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Connecting the dots – A literature review on learning analytics indicators from a learning design perspective

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Abstract

Background: During the past decade, the increasingly heterogeneous field of learning analytics has been critiqued for an over-emphasis on data-driven approaches at the expense of paying attention to learning designs.

Method and objective: In response to this critique, we investigated the role of learning design in learning analytics through a systematic literature review. 161 learning analytics (LA) articles were examined to identify indicators that were based on learning design events and their associated metrics. Through this research, we address two objectives. First, to achieve a better alignment between learning design and learning analytics by proposing a reference framework, where we present possible connections between learning analytics and learning design. Second, to present how LA indicators and metrics have been researched and applied in the past.

Results and conclusion: In our review, we found that a number of learning analytics papers did indeed consider learning design activities for harvesting user data. We also found a consistent increase in the number and quality of indicators and their evolution over the years.

KEYWORDS

framework, indicators, learning activities, learning analytics, learning design, learning events, metrics, review, transparency

1 | INTRODUCTION

Over the past three decades, the field of learning and education has evolved from traditional campus-based courses to become widely mediated by digital technologies in which students and teachers leave digital traces of data throughout the learning process. Examples of this include interaction with institutional Learning Management Systems (LMS) and participation in massive open online courses (MOOCs). Learning analytics (LA) has played a significant role in this development (Ferguson, 2012). Around 2009, LA developed as a field of study with the aim of improving learning and education by means of collecting and analysing educational data from teachers and learners. To date, a wide variety of approaches to conducting LA have been introduced, from basic counts such as login/logout time and frequency (Park & Jo, 2015; Rogers et al., 2014) to highly sophisticated inferences, for example, self-regulation (Ruiz et al., 2016; Schumacher & Ifenthaler, 2018) or engagement (Coffrin et al., 2014; Elbadrawy et al., 2015).

LA has stimulated interest among various communities in the learning sciences, for example, psychometrics (Drachsler & Goldhammer, 2020), neuroscience (Calle-Alonso et al., 2017) and so forth. These sister communities investigate, for instance, how LA can inform the use of constructs such as engagement, meta-cognitive skills, time planning and so forth. This widespread interest has made the field of LA increasingly heterogeneous, and as a result, it is challenging to obtain an overview of the field in order to identify best practices. In addition, the terminology used is also very heterogeneous; for example, LA metrics (measurements) and indicators are widely used interchangeably in the LA literature, and so the identification of effective LA approaches is not straightforward. To obtain an overview of the effective use of LA, initiatives such as the LACE evidence hub[1] have been created. The evidence hub aims to provide an overview of effective and ineffective LA studies according to four propositions; whether they improve and support learning outcomes, improve learning support and teaching, are used widely, and are used ethically (Ferguson & Clow, 2017). The need to create an overview of LA indicators has also been re-identified by other researchers in the field. In a recent article by (Saqr et al., 2022) examines if and to what extent frequently used indicators of success are portable across a homogenous set of courses. Nonetheless, identifying a suitable LA approach for a specific activity or construct remains a challenge due to the heterogeneity of the vast range of applications that LA has been used for and the terminology used to describe them.

A second problem in the field of LA is concerned with its data-driven approach and lack of alignment with pedagogical models, with the result that outcomes which are integrated into their educational context still scarce (Bakharia et al., 2016; Martin et al., 2016). More specifically, we can track a lot of data about the learning process, but it is not clear how to use the resulting datasets to identify relevant indicators that can be used to support this learning process (Ferguson, 2012). For example, in (Park et al., 2017), the authors track student behaviour from clickstream data (i.e., the number of clicks, number of views, number of downloads) along with timestamps. However, it is also not clear how to present these findings back to the teachers and learners in an intelligible format to improve the learning process (Chatti et al., 2014; Macfadyen et al., 2020). For example, if someone wants to use LA for reading comprehension, it is not clear what data needs to be collected nor how to use it to provide meaningful indicators about the students' progress in this particular area. Thus, there is a need for clear guidelines on the meaningful application of LA for different learning scenarios.

For a pedagogically meaningful implementation of LA that improves the learning and teaching process and provides positive effects on student learning outcomes, an alignment between LA and Learning design (LD) is essential (Blumenstein, 2020). In the late 1990s, LD started to appear in the literature for education, but the concept is as old as the concept of teaching (Conole & Fill, 2005). LD, or design for learning, is defined as the design or development of an actual unit of learning (for example, a course or a learning event), and it considers what, when, where and how to teach (Koper, 2006; Koper & Tattersall, 2005). A decade ago, in the early stages of LA, the significance of synergies among LA and LD had already been identified (Lockyer & Dawson, 2011), but a recent study concludes that research is still needed to investigate which LD activities are best suited for learners in a particular learning scenario (Macfadyen et al., 2020).

[1]https://lace.apps.slate.uib.no/evidence-hub/

In this study, we attempt to address these problems by answering the following research questions:

RQ1. *How are learning analytics indicators associated with learning events and learning activities (see Section 2.1 for definitions) related to learning design?*

- With this RQ, we aim to create a reference framework that allows us to depict the connection between LA and LD and investigate how the learning objectives are associated with learning activities from LA and LD and how these learning activities are used to identify the LA indicators. To dig deeper into the research and get an overview of the used indicators, we conducted a literature review using our proposed reference framework as a guideline. Hence, leading to our RQ2.

RQ2. *Which learning analytics indicators and metrics have been researched and used according to the learning analytics literature?*

- With this RQ, we aim to identify the list of indicators used in the past along with their metrics (see Section 2.2 for definition). Moreover, we present a list showing the evolution of the most commonly used indicators that have been developed and used over the past 10 years.

2 | ALIGNING LD WITH LA

A criticism of LA concerns its data-driven approach, which does not necessarily always align with the pedagogical aspects of education (Jivet et al., 2017, 2018). A study by (Macfadyen et al., 2020) argues that evidence-based research is required to see how practitioners make LD decisions or design activities and how learners respond to these decisions. Another dilemma that LA faces is that its widespread use in sister communities generates heterogeneity, making it difficult to identify effective LA approaches. Following this line of thought, we consider that aligning LA with LD is a step forward to address these issues.

Some scientific work has already been conducted to investigate the relationship between LA and LD. The work reported in (Toetenel & Rienties, 2016) extended and evaluated the seven steps framework in (Rienties & Toetenel, 2016) by analysing 157 LDs using LA techniques to evaluate the impact of teaching and learning. Several studies have already looked at possible connections between LA and LD. For example, the study by (Leclercq & Poumay, 2005; Verpoorten et al., 2007) presents a framework that shows how LD can be enhanced with LA for a case-based learning scenario. Studies such as (Bakharia et al., 2016) and (Martin et al., 2016) propose frameworks where LA can be used to inform teachers about the effectiveness of the LD of their courses. Further, in (Bakharia et al., 2016), the authors identified that analytics methods and tools enable teachers to evaluate their LD, for example temporal analytics, comparative analytics, cohort dynamics, contingency tools, and intervention tools. A study by (Martin et al., 2016) argues that the process of collecting and analysing data based on the quality matters framework also supports teachers in assessing their LD. Finally, a more recent study by (Blumenstein, 2020) states that aligning the students' learning activities and their learning outcomes leads to positive effects in student learning that result in collaborative and self-reliant learning skills.

Authors in (Lockyer et al., 2013; Mangaroska & Giannakos, 2017, 2018) recognize room for improvement in the alignment of LA and LD, including in the provision of common guidance on use, interpretation and reflection on the LA to analyse and redesign learning activities appropriately, and to evaluate the impact of LA outcomes on LD decisions.

Despite these efforts, studies show that a generalized framework or guidelines to align LA with LD is still missing. The systematic literature review reported in (Mangaroska & Giannakos, 2018) showed that only a minority of LA studies have actually been used to inform teachers and, in this way, to support their LD. A recent study on LD and LA by (Macfadyen et al., 2020) indicates that the challenges and future directions that still need attention are:

- There is a need for more comprehensive and practical studies that show which LD decisions can best inform LA approaches. It is crucial to appropriately describe how practitioners make these decisions and how learners acknowledge them.
- Research is needed to explore the personalization of learning activities; we need to establish who is teaching, who is learning, and how and for whom to design a particular and suitable learning activity.
- There is a need to explore design practices in order to support practitioners in designing learning activities as they engage more frequently with LA.
- There is a need for a methodological approach to the collection of LA and LD data from the literature to analyse and find out how to design the 'right' learning activity at the right 'time' for learners.

To address the challenge of providing a general alignment between LA and LD we propose a reference framework (see Figure 3), which is the continuation of the work presented in (Ahmad et al., 2022). Our framework highlights our synergic approach to LA and LD, which aims to answer our first research question that deals with the association of LA indicators, learning events and learning activities related to LD. There are four reasons why our proposed reference framework can be of value. First, it presents an overview that helps in investigating and understanding the process flow of LA-LD elements. Second, it assists in recognizing the data processing needed to classify LD events, LD-LA activities, LA indicators and LA metrics. Third, it displays the use of LD-LA activities and their connection to LA metrics and indicators presented in Tables A1 and A2. Finally, it proposes how activity outcomes from a LD can be visualized, validated, presented, or viewed with the support of LA indicators that are drawn from the unified description of LD-LA activity in our framework. We further used the proposed reference framework for the analysis of the literature presented in this article. In the following subsections, we present the definitions of the relevant LD and LA elements that compose our proposed reference framework. The selection of LD and LA elements are based on the scope of this study and the data harvested (see Tables A1 and A2).

2.1 | Learning design

LD is the pedagogic process used in teaching or learning that leads to the creation and sequencing of learning activities, the configuration of the environment in which it occurs, and the activities performed by the stakeholders to achieve the learning objective that leads to the learning outcome (Beetham & Sharpe, 2013; Conole & Fill, 2005; Mor et al., 2013). To create our reference framework, it is important to closely inspect and define the principal elements of LD (see Figure 1):

- Learning objectives: A learning objective is the desired outcome of single or multiple learning events and is used to establish learning activities to achieve the overall learning outcome (Morss & Murray, 2005). For example, if a teacher wants to design a course in Object-Oriented Programming (OOP), the learning objectives for the course may be for students to master basic concepts of OOP such as extension, inheritance, polymorphism and so forth.
- Learning events: A study by (Leclercq & Poumay, 2005) identified eight learning events: create, explore, practice, imitate, receive, debate, meta-learn/self-reflect and experiment. The combination of these events forms a training/learning strategy (Leclercq & Poumay, 2005; Verpoorten et al., 2007). This learning/teaching/training events model supports the standardization and consistency

