoption* (Vol. 13450, pp. 500–506). Springer International Publishing. https://doi.org/10.1007/978-3-031-16290-9_42

Braunack-Mayer, A. J., Street, J. M., Tooher, R., Feng, X., & Scharling-Gamba, K. (2020). Student and staff perspectives on the use of big data in the tertiary education sector: A scoping review and reflection on the ethical issues. *Review of Educational Research*, *90*(6), 788–823. https://doi.org/10.3102/0034654320960213

* Brown, A., Basson, M., Axelsen, M., Redmond, P., & Lawrence, J. (2023). Empirical evidence to support a nudge intervention for increasing online engagement in higher education. *Education Sciences, 13*(2), 145. https://doi.org/10.3390/educsci13020145

* Burke, K., & Fanshawe, M. (2021). The value of praxis-based assessment to stimulate practical engagement and classroom readiness in online initial teacher education. *Australian Journal of Teacher Education, 46*(10), 91–109. https://doi.org/10.14221/ajte.2021v46n10.6

* Chaka, C., & Nkhobo, T. (2019). Online module login data as a proxy measure of student engagement: the case of myUnisa, MoyaMA, Flipgrid, and Gephi at an ODeL institution in South Africa. *International Journal of Educational Technology in Higher Education*, *16*(1). https://doi.org/10.1186/s41239-019-0167-9

Charitopoulos, A., Rangoussi, M., & Koulouriotis, D. (2020). On the use of soft computing methods in educational data mining and learning analytics research: A review of years 2010–2018. *International Journal of Artificial Intelligence in Education, 30*(3), 371–430. https://doi.org/10.1007/s40593-020-00200-8

Chatti, M. A., Dyckhoff, A. L., Schroeder, U., & Thüs, H. (2012). A reference model for learning analytics. *International Journal of Technology Enhanced Learning*, *4*(5/6), Article 51815, 318. https://doi.org/10.1504/IJTEL.2012.051815

* Chen, B., Chang, Y.-H., Ouyang, F., & Zhou, W. (2018). Fostering student engagement in online discussion through social learning analytics. *The Internet and Higher Education*, *37*, 21–30. https://doi.org/10.1016/j.iheduc.2017.12.002

Christenson, S. L., Reschly, A. L., & Wylie, C. (Eds.). (2012). *Handbook of research on student engagement*. Springer.

Cohen, J. (1960). A coefficient of agreement for nominal scales. *Educational and Psychological Measurement, 20*(1), 37–46. https://doi.org/10.1177/001316446002000104

* Daumiller, M., Rinas, R., & Dresel, M. (2023). Relevance of students' goals for learning engagement and knowledge gains in an online learning course. *Behavioral Sciences (Basel, Switzerland)*, *13*(2). https://doi.org/10.3390/bs13020161

* Dobashi, K., Ho, C. P., Fulford, C. P., Grace Lin, M.-F., & Higa, C. (2022). Learning pattern classification using Moodle logs and the visualization of browsing processes by time-series cross-section. *Computers and Education: Artificial Intelligence*, *3*, 100105. https://doi.org/10.1016/j.caeai.2022.100105

* Doherty, C. (2023). Using web log analysis to evaluate healthcare students' engagement behaviours with multimedia lectures on YouTube. *PloS One*, *18*(4), e0284133. https://doi.org/10.1371/journal.pone.0284133

Drugova, E., Zhuravleva, I., Zakharova, U., & Latipov, A. (2024). Learning analytics driven improvements in learning design in higher education: A systematic literature review. *Journal of Computer Assisted Learning, 40*(2), 510–524. https://doi.org/10.1111/jcal.12894

* Elliott, R., & Luo, X. (2022). Learning management system analytics to examine the behavior of students in high enrollment STEM courses during the transition to online instruction. In *2022 IEEE frontiers in education conference (FIE)* (pp. 1–9). IEEE. https://doi.org/10.1109/FIE56618.2022.9962732

* Emerson, A., Cloude, E. B., Azevedo, R., & Lester, J. (2020). Multimodal learning analytics for game-based learning. *British Journal of Educational Technology*, *51*(5), 1505–1526. https://doi.org/10.1111/bjet.12992

* Fan, S., Chen, L., Nair, M., Garg, S., Yeom, S., Kregor, G., Yang, Y., & Wang, Y. (2021). Revealing impact factors on student engagement: Learning analytics adoption in online and blended courses in higher education. *Education Sciences*, *11*(10), 608. https://doi.org/10.3390/educsci11100608