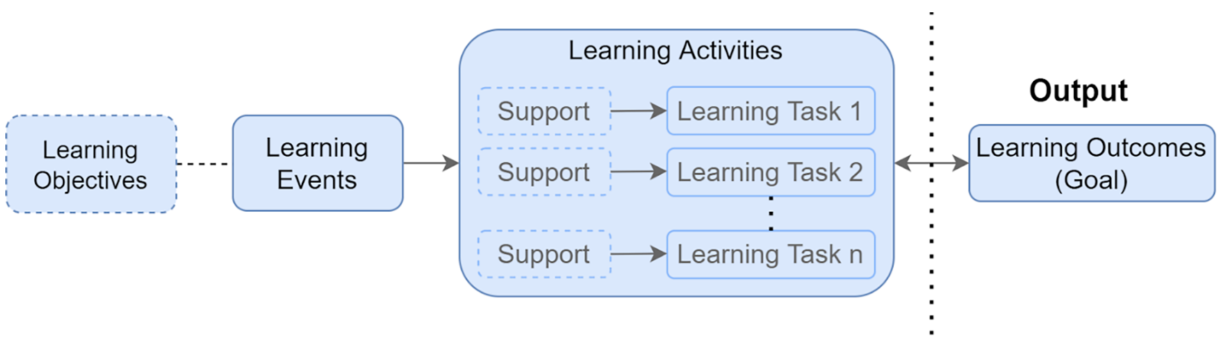

FIGURE 1 LD elements in the proposed framework. LD, learning designs

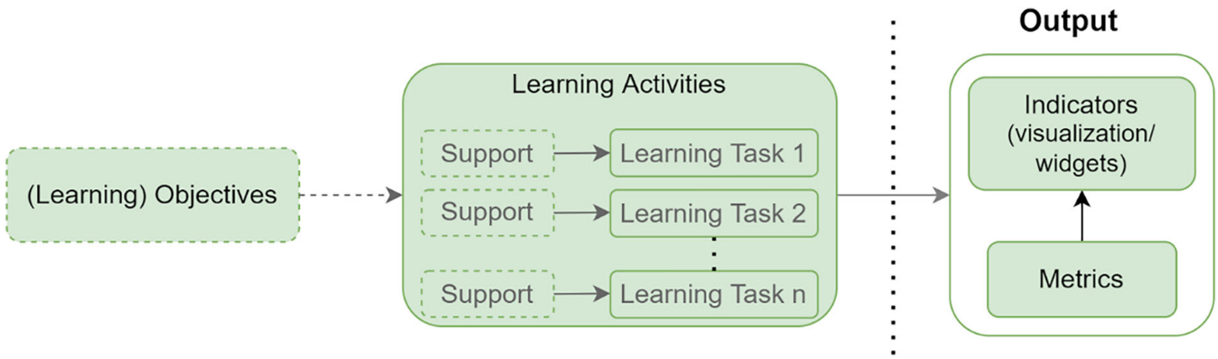

FIGURE 2 LA elements in the proposed framework. LA, learning analytics

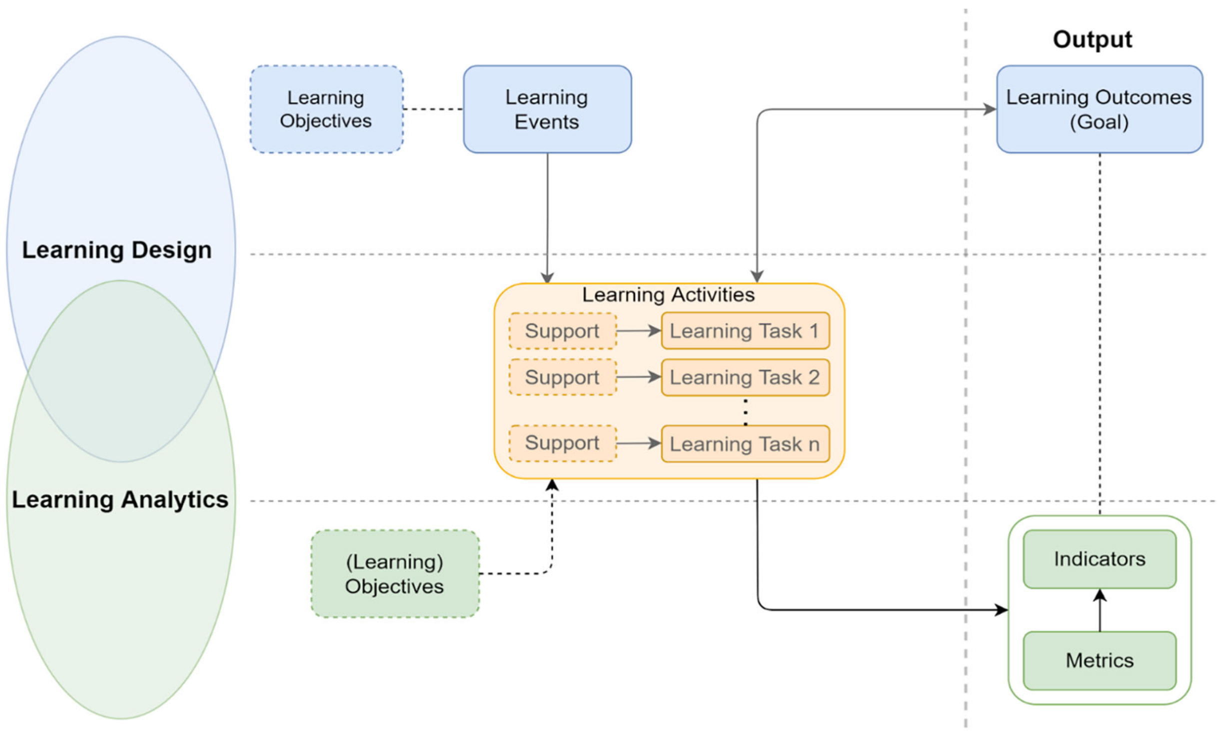

FIGURE 3 Proposed reference framework

of the elements that are combined in teaching and learning activities (Verpoorten et al., 2007). We will use these eight learning events to establish/categorize the learning activities. For example, to fulfil the learning objective, a teacher needs to think of the possible learning events that may satisfy the objective and form a training/learning strategy. In designing the OOP course, the learning events that can be used are practice, create and meta-learn/self-reflect.

- Learning activities: There are several definitions for learning activities, and in this article, we follow that of (Conole & Fill, 2005). A learning activity has three elements: context, learning and teaching approaches, and tasks. The context of a learning activity includes its difficulty level, the intended learning outcomes and the environment. The practitioner's over-arching task is to engage the learners in the learning activity to achieve the intended learning outcome by pursuing the set of tasks (Conole & Fill, 2005). A study by (Gruber, 2019) took the model of learning events and added learning activities to identify their outcomes in LD. Learning activities are split into in-class and online activities (Gruber, 2019; Kwakman, 2003). Examples of in-class activities are exercise, exam, presentation, discussion, group work and so forth. On the other hand, online activities are blogs, wikis, forums, photo and audio notes, online tests and quizzes, e-portfolios and so forth. Studies by (Morss & Murray, 2005) and (Conole & Fill, 2005) remark on the importance of the organization and the performance of learning activities to achieve the desired learning outcomes. For example, when designing the OOP course, the teacher may consider learning activities such as reading, writing, exercise, group work and so forth. To design an effective course, it is essential to clearly define all the possible learning activities (Kwakman, 2003). As per our proposed reference framework, there are two fundamental sub-elements of a learning activity.

- ◦ Support: Support is essential in the provision of relevant resources and the fulfilment of learning tasks (Lockyer et al., 2013), for example, feedback. To have an effective outcome and enhance learning it is important to have a teacher in the loop to provide relevant resources, a set of tools, techniques and necessary support that includes web links, files, videos, literature and so forth. (Kwakman, 2003). However, it could also be the case that support is not required according to the scenario or situation; it can be omitted (Gruber, 2019). For example, in the scenario of the OOP course, it is important to have support and resources prepared, such as a compiler, web links, files, videos and so forth, can be provided to help understand the topic and concepts more certainly.
- ◦ Learning tasks: A learning task is a user action which is part of a learning activity. A learning activity consists of one or more learning tasks. After the provision of required support, learners are expected to carry out their learning tasks (Conole & Fill, 2005; Lockyer et al., 2013). The elements of a learning task include the techniques used, related tools and resources, and the interactions and acts specified in the learning activity (Conole & Fill, 2005). For example, the OOP teacher expects their students to solve the problems provided in the assignment and present or submit their solutions.
- Learning outcomes: A learning outcome is the ultimate result of a learning objective or a reflection of the desired state (Morss & Murray, 2005). It indicates a change in the state of knowledge, thoughts, beliefs, and approaches (Bakkenes et al., 2010). A learning outcome is attained through an array of tasks with the required tools, resources, and support of the teacher (Conole & Fill, 2005). This outcome, as a result, leads to feedback for learners and ends up improving learning (Brown et al., 2016). For example, the teacher can expect that the students may have learned basic OOP concepts. Based on the assignments or quizzes results, the teacher can observe whether the students are performing as to the expectations or not.

2.2 | Learning analytics

LA is defined as 'the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs' (Siemens, 2010). In this study, we examined 161 publications concerning the application of LA. In these applications, we identified four common elements that we consider crucial for aligning LA with LD: learning objectives, learning activities, metrics, and indicators (see Figure 2).

- (Learning) objectives: We define a learning objective as the specific purpose behind the use of LA for a particular scenario. For example, a teacher wants to use LA to see how well students perform in his/her OOP course.
- Learning activities: The state-of-the-art of LA portrays a learning activity as a set of *learning tasks* that the learner carries out in a LMS environment with planned learning *support* to acquire learning objectives (Sung et al., 2016). This learning task is referred to as a user action, which generates digital trace data (Howison et al., 2011; Sung et al., 2016). Digital trace data is generated by human activity on systems such as an LMS environment, and is logged and stored digitally. Such activities might include, for example, posting, reading, writing, discussing, uploading an assignment and so forth. (Howison et al., 2011). Learning support includes the provision of a set of tools, tips, teacher–student interactions and resources, such as reading materials, assignment instructions, slides and so forth. Usually, LA implementations capture, store and analyse all these learning activities and use the data to improve learning (Chiu & Fujita, 2014; Gašević et al., 2015; Park & Jo, 2015; Phillips et al., 2012; Tan et al., 2017; Tervakari et al., 2014). We consider there to be a strong linkage between learning activities described in the LA literature and learning activities from LD (see Section 2.1 above). Consequently, we aligned these two in our proposed reference framework. For example, in the OOP course, the learning activities used/planned/appeared while designing the course can also be used/considered here, such as reading, writing, exercise, group work and so forth.
- Metrics: LA applications collect data from the interaction between learners and LMSs. To make sense of these captured data, they need to be categorized in a corresponding unit of measurement (e.g., number of views, login/logout frequency and time, number of posts, etc.). In this article, we refer to this unit of measurement as a metric. For example, the learning activities selected in the OOP course lead to the metrics (see Tables A1 and A2) in LA.
- Indicators: Metrics are used to create indicators; an indicator is the result of the analysis of one or multiple metrics and gives a more comprehensive picture of a particular (abstract) learner status, for example, student engagement and so forth. (see Table A2). An indicator covers a particular aspect of an abstract variable (e.g., student attention) by using relevant (measurable) items. It is taken as a way of establishing plausibility on how much a variable is met when direct measurements are not available. We consider that LA indicators, besides showing the learners' states and progress, are also the links that provide relevant information about the activity outcomes from the LD. For example, the objective of the OOP teacher is to see how well the students are performing, so, based on the selected learning activities, LA can present the teacher (or a person responsible for developing a LA dashboard) with the possible indicators that can be used or developed to visualize student engagement and performance (Coffrin et al., 2014) (see Tables A1 and A2).

2.3 | Reference framework

The reference scheme shown in Figure 3 assumes a connection between LD and LA. We derived this framework first by examining the essential elements of LD together with their corresponding sub-elements (Section 2.1) and the essential elements of LA together with their corresponding sub-elements (Section 2.2). Learning activities are considered the core element of LD (Koper, 2006; Koper et al., 2003; Mor & Craft, 2012). Therefore, in our reference framework (see Figure 3), we consider learning activities to be the core factor in the alignment of LA and LD.

In addition, research has shown the relationships between learning activities and outcomes from LD and how they both are connected to LA. LA studies the process of the learners and their context (Siemens, 2010). It is also used to measure and predict the learning outcomes of a designed course (Gruber, 2019; Lockyer et al., 2013; Mangaroska & Giannakos, 2017, 2018; Martin et al., 2016; Rienties & Toetenel, 2016) and it can also be used to evaluate the LD (Bakharia et al., 2016; Hernández-Leo et al., 2019; Leclercq & Poumay, 2005; Martin et al., 2016; Verpoorten et al., 2007). In our framework, this cyclic relationship is closed with the connection between outcomes from LD and indicators and metrics from LA (see Figure 3) extending previous work showing a possible connection between LD with LA (Gruber, 2019; Lockyer et al., 2013; Mangaroska & Giannakos, 2017, 2018; Martin et al., 2016; Rienties & Toetenel, 2016). Our framework expands on this by joining the learning activities from LA and LD and showing how a particular learning activity leads to LA metrics and forms an indicator. In this study, we used our proposed framework to provide examples of the actual alignment between LA and LD literature (see Tables A1 and A2), and show how the LA-LD activities lead to an actual LA indicator (visualization for a LA dashboard). Moreover, LA analytics indicators can provide information about the learning outcomes brought about by LD.

In a nutshell, LD in our proposed framework (see Figure 3) starts with learning objectives, where learning objectives have one or more learning event(s) (Leclercq & Poumay, 2005; Morss & Murray, 2005; Smith & Lynch, 2006; Verpoorten et al., 2007), which have learning activities (Gruber, 2019; Horton, 2011; Lockyer et al., 2013). If support is required (e.g., learning materials, teacher/expert guidance), then that is provided (Kwakman, 2003; Lockyer et al., 2013). The learning task is then initiated, and as a result, there will be a learning outcome(s) (Bakkenes et al., 2010; Gruber, 2019; Morss & Murray, 2005) for the desired learning objective. Whereas LA can help to clarify the LD outcomes (Gruber, 2019; Lockyer et al., 2013; Mangaroska & Giannakos, 2017, 2018; Martin et al., 2016; Rienties & Toetenel, 2016).

The systematic literature review reported in this article contributes to this process by identifying the learning activities in LA literature and harvesting their metrics (measurements) used in the same article (see Tables A1 and A2), which can be used to develop indicator(s) (e.g. students performance) for LD learning outcome(s).

3 | METHODOLOGY

To address the research questions, we conducted a literature review following the guidelines of the PRISMA statement (Liberati et al., 2009), an evidence-based set of step-by-step procedures for reporting systematic literature reviews and meta-analyses. As per PRISMA, a systematic literature review has four steps, that is, identification, screening, eligibility and inclusion of articles. In the identification step, results are fetched and identified in research databases screening using search filters and terms. While screening the studies, duplicate studies are removed, and further, based on the focus of our review, some articles are removed in the reading, scanning and skimming of the titles and abstracts. Based on the inclusion and exclusion criteria in the eligibility step, the full-text articles are accessed.

For this review, we searched all the publications related to Technology Enhanced Learning (TEL) from the Learning Analytics and Knowledge Conference (LAK) series from 2011 to 2020, publications in the Journal of Learning Analytics (JLA), proceedings of the European Conference for Technology Enhanced Learning (ECTEL) from 2012 to 2020, IEEE Transactions on Learning Technologies, as well as special issues for LA in the Journal of Computer Assisted Learning (JCAL). Since LA was officially established in the year 2011, we started searching for LA literature from 2011. The reason for looking into the above libraries for LA articles is that we believe these are the main outlets for high-quality LA publications.

The search terms/filters used to harvest the papers were *learning analytics*, *learning analytics indicators*, *learning analytics metrics (or measurements)*, *learning analytics visualization (or visualization)*, *visualization (or visualization)*, *visualize (or visualize)*, *learning analytics dashboard*, *learning analytics application*, *learning analytics tool*, between 2011 and 2020. The reason for using similar or different search terms was, for example, that the authors sometimes prefer to use the term 'plot' instead of 'figure' throughout their articles. Apart from the above listed libraries/databases, we also looked for LA literature in google scholar (with the above-mentioned searched terms) for further articles that may be important and we may have missed it.

We harvested 237 papers in total. From the selection of papers, the first screening was performed by scanning/evaluating the titles and abstracts and excluded duplications. We then further narrowed down the number of articles based on the inclusion and exclusion criteria as follows:

Inclusion criteria:

1. The full text is in English
2. The article is presenting a LA application, LA dashboard, or LA tool
3. The article is describing and presenting LA indicators (visualizations/widgets), metrics, learning activities and their applications

Exclusion criteria:

1. Theory or policy papers that have no basic LA concept (indicators or metrics)
2. Papers that present applications which have no basic LA concept (indicators or metrics)

In the inclusion criteria, the first point must be fulfilled, while for the following two points, if one of them is satisfied, the article is included. In the exclusion criteria, both the points must be checked and are mandatory to be followed.