Fincham, E., Whitelock-Wainwright, A., Kovanović, V., Joksimović, S., van Staalduinen, J.-P., & Gašević, D. (2019). Counting clicks is not enough. In *Proceedings of the 9th international conference on learning analytics & knowledge* (pp. 501–510). ACM. https://doi.org/10.1145/3303772.3303775

* Flanagan, B., Majumdar, R., & Ogata, H. (2022). Early-warning prediction of student performance and engagement in open book assessment by reading behavior analysis. *International Journal of Educational Technology in Higher Education*, *19*(1). https://doi.org/10.1186/s41239-022-00348-4

Forsström, S., Bond, M., & Njå, M. (2024). A meta-scoping review of programming and robotics in primary and secondary education. https://doi.org/10.5281/zenodo.13828377

Foster, C., & Francis, P. (2020). A systematic review on the deployment and effectiveness of data analytics in higher education to improve student outcomes. *Assessment & Evaluation in Higher Education, 45*(6), 822–841. https://doi.org/10.1080/02602938.2019.1696945

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. *Review of Educational Research, 74*(1), 59–109. https://doi.org/10.3102/00346543074001059

Fredricks, J. A., Filsecker, M., & Lawson, M. A. (2016). Student engagement, context, and adjustment: Addressing definitional, measurement, and methodological issues. Learning and Instruction, 43, 1–4. https://doi.org/10.1016/j.learninstruc.2016.02.002

Fritz, J. (2013). *Using analytics at UMBC: Encouraging student responsibility and identifying effective course designs*. EDUCAUSE Center for Applied Research.

* Garbers, S., Crinklaw, A. D., Brown, A. S., & Russell, R. (2023). Increasing student engagement with course content in graduate public health education: A pilot randomized trial of behavioral nudges. *Education and Information Technologies*, 1–17. https://doi.org/10.1007/s10639-023-11709-5

Gardner, C., Jones, A., & Jefferis, H. (2020). Analytics for tracking student engagement. *Journal of Interactive Media in Education*, *2020*(1), Article 22. https://doi.org/10.5334/jime.590

Garrison, D. R., Anderson, T., & Archer, W. (1999). Critical inquiry in a text-based environment: Computer conferencing in higher education. *The Internet and Higher Education, 2*(2–3), 87–105.
Gašević, D., Jovanovic, J., Pardo, A., & Dawson, S. (2017). Detecting learning strategies with analytics: Links with self-reported measures and academic performance. *Journal of Learning Analytics., 4*(2), 113–128.
Gašević, D., Tsai, Y.-S., Dawson, S., & Pardo, A. (2019). How do we start? An approach to learning analytics adoption in higher education. *The International Journal of Information and Learning Technology, 36*(4), 342–353.
* González, C., López, D., Calle-Arango, L., Montenegro, H., & Clasing, P. (2022). Chilean university students' digital learning technology usage patterns and approaches to learning. *ECNU Review of Education*, *5*(1), 37–64. https://doi.org/10.1177/20965311211073538
Gough, D., Oliver, S., & Thomas, J. (Eds.). (2012). An Introduction to systematic reviews. Sage.
* Guo, Y., & Lee, D. (2023). Differential usage of learning management systems in chemistry courses in the time after COVID-19. *Journal of Chemical Education*, *100*(5), 2033–2038. https://doi.org/10.1021/acs.jchemed.2c00850
Gusenbauer, M., & Haddaway, N. R. (2020). Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of google scholar, PubMed and 26 other resources. *Research Synthesis Methods, 11*(2), 181–217. https://doi.org/10.1002/jrsm.1378
Guzmán-Valenzuela, C., Gómez-González, C., Rojas-Murphy Tagle, A., & Lorca-Vyhmeister, A. (2021). Learning analytics in higher education: A preponderance of analytics but very little learning? *International Journal of Educational Technology in Higher Education, 18*(1), 23. https://doi.org/10.1186/s41239-021-00258-x
* Hakulinen, L., Auvinen, T., & Korhonen, A. (2015). The effect of achievement badges on students' behavior: An empirical study in a university-level computer science course. *International Journal of Emerging Technologies in Learning (IJET)*, *10*(1), 18. https://doi.org/10.3991/ijet.v10i1.4221
Halverson, L. R., & Graham, C. R. (2019). Learner engagement in blended learning environments: A conceptual framework. *Online Learning*, *23*(2). https://doi.org/10.24059/olj.v23i2.1481
Henrie, C. R., Halverson, L. R., & Graham, C. R. (2015). Measuring student engagement in technology-mediated learning: A review. *Computers & Education, 90*, 36–53. https://doi.org/10.1016/j.compedu.2015.09.005
* Henrie, C. R., Bodily, R., Larsen, R., & Graham, C. R. (2018). Exploring the potential of LMS log data as a proxy measure of student engagement. *Journal of Computing in Higher Education*, *30*(2), 344–362. https://doi.org/10.1007/s12528-017-9161-1
Higher Education Commission (HEC). 2016. From bricks to bricks: the potential of data analytics in higher education. http://www.policyconnect.org.uk/hec/sites/site_hec/files/report/419/fieldreportdownload/frombrickstoclicks-hecreportforweb.pdf
* Hisey, F., Zhu, T., & He, Y. (2024). Use of interactive storytelling trailers to engage students in an online learning environment. *Active Learning in Higher Education*, *25*(1), 151–166. https://doi.org/10.1177/14697874221107574
Hong, Q. N., Pluye, P., Fàbregues, S., Bartlett, G., Boardman, F., Cargo, M., Dagenais, P., Gagnon, M.-P., Griffiths, F., Nicolau, B., O'Cathain, A., Rousseau, M.-C., & Vedel, I. (2018). *Mixed methods appraisal tool (MMAT), version 2018*. Registration of Copyright (#1148552), Canadian Intellectual Property Office, Industry Canada.
* Huang, C., Han, Z., Li, M., Wang, X., & Zhao, W. (2021). Sentiment evolution with interaction levels in blended learning environments: Using learning analytics and epistemic network analysis. *Australasian Journal of Educational Technology*, *37*(2), 81–95. https://doi.org/10.14742/ajet.6749
Ifenthaler, D., & Yau, J.Y.-K. (2020). Utilising learning analytics to support study success in higher education: A systematic review. *Educational Technology Research and Development, 68*(4), 1961–1990. https://doi.org/10.1007/s11423-020-09788-z
Iglesias-Pradas, S., Ruiz-de-Azcárate, C., & Agudo-Peregrina, Á. F. (2015). Assessing the suitability of student interactions from Moodle data logs as predictors of cross-curricular competencies. *Computers in Human Behavior, 47*, 81–89. https://doi.org/10.1016/j.chb.2014.09.065
* Jan, S. K. (2018). Identifying online communities of inquiry in higher education using social network analysis. *Research in Learning Technology*, *26*(0). https://doi.org/10.25304/rlt.v26.2064
Johar, N. A., Kew, S. N., Tasir, Z., & Koh, E. (2023). Learning analytics on student engagement to enhance students' learning performance: A systematic review. *Sustainability, 15*(10), 7849. https://doi.org/10.3390/su15107849
* Kalaitzopoulou, E., Matthews, P., Mystakidis, S., & Christopoulos, A. (2023). Engagement with optional formative feedback in a portfolio-based digital design module. *Information*, *14*(5), 287. https://doi.org/10.3390/info14050287
Kaliisa, R., Misiejuk, K., López-Pernas, S., Khalil, M., & Saqr, M. (2024). Have learning analytics dashboards lived up to the hype? A systematic review of impact on students' achievement, motivation, participation and attitude. In *Proceedings of the 14th learning analytics and knowledge conference* (pp. 295–304). ACM. https://doi.org/10.1145/3636555.3636884
* Kannan, V., Kuromiya, H., Gouripeddi, S. P., Majumdar, R., Madathil Warriem, J., & Ogata, H. (2020). Flip & pair—A strategy to augment a blended course with active-learning components: effects on engagement and learning. *Smart Learning Environments*, *7*(1). https://doi.org/10.1186/s40561-020-00138-3
* Karapiperis, D., Tzafilkou, K., Tsoni, R., Feretzakis, G., & Verykios, V. S. (2023). A probabilistic approach to modeling students' interactions in a learning management system for facilitating distance learning. *Information*, *14*(8), 440. https://doi.org/10.3390/info14080440
* Kim, D., Park, Y., Yoon, M., & Jo, I.-H. (2016). Toward evidence-based learning analytics: Using proxy variables to improve asynchronous online discussion environments. *The Internet and Higher Education*, *30*, 30–43. https://doi.org/10.1016/j.iheduc.2016.03.002
Kohnke, L., Foung, D., & Chen, J. (2022). Using learner analytics to explore the potential contribution of multimodal formative assessment to academic success in higher education. *Sage Open, 12*(2), 21582440221089957. https://doi.org/10.1177/21582440221089957
* Kritzinger, A., Lemmens, J., & Potgieter, M. (2018, June 20–22). Improving the quality of learning in a blended learning environment for first-year biology. In *Proceedings of the 4th international conference on higher education advances (HEAd'18).* Universitat Politècnica València. https://doi.org/10.4995/HEAd18.2018.7917
Kuh, G. D. (2007). How to help students achieve. *Chronicle of Higher Education, 53*(41), 12–13.