One hundred seventy-five papers were identified, which we then read in full, and considered whether our inclusion criteria were addressed in the content of the papers. We excluded another

TABLE 1 Identified types of learning activities

Description	Explanation	References
1. Papers that only consider procedural actions	In 11 publications that only consider procedural actions as learning activities (i.e., keystroke, hits/clicks, clickstream, views, downloads, interactions, and visits) to apply LA techniques.	(Aguiar et al., 2014; Bakharia & Dawson, 2011; Brouwer et al., 2016; Casey, 2017; Hlosta et al., 2017; Labba et al., 2020; Park et al., 2017; Park & Jo, 2015; Saqr et al., 2018; Wolff et al., 2013; Yu & Jo, 2014)
2. Papers that only consider LD learning activities	Our review shows that 81 of the publications only consider LD learning activities in the development of learning analytics indicators, that is, analysis, collaboration, design, examine, exercise, feedback, forum discussion, game/puzzle, group work, presentation, problem-solving, reading, search, survey, watching videos, assignment/homework, comments, discourse, exam, exercise, peer review/assessment, posts, presentation, question, questionnaire, quiz, review, self-learning/reporting, task, test, vote (poll) and writing.	(Abolkasim et al., 2016; Agnihotri et al., 2017; Ahn, 2013; Akhuseyinoglu et al., 2020; Akintunde et al., 2020; Barber & Sharkey, 2012; Bogarin et al., 2014; Brown et al., 2016; Chatti et al., 2014; Chiu & Fujita, 2014; Cooper & Khosravi, 2018; Delnoij et al., 2020; der Zee et al., 2018; Erickson et al., 2020; Fancsali, 2011; Faucon et al., 2020; Feild et al., 2018; Ferguson & Clow, 2015; Ferguson & Shum, 2011; Ferreira et al., 2020; Gasevic et al., 2017; Gašević et al., 2014; Gunnarsson & Alterman, 2014; Håklev et al., 2017; Harrer & Göhnert, 2015; Hecking et al., 2016; Holman et al., 2013; Iandoli et al., 2014; Jo et al., 2014; Jovanović et al., 2020; Jung & Wise, 2020; Kennedy et al., 2015; Kim et al., 2020; Klebanov et al., 2019; Li et al., 2015; Malekian et al., 2020; Manai et al., 2016; Matcha et al., 2020; McAuley et al., 2012; McKay et al., 2012; Melero et al., 2015; Méndez et al., 2014; Molenaar et al., 2020; Muñoz-Merino et al., 2013; Nikolayeva et al., 2020; Ochoa Xavier & Castells, 2018; Papamitsiou et al., 2014; Papoušek et al., 2016; Pardo, Mirriahi, et al., 2016; Pardos & Jiang, 2020; Poquet & Jovanovic, 2020; Pursel et al., 2015; Rogers et al., 2014; Sadallah et al., 2015; Saint et al., 2020; Santos et al., 2014; Saqr & Viberg, 2020; Schlotterbeck et al., 2020; Schneider et al., 2016; Schumacher & Ifenthaler, 2018; Sedrakyan et al., 2017; Shabrina et al., 2020; Sharkey, 2011; Sharma et al., 2020; Shum et al., 2016; Smolin & Butakov, 2012; Southavilay et al., 2013; Srivastava et al., 2020; Tan et al., 2017; Tuti et al., 2020; Uzir et al., 2020; Venant et al., 2017; Verbert et al., 2011; Vesin et al., 2013; Vozniuk et al., 2014; Waddington & Nam, 2014; Wang et al., 2015; Wang et al., 2016; Wise et al., 2014; You, 2016; Zhu et al., 2016)
3. Papers that consider LD activities and procedural actions together	108 of the publications consider LD activities and procedural actions together, that is, assessment, assignment, clickstream, collaboration, comments, design, discourse, downloads, exam, examine, exercise, feedback, forum discussion, game/puzzle, group work, hits/clicks, homework, interactions, keystroke, peer-review, posts, presentation, problem-solving, question, questionnaire, quiz, reading, reporting, review, search, self-learning, survey, task, test, views, visits, vote (poll), watching videos and writing.	(Abolkasim et al., 2016; Agnihotri et al., 2017; Ahn, 2013; Akhuseyinoglu et al., 2020; Aljohani et al., 2019; Allen et al., 2016; Barber & Sharkey, 2012; Beheshitha et al., 2016; Benedetto et al., 2020; Bogarin et al., 2014; Brown et al., 2016; Chatti et al., 2014; Chen et al., 2017; Chiu & Fujita, 2014; Coffrin et al., 2014; Conijn et al., 2016; Cooper & Khosravi, 2018; Corrin & de Barba, 2014; Davis et al., 2017, 2018; de Quincey et al., 2019; der Zee et al., 2018; Elbadrawy et al., 2015; Fancsali, 2011; Feild et al., 2018; Ferguson & Clow, 2015; Ferguson & Shum, 2011; Figueira, 2015; Gasevic et al., 2017; Gašević et al., 2014; Grawemeyer et al., 2016; Gunnarsson & Alterman, 2014; Håklev et al., 2017; Harrer & Göhnert, 2015; Hart et al., 2017; Hecking et al., 2016; Holman et al., 2013; Iandoli et al., 2014; Iraj et al., 2020; Jo et al., 2014; Jovanović et al., 2017, 2019; Käser et al., 2017;

(Continues)

TABLE 1 (Continued)

Description	Explanation	References
		Kennedy et al., 2015; Khan & Pardo, 2016; Kia et al., 2020; Klebanov et al., 2019; Koulocheri & Xenos, 2013; Kump et al., 2012; Li et al., 2015; Liu et al., 2014; Lowes et al., 2015; Manai et al., 2016; Matcha et al., 2019, 2020; McAuley et al., 2012; McKay et al., 2012; Melero et al., 2015; Méndez et al., 2014; Molenaar et al., 2020; Monroy et al., 2013; Muñoz-Merino et al., 2013; Niaki et al., 2019; Ochoa Xavier & Castells, 2018; Papamitsiou et al., 2014; Papoušek et al., 2016; Pardo, et al., 2016; Pardo, Mirriahi, et al., 2016; Paule Ruiz et al., 2015; Pursel et al., 2015; Quick et al., 2020; Rogers et al., 2014; Ruiz et al., 2016; Sadallah et al., 2015; San Pedro et al., 2015; Santos et al., 2013, 2014; Scheffel et al., 2017; Schneider et al., 2016; Schumacher & Ifenthaler, 2018; Sedrakyan et al., 2017; Sharkey, 2011; Sher et al., 2020; Shimada et al., 2018; Shum et al., 2016; Smolin & Butakov, 2012; Southavilay et al., 2013; Syed et al., 2019; Tan et al., 2017; Tervakari et al., 2014; Tuti et al., 2020; Uzir et al., 2020; Van Goidsenhoven et al., 2020; van Leeuwen & Rummel, 2020; Venant et al., 2017; Verbert et al., 2011; Vesin et al., 2013; Vozniuk et al., 2014; Waddington & Nam, 2014; Wang et al., 2015, 2019; Wang et al., 2016; Wei et al., 2020; Wise et al., 2014; You, 2016; Yousuf et al., 2020; Zhang et al., 2020; Zhu et al., 2016)
4. No explicit learning activities are mentioned	There are 12 research papers found that do not have any link to learning activities but only have metrics. The indicators are academic success, predict early alert and student retention, epistemic network analysis, online discussion behaviour, recommendations, engagement and disengagement, passing probability, measure success retention, assignments quality, and carelessness.	(Dawson et al., 2017; De-la-Fuente-Valentin et al., 2015; Duval, 2011; Fougt et al., 2018; Govaerts et al., 2011; Harrison et al., 2015; Hershkovitz et al., 2013; Joksimović et al., 2016; Lauria et al., 2012; McAuley et al., 2012; Nam et al., 2014; Worsley, 2018)

14 because they did not specify the metrics or measurements they used to develop the indicator and visualization in the dashboard. As a result, 161 articles were compiled to create this overview. The extraction process of data from all the selected papers was conducted in a structured and organized manner. The first step was to categorize all the research papers by their publication platform and relevance. After inspecting each article, we listed the data in a spreadsheet (e.g., title, objectives, metrics, indicators, learning activities, data source, stakeholders, evaluation methods/approaches, dataset size, keywords, country, year, authors, and reference). To make the data more readable, we grouped the learning activities (and their metrics and indicators) by learning events, based on the approach of (Gruber, 2019). The data extraction and population/reporting of data into the spreadsheet were done by two researchers, where the papers were equally divided. The rest of the process was carried out by the main researcher of the paper.

In total, 131 papers originated from LAK and ECTEL, 21 from JCAL, Journal of Learning Analytics and IEEE Transactions on Learning Technologies, and nine from additional journals and conferences found on Google Scholar. We consider that the number, variety, and selection of sources in this review are sufficient to provide a valid and general overview of the use of LA indicators in the field.

The final results are categorized, analysed, and reported in Tables A1 and A2. Due to the significant number of records, we agreed to present the data in two separate appendices for better understanding and presentation.

4 | ANALYSIS OF THE LITERATURE

When closely examining the literature, we encountered a heterogeneous field in terms of approaches and terminology used. For example, the terms indicators and metrics had different meanings in different papers, therefore we had to thoroughly read the selected articles from top to bottom and analyse them based on our defined terminology (see Section 2).

To explore how the state-of-the-art of LA aligns with LD activities, we extracted the learning activities, indicators, and metrics from the 161 LA studies identified in the process described in Section 3. In the

TABLE 2 The list of similar indicators merges into a single cluster

Indicators originally named in the literature	Clusters of indicators
At-risk students (Aguiar et al., 2015; Hlosta et al., 2017; Lauria et al., 2012; Rogers et al., 2014; Syed et al., 2019; Wolff et al., 2013), Academic success (Nam et al., 2014), Dropout prediction (Aguiar et al., 2015; Manrique et al., 2019; Waddington & Nam, 2014), Dropping out (Aguiar et al., 2014), Early warning (Aguiar et al., 2015; Brown et al., 2016; Harrison et al., 2015; Hlosta et al., 2017; Waddington & Nam, 2014), Final grade prediction (Brouwer et al., 2016; Hart et al., 2017; Koulocheri & Xenos, 2013), Grade prediction (de Quincey et al., 2019; Elbadrawy et al., 2015; Figueira, 2015; Jo et al., 2014; Waddington & Nam, 2014), Exam success prediction (Lowes et al., 2015; Rogers et al., 2014), Success prediction (Barber & Sharkey, 2012; Conijn et al., 2016; Kennedy et al., 2015; McKay et al., 2012), Predict performance (Arnold & Pistilli, 2012; Barber & Sharkey, 2012; Boroujeni et al., 2016; Brouwer et al., 2016; Davis et al., 2018; Pardo, et al., 2016; Pardo, Mirriahi, et al., 2016; You, 2016), Predict performance (social network analysis) (Paredes & Chung, 2012), Predict academic achievement (Yu & Jo, 2014), Predict college major (by middle school learning behaviour) (San Pedro et al., 2015), Predict course successful completion (Santos et al., 2014), Predict early alert and student retention (Dawson et al., 2017), Predictive analytics (San Pedro et al., 2015), Passing rate prediction (Brouwer et al., 2016), Retention prediction (Robinson et al., 2016; Wolff et al., 2013), Prediction (A pilot study and proposal) (Fancsali, 2011; Sharkey, 2011), Predict performance (Game) (Käser et al., 2017), Passing probability (De-la-Fuente-Valentin et al., 2015), Retention (College student) (Lauria et al., 2012), Retention (Harrison et al., 2015), Assessment readiness prediction (Malekian et al., 2020), Predict student performance (Jovanović et al., 2020), Predicting learners' performance (Tuti et al., 2020), Predicting student success (Van Goidsenhoven et al., 2020), Predict students' choices (Faucon et al., 2020), Predicting learners' effortful behaviour (multimodal data LA) (Sharma et al., 2020), Predicting student performance (mouse movement) (Wei et al., 2020), Automated grading (mathematics) (Erickson et al., 2020), Reflections (automated assessment) (Jung & Wise, 2020)	Predictive analytics
Course difficulty (Méndez et al., 2014), Course difficulty level (Elbadrawy et al., 2015), Perceived difficulty, Cognitive load (Jovanović et al., 2019), Perceived difficulty and discrimination of text (Benedetto et al., 2020)	Course activities difficulty
Social network analysis (Ahn, 2013; Joksimović et al., 2016; Zhu et al., 2016), Social network analysis (Discussion forum) (Hecking et al., 2016), Collaboration network (Southavilay et al., 2013), Epistemic network (Fougt et al., 2018), Classifying student behaviour (Håklev et al., 2017), Group participation (Tervakari et al., 2014), Connectedness (Scheffel et al., 2017), Online discussion (forum) behaviour (McAuley et al., 2012), Collaboration (Scheffel et al., 2017), Collaborative learning (Harrer & Göhnert, 2015), Mediation analysis (Niaki et al., 2019), Peer assessment ability (Vozniuk et al., 2014), Predict performance (social network analysis) (Paredes & Chung, 2012), Epistemic network analysis of online discussions (Ferreira et al., 2020), Forum network analysis (Poquet & Jovanovic, 2020), Diffusion network analytics and clustering students' by roles (Saqr & Viberg, 2020)	Social analysis
Self-regulated learning (Chen et al., 2017; Davis et al., 2018; Pardo et al., 2016), Self-regulation (Davis et al., 2018; Ruiz et al., 2016; Schumacher & Ifenthaler, 2018), Self-efficacy (Jovanović et al., 2019), Self-motivation (Chen et al., 2017; de Quincey et al., 2019; Govaerts et al., 2011), Alerting (Manai et al., 2016), Self-reflection (Manai et al., 2016; Santos et al., 2013), Feedback (Corrin & de Barba, 2014; Khan & Pardo, 2016), Metacognitive awareness (Davis et al., 2017), Awareness (Brouwer et al., 2016; Govaerts et al., 2011), Video analytics (Self-reflection) (Gašević et al., 2014), Resource usage awareness (Santos et al., 2013), Self-regulated learning (Kia et al., 2020; Molenaar et al., 2020; Saint et al., 2020), Self-regulated learning (behavioural logs) (Quick et al., 2020), Reflections (automated assessment) (Jung & Wise, 2020), Self-assessment feedback (Delnoij et al., 2020), Self-directed learning and student feedback (Yousuf et al., 2020)	Self-regulation
Affective state (Allen et al., 2016; Grawemeyer et al., 2016), Self-reported affective state, Emotion (Sedrakyan et al., 2017), Emotional state (Ruiz et al., 2016), Measure a fixed mindset, Measure belonging uncertainty, Measure stereotype threat (Questionnaires) (Manai et al., 2016)	Affective state
Time distribution (Santos et al., 2013), Time Planning (Harrer & Göhnert, 2015), Timeline (status and goal) (Schumacher & Ifenthaler, 2018), Temporal analysis (Papamitsiou et al., 2014), Time management and learning strategies/tactics (Uzir et al., 2020)	Analysis of time management
Curriculum planning/designing, Teacher curriculum usage (Monroy et al., 2013), Content quality (Gunnarsson & Alterman, 2014), Syllabus quality/design (Smolin & Butakov, 2012)	Curriculum analytics
Academic performance (Matcha et al., 2019), Performance (Agnihotri et al., 2017; Aljohani et al., 2019; Coffrin et al., 2014; Elbadrawy et al., 2015; Iandoli et al., 2014; Park & Jo, 2015; Syed et al., 2019; Venant et al., 2017), Student efficiency (Muñoz-Merino et al., 2013), Cognitive activity, Eye fixations (eye-tracking) (Chatti et al., 2014), Presentation skills (Multimodal) (Ochoa Xavier & Castells, 2018; Schneider et al., 2016), Procrastination (Agnihotri et al., 2017; Davis et al., 2018; Paule Ruiz et al., 2015), Productivity (Scheffel et al., 2017), User knowledge level (Kump	Performance