Larrabee Sønderlund, A., Hughes, E., & Smith, J. (2019). The efficacy of learning analytics interventions in higher education: A systematic review. *British Journal of Educational Technology, 50*(5), 2594–2618. https://doi.org/10.1111/bjet.12720

Lawson, H., & Lawson, M. (2020). Student engagement and disengagement as a collective action problem. *Education Sciences, 10*(8), 212. https://doi.org/10.3390/educsci10080212

* Lee, J.-E., & Recker, M. (2021). The effects of instructors' use of online discussions strategies on student participation and performance in university online introductory mathematics courses. *Computers & Education*, *162*, 104084. https://doi.org/10.1016/j.compedu.2020.104084

* Lee, J.-E., & Recker, M. (2022). Predicting student performance by modeling participation in asynchronous discussions in university online introductory mathematical courses. *Educational Technology Research and Development*, *70*(6), 1993–2015. https://doi.org/10.1007/s11423-022-10153-5

* Lewis, S., Heath, G., Lim, L., & Roberts, R. (2021). "I'm not a number, I'm someone to them": Supporting commencing university students' through technology-mediated personalised communication. *Student Success*, *12*(1), 24–34. https://doi.org/10.5204/ssj.1623

* Li, T., Fan, Y., Tan, Y., Wang, Y., Singh, S., Li, X., Raković, M., van der Graaf, J., Lim, L., Yang, B., Molenaar, I., Bannert, M., Moore, J., Swiecki, Z., Tsai, Y.-S., Shaffer, D. W., & Gašević, D. (2023). Analytics of self-regulated learning scaffolding: Effects on learning processes. *Frontiers in Psychology*, *14*, 1206696. https://doi.org/10.3389/fpsyg.2023.1206696

* Lin, Y., Zhang, Y., Yang, Y., Lu, Y., Zhou, P., & Wang, Y. (2023). "Free selection and invitation" online peer assessment of undergraduates' research competencies, flow, motivation and interaction in a research methods course. *Journal of Computing in Higher Education*. https://doi.org/10.1007/s12528-023-09374-1

* Linden, K., van der Ploeg, N., & Roman, N. (2023). Explainable learning analytics to identify disengaged students early in semester: an intervention supporting widening participation. *Journal of Higher Education Policy and Management*, *45*(6), 626–640. https://doi.org/10.1080/1360080X.2023.2212418

* Liu, D., Richards, D., Froissard, C., & Atif, A. (2015). *Validating the effectiveness of the Moodle engagement analytics plugin to predict student academic performance*. Americas Conference on Information Systems.

* Ma, J., Han, X., Yang, J., & Cheng, J. (2015). Examining the necessary condition for engagement in an online learning environment based on learning analytics approach: The role of the instructor. *The Internet and Higher Education*, *24*, 26–34. https://doi.org/10.1016/j.iheduc.2014.09.005

Macfadyen, L. P., & Dawson, S. (2010). Mining LMS data to develop an "early warning system" for educators: A proof of concept. *Computers & Education, 54*(2), 588–599. https://doi.org/10.1016/j.compedu.2009.09.008

Martin, A. J. (2007). Examining a multidimensional model of student motivation and engagement using a construct validation approach. *The British Journal of Educational Psychology, 77*(Pt 2), 413–440. https://doi.org/10.1348/000709906X118036

Martin, F., & Borup, J. (2022). Online learner engagement: Conceptual definitions, research themes, and supportive practices. *Educational Psychologist, 57*(3), 162–177. https://doi.org/10.1080/00461520.2022.2089147

Masiello, I., Mohseni, Z., Palma, F., Nordmark, S., Augustsson, H., & Rundquist, R. (2024). A current overview of the use of learning analytics dashboards. *Education Sciences, 14*(1), 82. https://doi.org/10.3390/educsci14010082

* Matz, R., Schulz, K., Hanley, E., Derry, H., Hayward, B., Koester, B., Hayward, C., & McKay, T. (2021). Analyzing the efficacy of ECoach in supporting gateway course success through tailored support. In M. Scheffel, N. Dowell, S. Joksimovic, & G. Siemens (Eds.), *LAK21: 11th international learning analytics and knowledge conference* (pp. 216–225). ACM. https://doi.org/10.1145/3448139.3448160

McClenney, K., Marti, C. N., & Adkins, C. (2012). Student engagement and student outcomes: Key findings from. Community college survey of student engagement. (1–6). CCCSE.