(Continues)

TABLE 2 (Continued)

Indicators originally named in the literature	Clusters of indicators
et al., 2012), Student interaction patterns (relation to performance) (Saqr et al., 2018), Student comparison (Aljohani et al., 2019; de Quincey et al., 2019), Performance rating (Majumdar et al., 2018), Predict performance (Arnold & Pistilli, 2012; Barber & Sharkey, 2012; Boroujeni et al., 2016; Brouwer et al., 2016; Davis et al., 2018; Pardo, et al., 2016; Pardo, Mirriahi, et al., 2016; You, 2016), Predict performance (social network analysis) (Paredes & Chung, 2012), Predict performance (Game) (Käser et al., 2017), Teachers comparison (van Leeuwen & Rummel, 2020), Predict student performance (Jovanović et al., 2020), Predicting learners' performance (Tuti et al., 2020), Analysing performance behaviour (on learning record stores) (Labba et al., 2020), Procrastination (teacher email reminder intervention) (Nikolayeva et al., 2020), Student-controlled social comparison (Akhuseyinoglu et al., 2020)	
Course assessments (Cooper & Khosravi, 2018), Course planning (Brown et al., 2016), Course recommendation (Pardos & Jiang, 2020)	Course analytics
Dataset evaluation (for recommender systems) (Verbert et al., 2011), Recommendations (Duval, 2011), Recommendations for successful course completion (Schumacher & Ifenthaler, 2018), Resource recommendation (Chavarriaga et al., 2014; Vesin et al., 2013), Course recommendation (Pardos & Jiang, 2020), Learning resource recommendations (Keyword extraction from videos) (Schulten et al., 2020), Learning path recommenders and students' activities (course and review periods) (Zhang et al., 2020)	Recommendations
Writing engagement (Liu et al., 2014), Writing analysis, Reflective writing (Shum et al., 2016), Text analysis (Allen et al., 2016), Assignments quality (Fougt et al., 2018) Writing analytics (Conijn et al., 2020; Southavilay et al., 2013)	Writing analytics
Exploratory dialogue (Ferguson & Shum, 2011), Discourse analysis (Chiu & Fujita, 2014; Hecking et al., 2016; Wang et al., 2016), Discussion engagements (Wise et al., 2014), Discussion contribution quantity & quality (Tan et al., 2017), Discussion forum quality (Beheshitha et al., 2016), Teacher discourse analysis (Schlotterbeck et al., 2020)	Discourse analytics
Learning behaviour patterns (Jovanović et al., 2017), Learning patterns (Govaerts et al., 2011; Wang et al., 2019), Student interaction patterns (relation to performance) (Saqr et al., 2018), Student interaction patterns (Bakharia & Dawson, 2011), Student behaviour (Park et al., 2017), Learning behaviour (Ferguson & Clow, 2015; Venant et al., 2017), Learning strategies (Venant et al., 2017), Learning strategies (Davis et al., 2018; Gasevic et al., 2017; Matcha et al., 2019), Learning strategy (Game) (Käser et al., 2017), Students consistency clusters (Sher et al., 2020), Time Management and Learning Strategies/tactics (Uzir et al., 2020), Predicting learners' effortful behaviour (multimodal data LA) (Sharma et al., 2020), Learning strategies (trace data) (Quick et al., 2020), Analysing performance behaviour (on learning record stores) (Labba et al., 2020)	Learning (behaviour) patterns
Badges earned (Holman et al., 2013), Gamification (Melero et al., 2015), Game-based learning, Learning strategy (Game), Predict performance (Game) (Käser et al., 2017), Game analytics (math classrooms) (Shabrina et al., 2020), Game Analytics (curriculum sequencing) (Akintunde et al., 2020)	Game analytics
Video analytics (Self-reflection) (Gašević et al., 2014), Video analytics (Li et al., 2015), Comment analytics (YouTube videos) (Abolkasim et al., 2016), Video engagements/analytics (der Zee et al., 2018), Lecture videos thermal analytics (Srivastava et al., 2020)	Video analytics
Reading analytics (Klebanov et al., 2019; Sadallah et al., 2015; Tan et al., 2017), Ideal reading material (Sadallah et al., 2015), Active reading rating (Majumdar et al., 2018)	Reading analytics
Engagement and disengagement (Multimodal) (Worsley, 2018), Engagement and disengagement (Feild et al., 2018), Engagement (Coffrin et al., 2014; Papoušek et al., 2016), Long term engagement (Zhu et al., 2016), Measure engagement (Boroujeni et al., 2016), Keystroke analytics (Casey, 2017), Clickstream analysis (Park et al., 2017), Video engagements/analytics (der Zee et al., 2018), Carelessness (Hershkovitz et al., 2013), Engaged concentration (Wang et al., 2015), Initiative, Responsiveness, Presence (Scheffel et al., 2017), Engagement rating, Attendance rating (Majumdar et al., 2018), Online change detection (Shimada et al., 2018), Collaborative engagement (Child robot Interaction) (Kim et al., 2020), Students' engagement with personalized feedback (Iraj et al., 2020)	Engagement
Learning progress (LMS Usage) (Muñoz-Merino et al., 2013), Student progress (LMS activities) (Manai et al., 2016), Measure success (Joksimović et al., 2016), MOOC completion (Pursel et al., 2015), User knowledge level (Kump et al., 2012), Predicting Student Success (Van Goidsenhoven et al., 2020)	Progress
Students classification (Li et al., 2015; Papamitsiou et al., 2016), Pass-fail classification (Casey, 2017), Clustering (educational data mining) (Bogarin et al., 2014), Competency (Davis et al., 2017), Students consistency clusters (Sher et al., 2020)	Clustering

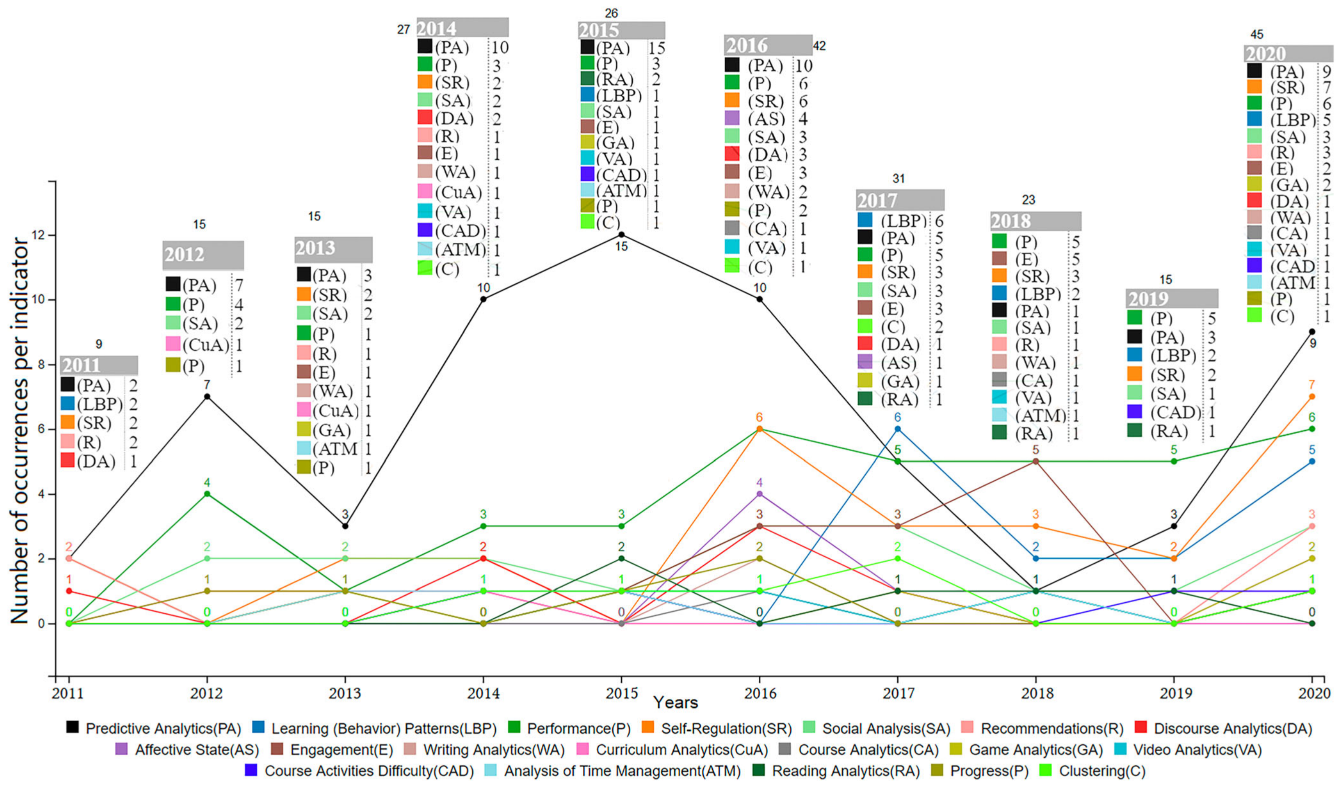

FIGURE 4 The number of occurrences of the most commonly used indicators over the past 10 years

present section, we start by considering how learning activities are described and used in the literature of LA and then provide an overview of the learning activities that are most frequently described in the literature as being used for collecting user data. We then discuss the difference between metrics and indicators and show how indicators are dependent on metrics. In the analysis section, we merge indicators and create clusters to show their relevance and popularity among researchers. Lastly, we provide a visual representation of our main findings.

4.1 | Description of learning activities

Our comprehensive literature review recognized that publications used the terms 'activities' and 'learning activities' indiscriminately. In this article, we always refer to this term as 'learning activities'. Regarding the learning activities, we also identified cases where the learning activities described in the analysed publications do not necessarily align with the LD definition of learning activities. For example, in the paper (Park & Jo, 2015), the authors consider clicks/views as actions. However, mere/procedural actions (e.g., clicks, views, etc.) are not considered as learning activities in LD (Horton, 2011). Based on the alignment between LA and LD, we identified four different ways in which learning activities have been described in the LA literature: 1. procedural actions, 2. LD activities, 3. LD activities and procedural actions, and 4. no explicit activities mentioned, see Table 1.

Ten publications fell into the first description because they only consider procedural actions as learning activities when collecting data from LMS to apply LA techniques. For example, in (Casey, 2017) the authors consider keystrokes, hits and clicks to measure keystroke and pass-fail classification, while in (Park et al., 2017), the authors consider views, downloads and clickstream analysis when measuring student behaviour. We identified 58 publications that collect data only from LD learning activities and fall into the second description. For example, in (Rogers et al., 2014), student learning activities from current and previous courses are used to measure at-risk students and exam success prediction. A study by (Fancsali, 2011) presents a second example, where group work, peer review, and assessment are considered to predict student grades. Further, 93 research publications fall into the third description (learning activities and procedural actions). For example, in (Jovanović et al., 2017), learning activities like reading, views, and exercise are used to find learning behaviour patterns. A study by (Chen et al., 2017) shows another example of this category. In this study, the learning activities like clickstream, views, quiz, assignment, homework, and watching videos are used to measure self-motivation and self-regulated learning. We identified 12 research papers that fall into the fourth description. These papers do not explicitly mention any learning activity for collecting data, instead, they only state the metrics they used for the development of the indicators. For example, (Dawson et al., 2017) mentions metrics such as student gender and age, student academic load, intervention attempts, student study period and semesters, number of students, total enrolments, and academic data (like current course & semester outcomes) in relation to the development of an indicator to 'predict early alert & student retention'.

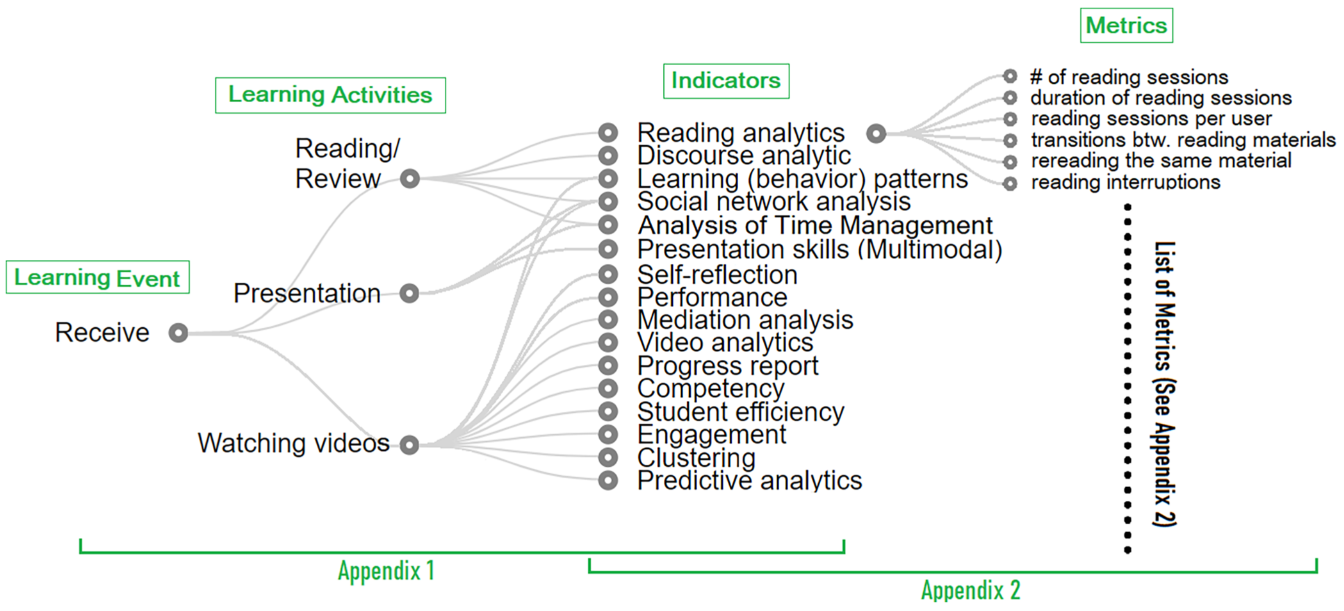

FIGURE 5 A tree view of 'receive' event followed by the learning activities, indicators, and metrics.

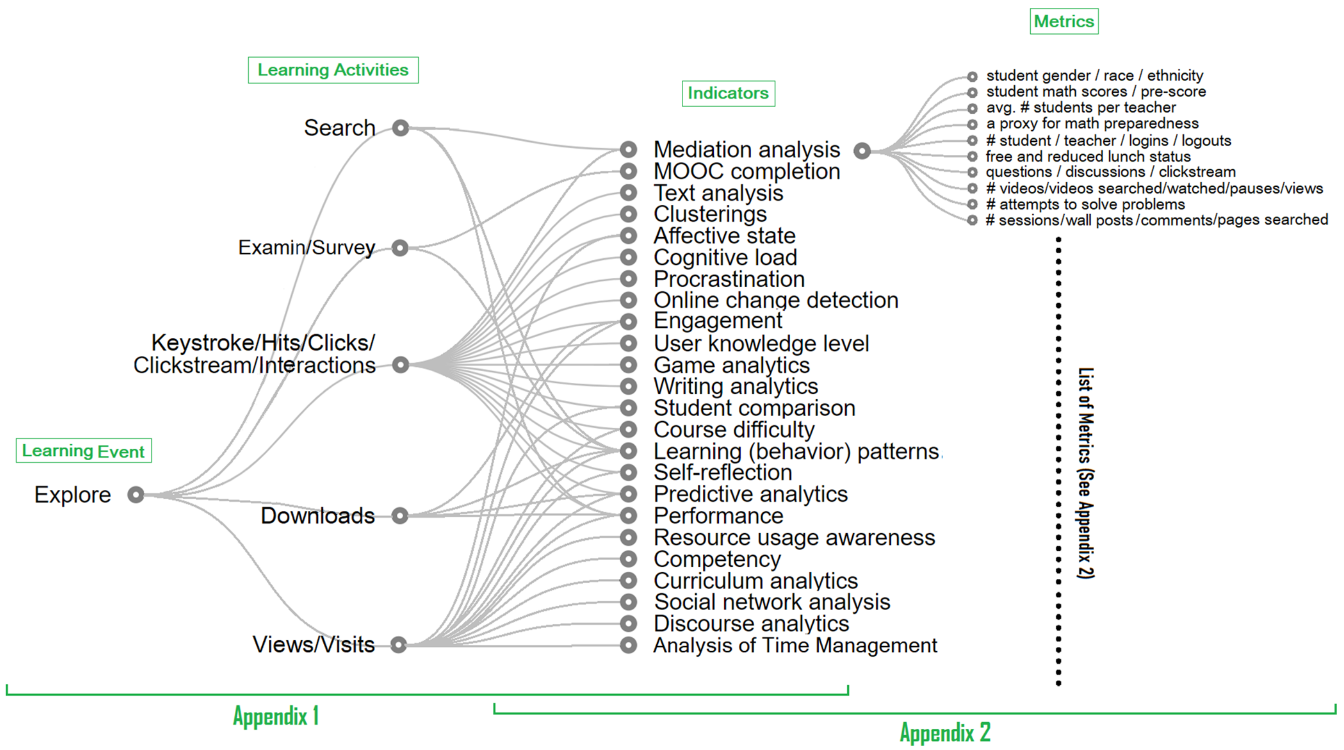

FIGURE 6 A tree view of 'explore' event followed by the learning activities, indicator, and metrics.

4.1.1 | Popular learning activities

Overall, we identified a total of 40 distinctive learning activities from the 161 papers. Seven of them were only procedural actions. We excluded them since procedural actions should not be considered as learning activities in terms of LD (Horton, 2011). We were left with 33 different learning activities that are useful in designing a course. The top three most commonly identified learning activities are tests/quizzes, watching videos and questions/questionnaires.

The learning activity 'tests/quizzes' appeared in 16 publications. An example of this learning activity is found in (Paule Ruiz et al., 2015), in which the authors recorded the times of the first attempts in solving the tests/quizzes and the time taken until the quizzes were completed. The learning activity 'watching videos'

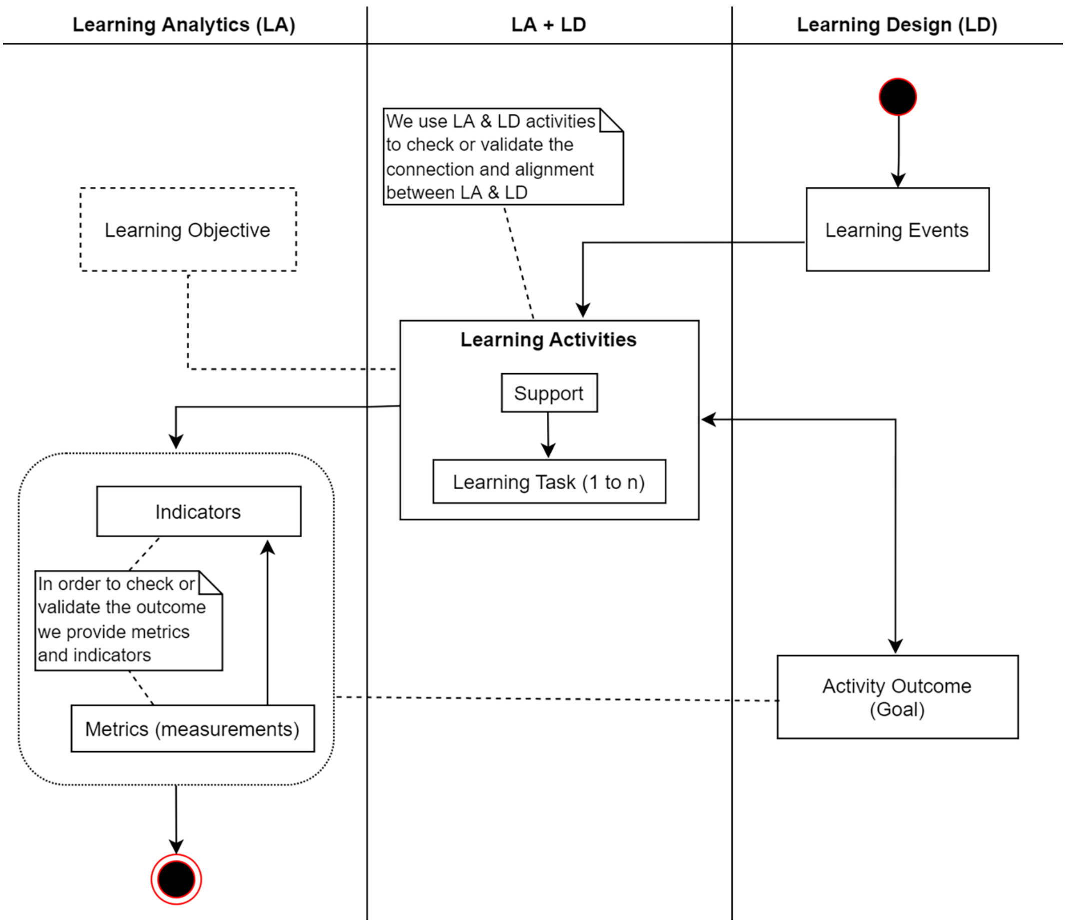

FIGURE 7 Process flow

appeared in 17 publications. Analysis of this learning activity is exemplified by (Muñoz-Merino et al., 2013), in which to measure the efficiency of a user, the authors gathered watched videos time length, the total time spent on completed videos, and the number of times a video was repeated. Further, in (Gašević et al., 2014), the authors used video annotations to support and measure self-reporting, where they also captured video access times, duration of access, frequency of access and so forth. The learning activity 'questions' appeared in 15 publications. A study by (McAuley et al., 2012) exemplifies the use of this learning activity. In this study, a learner posts a question and other students answer the question, and a teacher (superuser) has the right to accept the most suitable answer.

4.2 | Metrics and indicators

While extracting the indicators used in the published papers, we have found that many studies mixed the terms 'metrics' and 'indicators'. As stated in Section 2.2, in this study, the term 'metric' is referred to as the data collected (measurements) about the learning activity that a learner carries out in a learning environment. Metrics are used to create indicators. An 'indicator' then, is the result of a metric or combination of multiple metrics that give a more comprehensive picture of a particular learner's status, for example, predict student grade, self-reflection and so forth.

Our analysis enabled us to identify that every indicator is the formation of a single metric or multiple metrics (see Table A2). However, some specific advance indicators are the product of multiple indicators. For example, the indicator 'productivity' contains indicators like initiative, responsiveness, presence and connectedness. According to (Scheffel et al., 2017), these indicators have the following metrics.

- **Initiative** = *number of posts (discussion, blog, files, pages)*
- **Responsiveness** = *number of comments (discussion, blog, files, pages)*
- **Presence** = *number of views*
- **Connectedness** = *number of contacts made*
- ***Productivity*** = *(Initiative + Responsiveness)/Presence* (Scheffel et al., 2017).

4.2.1 | Clusters of indicators

In our literature review, we have found 135 indicators in total. Many of these indicators share similar goals and also work in similar ways. However, different studies named them differently (e.g., predict academic achievement, exam success prediction, predict exam grades, etc.). For our analysis, we decided to cluster similar indicators. For example, we merged 'predict academic achievement', 'exam success prediction', 'predict exam grades', and so forth, to 'predictive analytics'. A second example consists of the indicators self-motivation, self-reflection, self-regulated learning, alerting, awareness to 'self-regulation'. Through this process, we identified a total of 19 clusters of indicators, and the full list of indicators and clusters of indicators is displayed in Table 2 in no specific order. A few of the indicators fall into two different clusters. For example, the indicator 'predict performance' lies in 'predictive analytics', 'performance' as well as in 'game analytics'. Similarly, video engagements/analytics (der Zee et al., 2018) appear in 'engagement' as well as in 'video analytics'.

4.2.2 | Most popular indicators

The three clusters of indicators that occurred the most are 'predictive analytics', 'performance', and 'self-regulation'. The indicator cluster of 'predictive analytics' appeared 62 times in the sample of research publications. Predictive analytics was used to predict course successful completion (Santos et al., 2014), predict early alert & student retention (Dawson et al., 2017), dropout prediction (Aguiar et al., 2014, 2015; Manrique et al., 2019; Waddington & Nam, 2014) and so forth. The second most frequently identified indicator cluster was 'performance' which appeared 35 times, this indicator mostly being used to measure the student academic performance (Agnihotri et al., 2017; Aljohani et al., 2019; Coffrin et al., 2014; Elbadrawy et al., 2015; Iandoli et al., 2014; Matcha et al., 2019; Park & Jo, 2015; Syed et al., 2019; Venant et al., 2017). The third most popular indicator cluster was 'self-regulation' which appeared 24 times, and was used in the design of dashboards to provide effective feedback (Corrin & de Barba, 2014) and to alert students about their progress (Manai et al., 2016). The full list of indicators and corresponding metrics is shown in Table A2.

Figure 4 presents the number of occurrences of the most commonly used indicators over the past 10 years, where the cluster 'predictive analytics' was the only cluster of indicators that was used consistently and was popular among the LA researchers. This cluster of indicators was proposed in the year 2011, and in the following year 2012, it was implemented and presented by quite a few publications. But solely in the year 2018, the popularity graph of predictive analytics dropped sharply, but in the year 2020 again, its popularity jumped up notably among the LA society of researchers.

Further, in Figure 4, the cluster of indicators that have also been popular in the LA publications since 2011 are 'performance' and 'self-regulation', which have appeared and been reported in the last 5 years consistently. A cluster of indicators worth mentioning is 'affective state', which appeared in the year 2016 with quite a high popularity, and also picked up in the following year 2017, but disappeared from then on. We can also observe how the cluster of indicators 'learning (behaviour) patterns' was introduced in 2011 and since 2017 is becoming more prominent.

We connected the extracted metrics with their corresponding indicators and the indicators with their corresponding learning activities. Finally, we connected the learning activities with the corresponding learning events to examine how state-of-the-art LA fits our proposed classification framework (see Section 2.3) and how it aligns with LD (see Tables A1 and A2). This enables us to obtain a holistic view of how LD and LA are related to each other. We identified that this relationship could be clearly represented as tree data structures. There are eight learning events (see Section 2.1) that come as a pragmatic tool that has been shown to be valid in practice (i.e., Receive, Explore, Practice, Imitate, Create, Debate, Meta-learn and Experiment) (Leclercq & Poumay, 2005; Verpoorten et al., 2007). We generated two trees as an example for learning events 'Receive' and 'Explore' following our proposed reference framework (see Figures 5 and 6). These figures were created using the D3[2] visualization library to exemplify two out of the eight learning events. Figure 5 shows the tree view for the event 'Receive'. For example, the inclusion of the event 'Receive' in the design of a course implies that four possible learning activities could take place, that is, reading, review, presentation and watching videos (see Figure 5). Every learning activity can have multiple indicators. For example, the learning activities 'reading' and 'review' have five possible indicators, that is, reading analytics, discourse analytics, learning behaviour patterns, social network analysis and analysis of time management (see Figure 5). Further, each indicator consists of multiple metrics. For example, reading analytics has six metrics (measurements), that is, number of reading sessions, duration of reading sessions, reading sessions per user, transitions between reading materials, rereading the same material, and reading interruptions (see Figure 5). In this manner, Figure 6 shows a tree view for the event 'Explore', which is followed by its corresponding learning activities, indicators, and metrics.

A full list showing the identified connections among learning events, learning activities, indicators and metrics is shown in Table A1 (learning events, learning activities, indicators) and Table A2 (indicators and metrics).

5 | DISCUSSION AND CONCLUSION

o study the association of LA indicators with learning events and learning activities of LD (RQ1), first, we proposed a reference framework. The reference framework is based on a general literature research on LD and LA, which shows how LA indicators have already been associated with LD events and learning activities, as exemplified in Figures 5 and 6 (see Tables A1 and A2 for full details). The proposed reference framework (see Figure 3) helped us to organize and analyse the results from our literature review (see Tables A1 and A2). This framework enabled us to organize the LA indicators identified in the literature in terms of the LD events and learning activities related to them. As learning activities play a fundamental role in LD (Mor & Craft, 2012) as well as in LA, our reference framework uses learning activities as a common factor in LA and

[2]https://d3js.org/

LD to establish a link and further lead us to meaningful indicators. A process flow of this framework is displayed in Figure 7.