Merceron, A. (2015, September). Educational data mining/learning analytics: methods, tasks and current trends. In *Proceedings of DeLFI workshops 2015* (pp. 101–109). September 1, 2015. München, Germany. https://pdfs.semanticscholar.org/1d3a/de2c0a5a60be82030616b99ebd8426238098.pdf

* Mohammadhassan, N., & Mitrovic, A. (2022). Investigating the effectiveness of visual learning analytics in active video watching. In M. M. Rodrigo, N. Matsuda, A. I. Cristea, & V. Dimitrova (Eds.), *Lecture notes in computer science. Artificial intelligence in education* (Vol. 13355, pp. 127–139). Springer International Publishing. https://doi.org/10.1007/978-3-031-11644-5_11

Mougiakou, S., Vinatsella, D., Sampson, D., Papamitsiou, Z., Giannakos, M., & Ifenthaler, D. (2023). Learning analytics. In S. Mougiakou, D. Vinatsella, D. Sampson, Z. Papamitsiou, M. Giannakos, & D. Ifenthaler (Eds.), *Advances in analytics for learning and teaching. Educational data analytics for teachers and school leaders* (pp. 131–188). Springer International Publishing.

* Nadeem, M., & Blumenstein, M. (2021). Embedding online activities during lecture time: Roll call or enhancement of student participation? *Journal of University Teaching and Learning Practice*, *18*(8). https://doi.org/10.53761/1.18.8.11

* Naeem, U., & Bosman, L. (2023). Learner engagement analytics in a hybrid learning environment. In *2023 IEEE global engineering education conference (EDUCON)* (pp. 1–7). IEEE. https://doi.org/10.1109/educon54358.2023.10125108

* Nguyen, Q., Huptych, M., & Rienties, B. (2018). Linking students' timing of engagement to learning design and academic performance. In A. Pardo, K. Bartimote-Aufflick, G. Lynch, S. B. Shum, R. Ferguson, A. Merceron, & X. Ochoa (Eds.), *Proceedings of the 8th international conference on learning analytics and knowledge* (pp. 141–150). ACM. https://doi.org/10.1145/3170358.3170398

* Nguyen, N. B. C. (2022). Improving online learning design for employed adult learners. In P. Fotaris & A. Blake (Eds.), *Proceedings of the European conference on e-learning. Vol. 21: no. 1. Proceedings of the 21st European conference on e-learning: 27–28 October 2022, Brighton: ECEL 2022* (pp. 302–309). Academic Conferences International Limited.

* Nkomo, L. M., & Nat, M. (2021). Student engagement patterns in a blended learning environment: An educational data mining approach. *TechTrends*, *65*(5), 808–817. https://doi.org/10.1007/s11528-021-00638-0

* O'Brien, M., & Verma, R. (2019). How do first year students utilize different lecture resources? *Higher Education*, *77*(1), 155–172. https://doi.org/10.1007/s10734-018-0250-5

* Oliveira, E., Galvao de Barba, P., & Corrin, L. (2021). Enabling adaptive, personalised and context-aware interaction in a smart learning environment: Piloting the iCollab system. *Australasian Journal of Educational Technology*, *37*(2), 1–23. https://doi.org/10.14742/ajet.6792
* Ouyang, F., & Xu, W. (2022). The effects of three instructor participatory roles on a small group's collaborative concept mapping. *Journal of Educational Computing Research*, *60*(4), 930–959. https://doi.org/10.1177/07356331211057283
* Ouyang, F., Wu, M., Zheng, L., Zhang, L., & Jiao, P. (2023). Integration of artificial intelligence performance prediction and learning analytics to improve student learning in online engineering course. *International Journal of Educational Technology in Higher Education*, *20*(1), 4. https://doi.org/10.1186/s41239-022-00372-4

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., . . . Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ (Clinical Research Ed.), 372*, 71. https://doi.org/10.1136/bmj.n71

* Papamitsiou, Z., & Economides, A. A. (2014). Learning analytics and educational data Mining in Practice: A systematic literature review of empirical evidence. *Educational Technology & Society*, *17*(4), 49–64.
* Papamitsiou, Z., Pappas, I. O., Sharma, K., & Giannakos, M. N. (2020). Utilizing multimodal data through fsQCA to explain engagement in adaptive learning. *IEEE Transactions on Learning Technologies*, *13*(4), 689–703. https://doi.org/10.1109/TLT.2020.3020499

Paulsen, L., & Lindsay, E. (2024). Learning analytics dashboards are increasingly becoming about learning and not just analytics - A systematic review. *Education and Information Technologies*. https://doi.org/10.1007/s10639-023-12401-4

Pekrun, R., Goetz, T., Frenzel, A. C., Barchfeld, P., & Perry, R. P. (2011). Measuring emotions in students' learning and performance: The achievement emotions questionnaire (AEQ). *Contemporary Educational Psychology, 36*(1), 36–48. https://doi.org/10.1016/j.cedpsych.2010.10.002

Pekrun, R., Vogl, E., Muis, K. R., & Sinatra, G. M. (2017). Measuring emotions during epistemic activities: The epistemically-related emotion scales. *Cognition & Emotion, 31*(6), 1268–1276. https://doi.org/10.1080/02699931.2016.1204989

Petticrew, M., & Roberts, H. (2006). Systematic Reviews in the Social Sciences. Blackwell Publishing.