Our proposed alignment of LD events and activities and LA metrics and indicators is a step forward towards a better alignment of these two fields which is a need already mentioned by different studies (Blumenstein, 2020; Macfadyen et al., 2020; Mangaroska & Giannakos, 2017, 2018). This framework, therefore, provides an answer to our RQ1 regarding how LA indicators are associated with learning events and learning activities related to the LD.

To answer our second research question, 'Which learning analytics indicators have been researched and used in the past 10 years according to the learning analytics literature?', we conducted a literature review in which we analysed LA indicators based on their corresponding (learning) activities. First, we identified a disorganized field where there was no clear definition of indicators, metrics and so forth. Moreover, the field also showed some discrepancy in the definition of learning activities. Indeed, as pointed in our results, many research papers considered procedural actions such as mouse clicks to be learning activities. This particular finding aligns with the concern that the data driven approach of LA does not necessarily align with pedagogy (Jivet et al., 2017, 2018; Macfadyen et al., 2020). Nonetheless, through our analysis we were able to identify these issues and to create a list of LA indicators and their corresponding metrics. Analysis from our literature review provides an overview of the published list of indicators ordered by their year of publication (see Table A2 for full details). Furthermore, our analysis of the literature shows how the use of indicators and metrics has evolved over the past decade of LA (see Figure 4). This overview enables us to get a glimpse of how the field has been evolving, what have been the most commonly used indicators by the research community and provides us with hints regarding future research on LA indicators.

Furthermore, we consider that the alignment between LA and LD proposed by our framework can also contribute to the assessment and improvement of LD. LA indicators can also evaluate and denote learning activities and tasks through activity outcomes in LD, providing information that supports the redesign and improvement of the learning activities and so leading to improvement in learning. Most of the work in the field of LD is done on the practices, depictions, and tools that support it and on the processes for distributing its results among the stakeholders (Mor & Craft, 2012). However, there is very little work done in terms of the practices, depictions, and tools used for the evaluation of the effects/results of the designs (Macfadyen et al., 2020; Mor & Craft, 2012).

We consider that by classifying the LA indicators with our proposed framework, we can support teachers and learning designers in understanding which indicators to use/select based on the events and learning activities. However, we recognize that LD is a complicated and broad field of study, and our approach may not be the only way of aligning these two sophisticated and partly similar fields.

These classified LA indicators enable the creation of a repository of commonly used practices that can help educational practitioners who want to apply LA to their LD. The results of our literature review show that it is possible to present the course designer with a list of indicators that align with the selected course activities and that have already been successfully used in the past. Moreover, our results can provide further support by showing the metrics (data from learners) that need to be collected in order to generate the desired indicators (see Table A2 for full details). We argue that a LA indicator repository that is structured according to our proposed reference framework can therefore help to bridge the existing gap between pedagogy and LA.

Another contribution of this research is the provision of clear definitions of 'metrics' and 'indicators'. While conducting the literature review, we identified a mixed-use of these terms. We argue that a clear definition of these terms can avoid some confusion, help to align the findings and move the field forward.

5.1 | Limitations

This study has four main limitations. First, the selected sample of publications was limited since we mostly focused on LAK proceedings. Therefore, we acknowledge that we might have missing indicators, metrics, and trends. Nonetheless, we consider that our sample of publications was good enough to provide satisfactory answers to our research questions. The study will be continued, and we will be adding new sources of literature. Second, there may be bias in the clustering of indicators, for example, we put the indicator 'user knowledge level' in the cluster of 'progress' but one could also argue that this indicator can fit in 'performance'. Third, there could be a small margin of error in data harvesting due to human lapses or slips. Fourth, as mentioned in the discussion, we recognize that LD is a complicated and broad field of study, and our approach may not be the only way of aligning these two sophisticated and partly similar fields. Regardless of these limitations, we considered that the main findings of this study are valid enough to contribute to the state-of-the-art of LA and LD research.

5.2 | Future work

We foresee four main future research directions that could be grounded on this work and therefore contribute to support of learning through LA and LD. The first is to investigate how to present the results collected in this literature review to teachers, course designers and educational researchers with the purpose of supporting them with the design and evaluation of new educational interventions. Second, to investigate how, based on the proposed reference framework, LA dashboards can be used to evaluate the outcomes of the LD. Third, there is a need for an LA indicators repository, which takes LD events and activities as input and presents users with the possible LA indicators and metrics along with their visualization on a dynamic LA dashboard. Fourth, to investigate how to continuously, dynamically or automatically update this LA indicators repository (proposed in the previous point) with latest LA publications (indicators and metrics). This can be achieved by investigating how to automatically extract learning events, learning activities, indicators, and metrics from LA publications with the purpose to keep a LA repository up to date.

We believe that this study brings the field of LA a step closer to play a significant role in the development of education.

DATA AVAILABILITY STATEMENT

Data sharing is not applicable to this article as no new data were created or analyzed in this study.

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APPENDIX A

TABLE A1 The list of indicators used for learning events and learning activities

Learning event	Learning activities	Indicators
Create (Lowes et al., 2015)	Design (Cooper & Khosravi, 2018; Méndez et al., 2014; Monroy et al., 2013; Smolin & Butakov, 2012), Group work (Coffrin et al., 2014; de Quincey et al., 2019; Fancsali, 2011; Figueira, 2015; Iandoli et al., 2014; Koulocheri & Xenos, 2013; Ruiz et al., 2016; Santos et al., 2013; Tervakari et al., 2014), Collaboration (Chiu & Fujita, 2014; Elbadrawy et al., 2015; Håklev et al., 2017; Harrer & Göhnert, 2015; Southavilay et al., 2013; Vesin et al., 2013)	Classifying student behaviour, Collaborative learning, Collaboration network, Course Assessments, Course difficulty, Curriculum Planning/designing, Discourse Analysis, Emotional state, Group Participation, Engagement performance, Predictive analytics, Resource Recommendation, Resource usage awareness, Self-Regulation, Self-motivation, Syllabus quality/Design, Teacher curriculum usage, Time Distribution/Planning, Writing analytics, Student comparison
Explore (Ferguson & Clow, 2015; Venant et al., 2017)	Examine (Ferguson & Clow, 2015), Survey (Pursel et al., 2015), Search (Matcha et al., 2019; Niaki et al., 2019), Keystroke (Allen et al., 2016; Casey, 2017), Hits/Clicks (Aguiar et al., 2014; Brouwer et al., 2016; Casey, 2017; Conijn et al., 2016; de Quincey et al., 2019; Hlosta et al., 2017; Jovanović et al., 2019; Koulocheri & Xenos, 2013; Paule Ruiz et al., 2015; Syed et al., 2019), Clickstream (Chen et al., 2017; Davis et al., 2018; Niaki et al., 2019; Park et al., 2017; Shimada et al., 2018; Wolff et al., 2013), Views (Aguiar et al., 2014; Beheshitha et al., 2016; Chen et al., 2017; Coffrin et al., 2014; Conijn et al., 2016; de Quincey et al., 2019; Elbadrawy et al., 2015; Grawemeyer et al., 2016; Hart et al., 2017; Jovanović et al., 2017; Lowes et al., 2015; Park et al., 2017; Ruiz et al., 2016; Scheffel et al., 2017; Syed et al., 2019; Tervakari et al., 2014; Wang et al., 2019), Visits (Aljohani et al., 2019; Bakharia & Dawson, 2011; Corrin & de Barba, 2014; Davis et al., 2017; Matcha et al., 2019; Monroy et al., 2013; Park & Jo, 2015; Santos et al., 2013), Interactions (Bakharia & Dawson, 2011; Benedetto et al., 2020; Davis et al., 2018; Käser et al., 2017; Khan & Pardo, 2016; Kia et al., 2020; Kump et al., 2012; Labba et al., 2020; Liu et al., 2014; Pardo et al., 2016; San Pedro et al., 2015; Saqr et al., 2018; Sher et al., 2020; Uzir et al., 2020; Van Goidsenhoven et al., 2020; van Leeuwen & Rummel, 2020; Wei et al., 2020; Yousuf et al., 2020; Yu & Jo, 2014; Zhang et al., 2020), Downloads (Figueira, 2015; Matcha et al., 2019; Park et al., 2017; Yu & Jo, 2014)	Passing rate prediction, Final Grade Prediction, Performance prediction, Awareness, Affective State, At-Risk Students, Clickstream Analysis, Cognitive load, Competency, Course difficulty level, Curriculum Planning/designing, Discussion forum quality, Dropping out, Emotional state, Engagement and performance, Feedback, Predictive analytics, Game Based Learning, Group Participation, Keystroke analytics, Learning Strategy (Game), Learning behaviour/strategies, MOOC completion, Mediation analysis, Metacognitive Awareness, Online change detection, Pass-Fail Classification, Perceived difficulty, Procrastination, Resource Usage Awareness, Self-Regulation, Self-efficacy, self-motivation, Self-reflection, Self-regulated Learning, Student Interaction Patterns, Student behaviour, Student comparison, Student interaction patterns, Teacher curriculum usage, Text analysis, Time Distribution, User knowledge level, Writing Engagement
Practice	Exam (Agnihotri et al., 2017; Holman et al., 2013; Jo et al., 2014; Jovanović et al., 2019; Manai et al., 2016; McKay et al., 2012; Rogers et al., 2014; Waddington & Nam, 2014; You, 2016), Test (Brown et al., 2016; der Zee et al., 2018; Kump et al., 2012; Paule Ruiz et al., 2015), Quiz (Agnihotri et al., 2017; Aljohani et al., 2019; Chen et al., 2017; Conijn et al., 2016; Davis et al., 2017, 2018; Hart et al., 2017; Hecking et al., 2016; Holman et al., 2013; Melero et al., 2015; Paule Ruiz et al., 2015; Santos et al., 2014; Shimada et al., 2018), Exercise (Hecking et al., 2016; Jovanović et al., 2017, 2019; Matcha et al., 2019; Muñoz-Merino et al., 2013; Ruiz et al., 2016), Task (Bogarin et al., 2014; Chatti et al., 2014; Corrin & de	Badges earned, Predictive analytics, Performance, Affective State, Alerting, At-risk students, Classifying Student behaviour, Clustering (educational data mining), Cognitive activity, Cognitive load, Competency, Completion, Course Assessments, Course Planning, Discourse Analysis, Early Warning, Emotional state, Engagement and Disengagement, Eye fixations (eye tracking), Feedback, Game Based Learning, Gamification, Group Participation, Learning Behaviour Patterns, Learning Progress, Learning Strategies, Measure fixed mindset (Questionnaires), Metacognitive Awareness, Online change detection, Peer Assessment ability, Perceived difficulty, Procrastination, Resource usage awareness,

TABLE A1 (Continued)

Learning event	Learning activities	Indicators
	Barba, 2014; Kump et al., 2012; Schumacher & Ifenthaler, 2018; Tuti et al., 2020; Verbert et al., 2011), Writing (Allen et al., 2016; Liu et al., 2014; Shum et al., 2016; Southavilay et al., 2013), Group work (Coffrin et al., 2014; de Quincey et al., 2019; Fancsali, 2011; Figueira, 2015; Iandoli et al., 2014; Koulocheri & Xenos, 2013; Ruiz et al., 2016; Santos et al., 2013; Tervakari et al., 2014), Peer review/assessment (Fancsali, 2011; Figueira, 2015; Hart et al., 2017; Schumacher & Ifenthaler, 2018; Vozniuk et al., 2014) (Delnoij et al., 2020; Jovanović et al., 2020; Malekian et al., 2020; Saint et al., 2020; Schlotterbeck et al., 2020) Assignment/homework (Chen et al., 2017; Coffrin et al., 2014; Conijn et al., 2016; Corrin & de Barba, 2014; Feild et al., 2018; Hart et al., 2017; Kennedy et al., 2015; McKay et al., 2012; Paule Ruiz et al., 2015; Santos et al., 2014; Syed et al., 2019; Wang et al., 2019), Questions (Cooper & Khosravi, 2018; Davis et al., 2017, 2018; der Zee et al., 2018; Håklev et al., 2017; Jovanović et al., 2019; Käser et al., 2017; Khan & Pardo, 2016; Kump et al., 2012; McAuley et al., 2012; Papamitsiou et al., 2014; Papoušek et al., 2016; Pardo et al., 2016; Pardo, Mirriahi, et al., 2016), Questionnaire (Chiu & Fujita, 2014; Kump et al., 2012; Manai et al., 2016; McAuley et al., 2012; Ruiz et al., 2016)	Self-efficacy, Self-motivation, Self-regulated learning, Social Network Analysis, Student comparison, Student efficiency, Student progress, Temporal Analysis, Text Analysis, Time Distribution, Timeline (status and goal), User knowledge level, Video engagements/analytics, Writing analytics, Engagement, Procrastination, Self-motivation, Assessment Readiness Prediction
Imitate	Presentation (Harrer & Göhnert, 2015; Ochoa Xavier & Castells, 2018; Schneider et al., 2016), Exercise (Hecking et al., 2016; Jovanović et al., 2017, 2019; Matcha et al., 2019; Muñoz-Merino et al., 2013; Ruiz et al., 2016)	Academic Performance, Cognitive load, Collaborative Learning, Discourse Analysis, Emotional state, Learning Behaviour Patterns, Learning Progress, Learning Strategies, Perceived difficulty, Presentation skills (multimodal), Self-regulation, Self-efficacy, Social network analysis, Student efficiency, Time planning
Receive	Reading (Gasevic et al., 2017; Harrer & Göhnert, 2015; Jovanović et al., 2017; Klebanov et al., 2019; Majumdar et al., 2018; Sadallah et al., 2015; Tan et al., 2017; Wise et al., 2014), Review, (Wise et al., 2014), Watching videos, (Ahn, 2013; Chen et al., 2017; Coffrin et al., 2014; Davis et al., 2017; der Zee et al., 2018; Ferguson & Clow, 2015; Gasevic et al., 2017; Gašević et al., 2014; Håklev et al., 2017; Koulocheri & Xenos, 2013; Li et al., 2015; Muñoz-Merino et al., 2013; Niaki et al., 2019; Syed et al., 2019; Wang et al., 2019; You, 2016; Zhu et al., 2016), Presentation, (Harrer & Göhnert, 2015; Ochoa Xavier & Castells, 2018; Schneider et al., 2016)	At-risk students, Classifying Student behaviour, Collaborative Learning, Competency, Discussion Contribution Quantity & Quality, Discussion Engagements, Engagement and performance, Predictive analytics, Ideal reading material, Learning Behaviour Patterns, Learning Patterns, Learning Progress, Learning Strategies, Long Term Engagement, Mediation analysis, Metacognitive Awareness, Presentation Skills (Multimodal), Reading Analytics, Self-motivation, Self-regulated Learning, Social Network Analysis, Student Classification, Student efficiency, Time Planning, Video analytics, Video engagements/analytics, Writing Engagement, learning behaviour
Debate (Conijn et al., 2016; Iandoli et al., 2014)	Forum discussion (Aljohani et al., 2019; Barber & Sharkey, 2012; Beheshitha et al., 2016; Chiu & Fujita, 2014; Ferreira et al., 2020; Hecking et al., 2016; Iandoli et al., 2014; Malekian et al., 2020; Matcha et al., 2020; Poquet & Jovanovic, 2020; Santos et al., 2013; Saqr & Viberg, 2020; Scheffel et al., 2017; Sharkey, 2011; Tan et al., 2017; Uzir et al., 2020; Wang et al., 2016; Wise et al., 2014), Group work (Coffrin et al., 2014; de Quincey et al., 2019; Fancsali, 2011; Figueira, 2015; Iandoli et al., 2014; Koulocheri & Xenos, 2013; Ruiz et al., 2016; Santos et al., 2013;	Alerting, Classifying student behaviour, Cognitive load, Comment analytics (YouTube videos), Competency, Content quality, Course assessments, Discourse analysis, Discussion engagements, Discussion forum quality, Emotional state, Engagement and performance, Exploratory dialogue, Game Based Learning, Group Participation, Learning Strategy, Long Term Engagement, MOOC completion, Measure fixed mindset (Questionnaires), Mediation analysis, Metacognitive Awareness, Perceived difficulty, Predictive analytics, Reading analytics, Resource