Pintrich, P. R. (2000). The role of goal orientation in self-regulated learning. In *Handbook of self-regulation* (pp. 451–502). Academic Press.

* Poellhuber, L.-V., Poellhuber, B., Desmarais, M., Leger, C., Roy, N., & Manh-Chien Vu, M. (2023). Cluster-based performance of student dropout prediction as a solution for large scale models in a Moodle LMS. In I. Hilliger, H. Khosravi, B. Rienties, & S. Dawson (Eds.), *LAK23: 13th international learning analytics and knowledge conference* (pp. 592–598). ACM. https://doi.org/10.1145/3576050.3576146
* Rajabalee, B. Y., Santally, M. I., & Rennie, F. (2020). A study of the relationship between students' engagement and their academic performances in an eLearning environment. *E-Learning and Digital Media*, *17*(1), 1–20. https://doi.org/10.1177/2042753019882567

Redmond, P., Heffernan, A., Abawi, L., et al. (2018). An online engagement framework for higher education. *Online Learning, 22*(1), 183–204.

Reeve, J. (2012). A self-determination theory perspective on student engagement. In S. L. Christenson, A. L. Reschly, & C. Wylie (Eds.), *Handbook of research on student engagement* (pp. 149–172). Springer US. https://doi.org/10.1007/978-1-4614-2018-7_7

Reeve, J., & Tseng, C.-M. (2011). Agency as a fourth aspect of students' engagement during learning activities. *Contemporary Educational Psychology, 36*(4), 257–267. https://doi.org/10.1016/j.cedpsych.2011.05.002

* Rienties, B., Lewis, T., McFarlane, R., Nguyen, Q., & Toetenel, L. (2018). Analytics in online and offline language learning environments: The role of learning design to understand student online engagement. *Computer Assisted Language Learning*, *31*(3), 273–293. https://doi.org/10.1080/09588221.2017.1401548
* Rienties, B., Tempelaar, D., Nguyen, Q., & Littlejohn, A. (2019). Unpacking the intertemporal impact of self-regulation in a blended mathematics environment. *Computers in Human Behavior*, *100*, 345–357. https://doi.org/10.1016/j.chb.2019.07.007

Ryan, R. M. (1982). Control and information in the intrapersonal sphere: An extension of cognitive evaluation theory. *Journal of Personality and Social Psychology, 43*(3), 450–461. https://doi.org/10.1037/0022-3514.43.3.450

Salmela-Aro, K., Tang, X., Symonds, J., & Upadyaya, K. (2021). Student engagement in adolescence: A scoping review of longitudinal studies 2010–2020. *Journal of Research on Adolescence : The Official Journal of the Society for Research on Adolescence, 31*(2), 256–272. https://doi.org/10.1111/jora.12619

* Saqr, M., & López-Pernas, S. (2021). The longitudinal trajectories of online engagement over a full program. *Computers & Education*, *175*, 104325. https://doi.org/10.1016/j.compedu.2021.104325
* Saqr, M., López-Pernas, S., & Vogelsmeier, L. V. (2023). When, how and for whom changes in engagement happen: A transition analysis of instructional variables. *Computers & Education*, *207*, 104934. https://doi.org/10.1016/j.compedu.2023.104934
* Seo, K., Dodson, S., Harandi, N. M., Roberson, N., Fels, S., & Roll, I. (2021). Active learning with online video: The impact of learning context on engagement. *Computers & Education*, *165*, 104132. https://doi.org/10.1016/j.compedu.2021.104132
* Serembus, J. F., & Riccio, P. A. (2019). Relationship between student engagement and outcomes for online master of science in nursing students. *The Journal of Nursing Education*, *58*(4), 207–213. https://doi.org/10.3928/01484834-20190321-04
* Sherifi, D., Jia, Y., Hunt, T. J., & Ndanga, M. (2023). Evaluation of a PlayPosit guided group project's impact on student engagement in an undergraduate course. *Discover Education*, *2*(1). https://doi.org/10.1007/s44217-023-00057-8
* Smith, D., Pasieka, A., Becker, R., & Perdikoulias, C. (2022). Student success in asynchronous STEM education: Measuring and identifying contributors to learner outcomes. In *2022 IEEE global engineering education conference (EDUCON)* (pp. 473–479). IEEE. https://doi.org/10.1109/EDUCON52537.2022.9766578

* Strang, K. (2016). How student behavior and reflective learning impact grades in online business courses. *Journal of Applied Research in Higher Education*, *8*(3), 390–410. https://doi.org/10.1108/JARHE-06-2015-0048
Stojanov, A., & Daniel, B. K. (2024). A decade of research into the application of big data and analytics in higher education: A systematic review of the literature. *Education and Information Technologies, 29*(5), 5807–5831. https://doi.org/10.1007/s10639-023-12033-8
* Su, Y.-S., Ding, T.-J., & Lai, C.-F. (2017). Analysis of students engagement and learning performance in a social community supported computer programming course. *EURASIA Journal of Mathematics, Science and Technology Education*, *13*(9). https://doi.org/10.12973/eurasia.2017.01058a
* Summers, R. J., Higson, H. E., & Moores, E. (2021). Measures of engagement in the first three weeks of higher education predict subsequent activity and attainment in first year undergraduate students: A UK case study. *Assessment & Evaluation in Higher Education*, *46*(5), 821–836. https://doi.org/10.1080/02602938.2020.1822282
Sun, J.C.-Y., & Rueda, R. (2012). Situational interest, computer self-efficacy and self-regulation: Their impact on student engagement in distance education. *British Journal of Educational Technology, 43*(2), 191–204. https://doi.org/10.1111/j.1467-8535.2010.01157.x
* Suraworachet, W., Zhou, Q., & Cukurova, M. (2023). Impact of combining human and analytics feedback on students' engagement with, and performance in, reflective writing tasks. *International Journal of Educational Technology in Higher Education*, *20*(1). https://doi.org/10.1186/s41239-022-00368-0
Tafelski, J. J., Hejnal, T., Maring, C., McDowell, G., & Rencher, C. (2017). The cost of disengagement: Examining the real story of absenteeism in two Michigan counties. [Doctoral Dissertation; Michigan state.] ERIC. https://eric.ed.gov/?id=ED571750
* Tempelaar, D., Rienties, B., & Nguyen, Q. (2018). A multi-modal study into students' timing and learning regulation: time is ticking. *Interactive Technology and Smart Education*, *15*(4), 298–313. https://doi.org/10.1108/ITSE-02-2018-0015
Tempelaar, D., Rienties, B., & Nguyen, Q. (2020). Subjective data, objective data and the role of bias in predictive modelling: Lessons from a dispositional learning analytics application. *PLoS ONE, 15*(6), e0233977. https://doi.org/10.1371/journal.pone.0233977
* Tempelaar, D., Rienties, B., & Nguyen, Q. (2021). Enabling precision education by learning analytics applying trace, survey and assessment data. In *2021 International conference on advanced learning technologies (ICALT)* (pp. 355–359). IEEE. https://doi.org/10.1109/ICALT52272.2021.00114
Thomas, J., Graziosi, S., Brunton, J., Ghouze, Z., O'Driscoll, P., Bond, M., & Koryakina, A. (2023). EPPI-Reviewer: advanced software for systematic reviews, maps and evidence synthesis [Computer software]. EPPI-Centre Software. UCL Social Research Institute. https://eppi.ioe.ac.uk/cms/Default.aspx?alias=eppi.ioe.ac.uk/cms/er4
Tsai, Y. S., & Gašević, D. (2017, March). Learning analytics in higher education—challenges and policies: a review of eight learning analytics policies. In *Proceedings of the seventh international learning analytics & knowledge conference* (pp. 233–242).
* Veerasamy, A. K., Laakso, M.-J., & D'Souza, D. (2021). Formative assessment tasks as indicators of student engagement for predicting at-risk students in programming courses. *Informatics in Education.* https://doi.org/10.15388/infedu.2022.15
Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior, 89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027
Viberg, O., Khalil, M., & Baars, M. (2020). Self-regulated learning and learning analytics in online learning environments. In C. Rensing & H. Drachsler (Eds.), *Proceedings of the tenth international conference on learning analytics & knowledge* (pp. 524–533). ACM. https://doi.org/10.1145/3375462.3375483
* Walsh, J. N., & Rísquez, A. (2020). Using cluster analysis to explore the engagement with a flipped classroom of native and non-native English-speaking management students. *The International Journal of Management Education*, *18*(2), 100381. https://doi.org/10.1016/j.ijme.2020.100381
Wang, J.-Y., Yang, C.-H., Liao, W.-C., Yang, K.-C., Chang, I.-W., Sheu, B.-C., & Ni, Y.-H. (2022). Highly engaged video-watching pattern in asynchronous online pharmacology course in pre-clinical 4th-year medical students was associated with a good self-expectation, understanding, and performance. *Frontiers in Medicine, 8*, 799412. https://doi.org/10.3389/fmed.2021.799412
Wang, M.-T., Fredricks, J. A., Ye, F., Hofkens, T. L., & Linn, J. S. (2016). The math and science engagement scales: Scale development, validation, and psychometric properties. *Learning and Instruction, 43*, 16–26. https://doi.org/10.1016/j.learninstruc.2016.01.008
Wang, M.-T., Fredricks, J., Ye, F., Hofkens, T., & Linn, J. S. (2019). Conceptualization and assessment of adolescents' engagement and disengagement in school. *European Journal of Psychological Assessment, 35*(4), 592–606. https://doi.org/10.1027/1015-5759/a000431
* Wang, X., Di Sun, Cheng, G., & Luo, H. (2023). Key factors predicting problem-based learning in online environments: Evidence from multimodal learning analytics. *Frontiers in Psychology*, *14*, 1080294. https://doi.org/10.3389/fpsyg.2023.1080294
* Wang, J.-Y., Yang, C.-H., Liao, W.-C., Yang, K.-C., Chang, I.-W., Sheu, B.-C., & Ni, Y.-H. (2021). Highly engaged video-watching pattern in asynchronous online pharmacology course in pre-clinical 4th-year medical students was associated with a good self-expectation, understanding, and performance. *Frontiers in Medicine*, *8*, 799412. https://doi.org/10.3389/fmed.2021.799412
Wong, A., & Chong, S. (2018). Modelling adult learners' online engagement behaviour: Proxy measures and its application. *Journal of Computers in Education, 5*(4), 463–479. https://doi.org/10.1007/s40692-018-0123-z
Wu, T.-T., Lee, H.-Y., Wang, W.-S., Lin, C.-J., & Huang, Y.-M. (2023). Leveraging computer vision for adaptive learning in STEM education: effect of engagement and self-efficacy. *International Journal of Educational Technology in Higher Education*. https://doi.org/10.1186/s41239-023-00422-5
* Yildirim, D., & Gülbahar, Y. (2022). Implementation of learning analytics indicators for increasing learners' final performance. *Technology, Knowledge and Learning*, *27*(2), 479–504. https://doi.org/10.1007/s10758-021-09583-6

* Yilmaz, F. G. K., & Yilmaz, R. (2022). Learning analytics intervention improves students' engagement in online learning. *Technology, Knowledge and Learning*, *27*(2), 449–460. https://doi.org/10.1007/s10758-021-09547-w
* Yoon, M., Hill, J., & Kim, D. (2021). Designing supports for promoting self-regulated learning in the flipped classroom. *Journal of Computing in Higher Education*, *33*(2), 398–418. https://doi.org/10.1007/s12528-021-09269-z
* Yousuf, B., & Conlan, O. (2018). Supporting student engagement through explorable visual narratives. *IEEE Transactions on Learning Technologies*, *11*(3), 307–320. https://doi.org/10.1109/TLT.2017.2722416
Zacharis, N. Z. (2015). A multivariate approach to predicting student outcomes in web-enabled blended learning courses. *The Internet and Higher Education, 27*, 44–53. https://doi.org/10.1016/j.iheduc.2015.05.002
Zawacki-Richter, O., Kerres, M., Bedenlier, S., Bond, M., & Buntins, K. (Eds.). (2020). *Systematic reviews in educational research*. Springer Fachmedien Wiesbaden. https://doi.org/10.1007/978-3-658-27602-7
Zimmerman, B. J. (2000). Attaining self-regulation: A social cognitive perspective. In M. Boekaerts, P. R. Pintrich, & M. Zeidner (Eds.), *Handbook of self-regulation* (pp. 13–39). Academic Press.
* Zhu, J., Yuan, H., Zhang, Q., Huang, P.-H., Wang, Y., Duan, S., Lei, M., Lim, E. G., & Song, P. (2022). The impact of short videos on student performance in an online-flipped college engineering course. *Humanities & Social Sciences Communications*, *9*(1), 327. https://doi.org/10.1057/s41599-022-01355-6
* Zhou, X., Chen, S., Ohno, S., She, J., & Kameda, H. (2023). Motivational design for enhancing behavioral engagement in a flipped Chinese course. *Asia Pacific Education Review*. https://doi.org/10.1007/s12564-023-09849-x

## Publisher's Note