(Continues)

TABLE A1 (Continued)

Learning event	Learning activities	Indicators
	Tervakari et al., 2014), Comments (Abolkasim et al., 2016; Beheshitha et al., 2016; Figueira, 2015; Gunnarsson & Alterman, 2014; Koulocheri & Xenos, 2013; Niaki et al., 2019; Pursel et al., 2015; Santos et al., 2013; Scheffel et al., 2017; Tan et al., 2017; Wise et al., 2014), Posts (Ahn, 2013; Bogarin et al., 2014; Conijn et al., 2016; Ferguson & Shum, 2011; Gunnarsson & Alterman, 2014; Hart et al., 2017; Hecking et al., 2016; Lowes et al., 2015; Scheffel et al., 2017; Tervakari et al., 2014; Wise et al., 2014; Zhu et al., 2016), Discourse (Chiu & Fujita, 2014; Hecking et al., 2016; Wang et al., 2016), Review (Wise et al., 2014), Question (Cooper & Khosravi, 2018; Davis et al., 2017, 2018; der Zee et al., 2018; Håklev et al., 2017; Jovanović et al., 2019; Käser et al., 2017; Khan & Pardo, 2016; Klebanov et al., 2019; Kump et al., 2012; McAuley et al., 2012; Papamitsiou et al., 2014; Papoušek et al., 2016; Pardo et al., 2016; Pardo, Mirriahi, et al., 2016), Questionnaire (Chiu & Fujita, 2014; Kump et al., 2012; Manai et al., 2016; McAuley et al., 2012; Ruiz et al., 2016), Presentation (Harrer & Göhnert, 2015; Ochoa Xavier & Castells, 2018; Schneider et al., 2016), Vote (poll) (Figueira, 2015)	Usage Awareness, Self-Regulated Learning, Self-efficacy, Self-motivation, Self-reflection/Feedback, Social Network Analysis, Student comparison, Temporal Analysis, Time Distribution, User knowledge level, Video engagements/analytics, Procrastination
Meta-learn	Feedback (Corrin & de Barba, 2014; Grawemeyer et al., 2016; Khan & Pardo, 2016; Matcha et al., 2019; Ochoa Xavier & Castells, 2018; Schneider et al., 2016), Self-learning/reporting (Gasevic et al., 2017; Manai et al., 2016; Ruiz et al., 2016; Sedrakyan et al., 2017), Analysis (Chiu & Fujita, 2014), Peer review/assessment (Fancsali, 2011; Figueira, 2015; Hart et al., 2017; Schumacher & Ifenthaler, 2018; Vozniuk et al., 2014); (Delnoij et al., 2020; Jovanović et al., 2020; Malekian et al., 2020; Saint et al., 2020; Schlotterbeck et al., 2020), Review (Wise et al., 2014)	Academic Performance, Affective State, Completion, Discourse Analysis, Emotion, Emotional state, Feedback, Learning Strategies, Measure fixed mindset (Questionnaires), Peer Assessment ability, Presentation Skills (Multimodal), Self-Regulation, Self-Reported Affective State, Self-reflection, Student progress, Timeline (status and goal)
Experiment	Game (Holman et al., 2013; Käser et al., 2017; Melero et al., 2015), Problem solving (Akhuseyinoglu et al., 2020; Matcha et al., 2019; Molenaar et al., 2020; Niaki et al., 2019; San Pedro et al., 2015; Wang et al., 2015), Exercise (Hecking et al., 2016; Jovanović et al., 2017, 2019; Matcha et al., 2019; Muñoz-Merino et al., 2013; Ruiz et al., 2016)	Academic Performance, Badges earned, Cognitive load, Discourse Analysis, Emotional state, Engaged Concentration, Game Based Learning, Gamification, Learning Behaviour Patterns, Learning Progress (LMS Usage), Learning Strategies (Game), Mediation analysis, Perceived difficulty, Predict Performance (Game), Predictive analytics, Self-Regulation, Social Network Analysis, Student efficiency

TABLE A2 List of indicators and their matrices

Year	Indicators (sorted yearly 2011–2019)	Metrics
2011	Self-monitoring, learning patterns, awareness (Govaerts et al., 2011) Student interaction patterns (Bakharia & Dawson, 2011) Recommendations (Duval, 2011) Exploratory dialogue (Ferguson & Shum, 2011) Predictive analytics (proposal) (Sharkey, 2011) Prediction (A pilot study) (Fancsali, 2011) Dataset evaluation (for recommender systems) (Verbert et al., 2011)	# resources used, resource usage time, min/max/avg. # resources used, min/max/avg. time spent (Govaerts et al., 2011) Discussion forum interactions, forum visits/replies, isolated students, connections (Bakharia & Dawson, 2011) Time spent on the course, avg. time spent on a document, # documents/student, avg. time of the day students work, avg./max/min time spent, avg./max/min # documents used (Duval, 2011) Mean no. of posts per min, mean word count per min, mean no. of exploratory posts per min, mean word count exploratory posts per min, mean no. of posts per contributor, mean word count per contributor, mean exploratory posts per contributor, mean word count of exploratory posts per contributor (Ferguson & Shum, 2011) Student schedules, student demographics, # students/courses, student contact data, assignment/course grades, discussion forum activities, content usage tracking (Sharkey, 2011) Student age, sex, pell grant eligibility, GPA, avg. MBA course final exam score, avg. peer review score, student public/group msg. Count, inst. Private msg. Count, chapter view count, avg. assignment score, final exam/course grade, message creator/timestamp/content, forum messages (Fancsali, 2011) # Users/items/activities, publicly available, reads/tags/ratings/search, download/add to collection, collaborations, learning goal/task, learning sequence, competencies/experience level time (Verbert et al., 2011)
2012	Performance prediction, success prediction (Barber & Sharkey, 2012) User knowledge level (Kump et al., 2012) Online discussion (forum) behaviour (McAuley et al., 2012) Performance prediction (Arnold & Pistilli, 2012) Success prediction (McKay et al., 2012) Predict performance (Paredes & Chung, 2012) College student retention, at-risk students (Lauria et al., 2012)	Cumulative course points per week, prior credits earned, discussion post count, ratio of credits earned/attempted, attendance, days into the course of 1st activity, orientation participation, inactive time since last course, # messages to instructor (Barber & Sharkey, 2012) # User interactions/actions, questions/questionnaire, task solving/test, forum replies/answers (Kump et al., 2012) Reputation of person posting a question/answer, background of person, posting history, ratings, connections (McAuley et al., 2012) % Points earned in course/previous course, high school GPA, credits attempted (Arnold & Pistilli, 2012) Student record information, assignment/exam scores, in-class performance scores, standardized test scores, planned study hours, desired grade/study habits, student comparisons (McKay et al., 2012) Networks/connections, # edge, edge weight (Paredes & Chung, 2012) Gender, age, GPA/grades, # course sessions compared to course avg., # content resources viewed compared to course avg., full-time or part-time enrollment (Lauria et al., 2012)
2013	Final grade prediction (Koulocheri & Xenos, 2013) Time distribution, resource usage awareness, self-reflection (Santos et al., 2013) Badges earned (Holman et al., 2013) Resource recommendation (Vesin et al., 2013) Writing analytics, collaboration network (Southavilay et al., 2013)	# Bookmarks in group, # new blog posts in group blog, # topics that each user has uploaded on group discussion, # uploads of new files on group files page, # comments on bookmarks uploaded by other group members, # comments on blog posts in group blog, # comments on topics of group

(Continues)

TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
	Learning progress (LMS Usage), student efficiency (Muñoz-Merino et al., 2013) Social Network analysis (Ahn, 2013) At-risk students, retention prediction (Wolff et al., 2013) Teacher curriculum usage, curriculum planning/designing (Monroy et al., 2013) Carelessness (Hershkovitz et al., 2013)	discussion, # comments on files uploaded by other group members, # comments on wireposts of other group member (Koulocheri & Xenos, 2013) Time spent in application, # posts/tweets/comments/visits, discussion (group work) (Santos et al., 2013) Learning objectives reached, points earned, quiz/exam (Holman et al., 2013) Personal data (name, age, address, gender, prior knowledge), performance data (cognitive style, instruction mode, delivery mode, interaction kind, skills gained, reasoning ability, collaborative skill), learner history (knowledge level, prerequisites, current unit, current level, overall time, test results) (Vesin et al., 2013) Document revisions, collaboration - (group) writings/editings, writing sessions/days, text writings/editings location/time, Student most/least edits, # authors worked on each paragraph/section, # group members (Southavilay et al., 2013) # Completed/available/started videos, total video length/time Spent on videos, # attempted/available exercises, time spent on exercises/platform, # (recommended) exercise attempts (Muñoz-Merino et al., 2013) # Emails received/sent on social media, # wall posts received, # status messages posted, # links shared, # member pages user has joined/networks joined, # photos posted, # friends/connections, # posts written/videos posted (Ahn, 2013) # Clicks/views, clickstream, quiz grades (Wolff et al., 2013) # Logins/logouts, # days teacher logged, time span for visits, #visits, teacher activities compared to student grades (improved, remained the same, dropped) (Monroy et al., 2013) Student making error despite knowing the solution (slipping) (Hershkovitz et al., 2013)
2014	Group participation (Tervakari et al., 2014) Feedback (Corrin & de Barba, 2014) Writing engagement (Liu et al., 2014) Discussion engagements (Wise et al., 2014) Performance (Iandoli et al., 2014) Content quality (Gunnarsson & Alterman, 2014) Dropping out (Aguiar et al., 2014) Clustering (educational data mining) (Bogarin et al., 2014) Academic success, course recommendation (Nam et al., 2014) Temporal analysis (Z. K. Papamitsiou et al., 2014) Engagement and performance (Coffrin et al., 2014) Predict course successful completion (Santos et al., 2014) At-risk students, exam success prediction (Rogers et al., 2014) Video analytics (self-reflection) (Gašević et al., 2014) Peer assessment ability (Vozniuk et al., 2014) Course difficulty (Méndez et al., 2014)	# Content read/words produced/comments, student active/passive in discussions, activity timing, content views, web resources, discussions posts (Tervakari et al., 2014) Grades, # finished tasks, # logins, # course visits, learning activities (reading exams assignments.) (Corrin & de Barba, 2014) # interactions with the document, resource usage (Liu et al., 2014) Posts read, # posts/comments, # days/times students logged into discussion, avg. session/post length, % of sessions with posts, # reviews of own/other posts (Wise et al., 2014) Idea creation (mind map style), idea connection creation, website annotation, discussion (group participation), degree of centrality of discussion, discussion type (question/answer/challenge/pro/con), #content creation, #connection making (Iandoli et al., 2014) # Likes/comments/replies/posts, # promotions/tags, login time (Gunnarsson & Alterman, 2014) LMS activities (#hits/clicks #views #logins sessions) (Aguiar et al., 2014)

TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
	Predict exam grades (Jo et al., 2014; Waddington & Nam, 2014), Early warning, dropout prediction (Waddington & Nam, 2014) Discourse analysis (Chiu & Fujita, 2014) Predict academic achievement (Yu & Jo, 2014) Resource recommendation (Chavarriaga et al., 2014)	Course, device IP address, time & date, time spent on theoretical contents/ practical tasks/forums, time student took to check the content/access the task, time until task is submitted, # words/sentences written in forum posts, pass/fail students (Bogarin et al., 2014) Prior records, high school records, act/sat math scores, ap calculus exams, enrolled courses (Nam et al., 2014) Student activities, answering computer based tests, time spent on questions answered correctly/incorrectly, goal expectancy, preparedness of the student (Papamitsiou et al., 2014) Student weekly participation (assignment/quizzes), student (total/avg.) marks, cumulative grades in the first two to three weeks, students groups comparison, 'auditors' (watched video but did not participate), 'active' (participated in an assessment this week), 'qualified' (grades in 60th percentile in first two weeks), video views, assignment submissions (Coffrin et al., 2014) Total assignments, # submissions/posts, quiz/assignment grades, forum communication (Santos et al., 2014) Gender age, English speaking background, course repetitions, being enrolled full-time, exams history, avg. grade/GPA/overall grades, LMS login timings, prerequisite courses failing history, academic progress (Rogers et al., 2014) # Video annotations/annotations, #videos/videos watched (Gašević et al., 2014) Peer grading/rating, # peers, grades, mean/median of grades, # assignments/ reports (Vozniuk et al., 2014) course avg. grade is on avg. worse than the gpa of a student (Méndez et al., 2014) Course dependence (Pearson's correlation coefficient btw. Course pairs) LMS usage (login frequency login time resource activities resource usage time), learning regularity (by taking the mean and standard deviation of the intervals btw. Login times) (Jo et al., 2014; Waddington & Nam, 2014), Course information, lecture resources, assignment resources, exam preparation resources, other learning resources (Waddington & Nam, 2014) Student (age gender subject), student forum discussions, collaboration 80, questionnaire responses (opinions), analyse text (opinion elaboration evidence) (Chiu & Fujita, 2014) LMS studying time/login frequency, regularity of learning interval in LMS, # downloads, interactions with peers/instructor, forum activities (Yu & Jo, 2014) Resource rating, current student/former students competence (Chavarriaga et al., 2014)
2015	Passing probability (De-la-Fuente-Valentin et al., 2015) Gamification (Melero et al., 2015) Collaborative learning, time planning (Harrer & Göhnert, 2015) Predict exam success (Lowes et al., 2015)	Score in practical activities/theoretical activities, similarity to peers wrt to LMS usage (De-la-Fuente-Valentin et al., 2015) Quiz points, # attempts to solve question, # correct/incorrect attempts, total attempts, time spent (Melero et al., 2015)

(Continues)

TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
	Predict college major (by middle school learning behaviour), Predictive analytics (San Pedro et al., 2015) Learning behaviour (Ferguson & Clow, 2015) Dropout prediction, at-risk student, early warning (Aguiar et al., 2015) Grade prediction (performance, course difficulty), performance, course difficulty level (Elbadrawy et al., 2015) Early warning prediction, retention (Harrison et al., 2015) Procrastination (Paule Ruiz et al., 2015) Student classification, video analytics (Li et al., 2015) Reading analytics, ideal reading material (Sadallah et al., 2015) Predict student grades (Figueira, 2015) Performance (Park & Jo, 2015) MOOC completion (Pursel et al., 2015) Engaged Concentration (Wang et al., 2015) Predict college major (by middle school learning behaviour), predictive analytics (San Pedro et al., 2015) learning behaviour (Ferguson & Clow, 2015) Dropout prediction, at-risk student, early warning (Aguiar et al., 2015) Grade prediction (by performance & course difficulty level), performance, course difficulty level (Elbadrawy et al., 2015) Early warning prediction, retention (Harrison et al., 2015) Procrastination (Paule Ruiz et al., 2015) MOOC completion (Pursel et al., 2015) Student classification, video analytics (Li et al., 2015) Reading analytics, ideal reading material (Sadallah et al., 2015) Predict student grades (Figueira, 2015)	Time spent on reading/planning/discussion forum, make notes, present/post (Harrer & Göhnert, 2015) # Logins/days of access, total sessions, LMS activities (clicks, views, exams.), # posts viewed/created (Lowes et al., 2015) Student previous interactions, student knowledge (# problems solved), carelessness (making errors), affect and disengaged behaviours (boredom, engaged concentration, confusion & frustration), rankings (San Pedro et al., 2015) Completing (learners that complete the majority of assessments), auditing (learners that watch most of the videos but infrequently complete assessments), disengaging (learners that complete assessments at the start of the course but then reduce their engagement), sampling (learners that explore some course videos) (Ferguson & Clow, 2015) Gender, age, yearly absence/tardiness rate, # suspension incidents/ unexpected entries/withdrawals, whether student is new to the school district, quarter marking period avg., math proficiency level, whether a student was retained in a grade, whether a student graduated from high school on time (Aguiar et al., 2015) GPA over previous courses, avg. grade achieved, collaboration, forum discussions initiated/views, course material views, # course contributions (Elbadrawy et al., 2015) Student gender, age at commencement, age squared, highest degree, prior grade distribution, workload (courses), grades (Harrison et al., 2015) # Clicks in mandatory/recommended resources, # submitted assignments, time spent until completed quizzes, time until first click on a mandatory/ recommended resource, time until first submission of an assignment, time until first attempt in the evaluation test, student grade (Paule Ruiz et al., 2015) # Pauses/forward seeks/backward seeks, median duration of pauses, proportion of skipped video content, replayed video length, avg. video speed, effective video speed change (Li et al., 2015) # & Duration of reading sessions, reading sessions per user, transitions btw. Reading materials, rereading the same material, reading interruptions (Sadallah et al., 2015) Group work, file uploads/downloads/edit/changes/comments, read comments, peer grading, vote for accomplishment (Figueira, 2015) Login time/frequency, repository visits, time spent (Park & Jo, 2015) # Videos/posts per week, # comments per week, age, English skills, education level, MOOC pre-survey (Pursel et al., 2015) # Responses, time spent on a problem, avg. correctness in last 20 s, # total hints (Wang et al., 2015) Student previous interactions, student knowledge (# problems solved), carelessness (making errors), affect and disengaged behaviours (boredom, engaged concentration, confusion & frustration), rankings (San Pedro et al., 2015)

TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		Completing (learners that complete the majority of assessments), auditing (learners that watch most of the videos but infrequently complete assessments), disengaging (learners that complete assessments at the start of the course but then reduce their engagement), sampling (learners that explore some course videos) (Ferguson & Clow, 2015) Gender, age, yearly absence/tardiness rate, #suspension incidents/unexpected entries/withdrawals, whether student is new to the school district, quarter marking period avg., math proficiency level, whether a student was retained in a grade, whether a student graduated from high school on time (Aguiar et al., 2015) GPA over previous courses, avg. grade achieved, collaboration, forum discussions initiated/views, course material views, # course contributions (Elbadrawy et al., 2015) Student gender, age at commencement, age squared, highest degree, prior grade distribution, workload (courses), grades (Harrison et al., 2015) # Clicks in mandatory/recommended resources, # submitted assignments, time spent until completed quizzes, time until first click on a mandatory/recommended resource, time until first submission of an assignment, time until first attempt in the evaluation test, student grade (Paule Ruiz et al., 2015) # Videos/posts/comments per week, age, English skills, education level, MOOC pre-survey (Pursel et al., 2015) # Pauses/forward seeks/backward seeks, median duration of pauses, proportion of skipped video content, replayed video length, avg. video speed, effective video speed change (Li et al., 2015) # Reading sessions, duration of reading sessions, reading sessions per user, transitions btw. Reading materials, rereading materials, reading interruptions (Sadallah et al., 2015) Group work, file uploads/downloads/edit/changes/comments, read comments, peer grading, vote for accomplishment (Figueira, 2015)
2016	Passing rate prediction, final grade prediction, performance prediction, awareness (Brouwer et al., 2016) Discussion forum quality (Beheshitha et al., 2016) Presentation skills (multimodel) (Schneider et al., 2016) Self-regulation, emotional state (Ruiz et al., 2016) Affective state (Grawemeyer et al., 2016) Affective state, text analysis (Allen et al., 2016) Engagement (Papoušek et al., 2016) Student progress (LMS activities), Measure fixed mindset/belonging uncertainty/stereotype threat (Questionnaires), alerting, self-reflection (Manai et al., 2016) Social network analysis (discussion forum), discourse analysis (Hecking et al., 2016) Writing analysis, reflective writing (Shum et al., 2016)	Avg. Grade, # clicks in LMS, Lecture Attendance, Time spent on Videos/Courses, Time Submitted before Deadline, Time before first attempt (Brouwer et al., 2016) Avg. # messages posted, # Comments compared to class avg./top contributors, # posted messages per forum, # visualization views per forum (Beheshitha et al., 2016) Video Sensor Data, Body movement, # gestures (hand), Audio Sensor Data, voice speed/level, # pauses (Schneider et al., 2016) Student attendance, classroom activities (exercise, report or group work), Satisfaction questionnaire, positive emotion Items (enjoyment, hope, pride, confidence, excitement & interest), negative emotion Items (anxiety, anger, shame, hopelessness, boredom & frustration), Interviews (Ruiz et al., 2016) Feedback views/feedback followed (Grawemeyer et al., 2016)

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TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
	Long term engagement, social network analysis (Zhu et al., 2016) Feedback (Khan & Pardo, 2016) Students classification (Papamitsiou et al., 2016) Measure success, social network analysis (Joksimović et al., 2016) Retention prediction (Robinson et al., 2016) Discourse analysis (Wang et al., 2016) Success prediction (Kennedy et al., 2015) Predict performance (by self-regulation metrics), Self-regulated learning (Pardo et al., 2016) Course planning, early warning (Brown et al., 2016) Performance prediction (Pardo, Mirriahi, et al., 2016) Success prediction (Conijn et al., 2016) Comment analytics (YouTube Videos) (Abolkasim et al., 2016) Performance prediction (You, 2016) Measure engagement, predict performance (Boroujeni et al., 2016) Productivity = (Initiative + Responsiveness)/Presence, Collaboration (Scheffel et al., 2017) Eye fixations (eye tracking), cognitive activity (Chatti et al., 2014)	# Keystrokes/backspaces per essay, total keystrokes, longest/shortest time btw. Keystrokes per essay, mean/median keystroke latency, initial pause before writing essay, # pauses above 0.5/1/1.5/2/3 s (Allen et al., 2016) Questions/answers, avg. error rate for answers, error rates comparison, # attempts, response time, # learners, learners feedback on questions difficulty, % feedback (Papoušek et al., 2016) Student demographics, self-report survey, Student performance (assessment), course grades, final exam (Manai et al., 2016) Discussion threads (lectures/exercises/quizzes), users/anonymous users, user posts/anonymous posts, replies (Hecking et al., 2016) Formal/informal rubrics, words listed in rubrics, text patterns (Shum et al., 2016) Score/grade, # posts initiated/commented/replied/viewed, # video lectures downloaded/played (Zhu et al., 2016) Video clips interactions, questions next to video clips, resource access, dashboard access (Khan & Pardo, 2016) Total time to answer correctly, Total time to answer incorrectly, Total idle time, effort (composite feature), Actual Performance, Goal Expectancy (Z. Papamitsiou et al., 2016) student Achievement, Gender/age, Group (student, instructor), students mutual ties, ratings, existence of simmelian ties, social connections (MOOC), degree/closeness/betweenness centrality (Joksimović et al., 2016) Student Demographics, Previous MOOC enrollments/completed, Material status, Currently Employed/Enrolled in School, Bachelors/Advanced Degree, Parent with Bachelor/Advanced Degree, Continent of living (Robinson et al., 2016) Forum discussion, forum activities (posts, replies…) (Wang et al., 2016) # Assignment submissions, switch btw. Assignments without submitting one, total points (Kennedy et al., 2015) LMS Interactions (clicks, views.), Interactions with videos/multiple choice questions next to videos/questions in course notes, Access to HTML Resources, Expanding/Collapsing of a section, Dashboard access (Pardo et al., 2016) Test results, class size, # enrolled credit hours, course access timings, # student contacts with teacher/advisor, course earned points, difference from course avg., course logins (Brown et al., 2016) # Play pause events in the video for the week, # times a question next to a video clip was answered, # times a question in the course notes was answered, # questions answered correctly or incorrectly (Pardo, Mirriahi, et al., 2016) Assessment grade/avg. grade, # online sessions, total online time, avg. time per session, time until first activity, # course/resources views, irregularity of study time/interval, largest period of inactivity, # clicks/links/content views, # discussion posts/views, # quizzes started, # attempts per quiz/quizzes

TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		passed/quiz views, # assignments submitted, # assignment views, # wiki views (Conijn et al., 2016) Ranking videos, Variety, # ontology super classes, Balance/Disparity (Abolkasim et al., 2016) Exam Score (midterm + final), Regular Study (Time of Video Watching), Viewing Time, # Sessions/Messages/Late Submissions, Proof of Reading the Course Instructions (You, 2016) Peak on day hour/weekday, Weeks Similarity Measure, Periodicity of day hour/week hour/weekday, Delay in lecture view (Boroujeni et al., 2016) # Posts (discussion, blog, files, pages), # comments (discussion, blog, files, pages), # views, # contacts made, Final grades/Avg. score, Course, avg. # actions/connections (Scheffel et al., 2017) # Students, # fixations, fixation time stamp, task (introduction, instruction, hints, code editor, output), # tasks/completed tasks/submitted tasks, correct/incorrect tasks, solutions/time spent, sequence of saccades, eye movement coordinates, screen capture (video) (Chatti et al., 2014)
2017	Discussion contribution quantity and quality, reading analytics (Tan et al., 2017) Classifying student behaviour (Håklev et al., 2017) Metacognitive awareness, competency (Davis et al., 2017) Self-reported affective state, emotion (Sedrakyan et al., 2017) Learning behaviour/strategies, Performance (Venant et al., 2017) At-risk students, early warning (Hlosta et al., 2017) Procrastination, performance (Agnihotri et al., 2017) Clickstream analysis, student behaviour (Gruber, 2019) Game-based learning, learning strategy (Game), predict performance (Game) (Käser et al., 2017) Learning behaviour patterns (Jovanović et al., 2017) Learning strategies (Gasevic et al., 2017) Predict final grade (Hart et al., 2017) Pass–fail classification, keystroke analytics (Casey, 2017) Self-motivation, self-regulated Learning (Chen et al., 2017) Predict early alert & student retention (Dawson et al., 2017)	# Comments/likes/replies, avg. replies, network (discussions & connections) (Tan et al., 2017) # Answers/questions asked, # videos watched, time btw. Videos watched (Håklev et al., 2017) Quiz submission timeline, time watching videos/on platform, # videos accessed/forum visits/sessions per week/questions attempted, % of time spent on videos/quizzes, mean session length/time btw. Sessions, avg. time on platform per week, # visited video lectures/forum contributions (Davis et al., 2017) Student info., resources used (e.g., forums, blogs or files), # resource usage, student time/class avg. time, students comparison, student content creation (Sedrakyan et al., 2017) # Submissions/times help seeked, percent of commands executed successfully (% success), avg. time spent btw. Two submissions (Venant et al., 2017) student age/qualification/region/gender, declared disability, # previous attempts, # currently studied credits, # consecutive active days, first and last day of activity, # click/avg. and median of clicks, # materials visited per day, # active days in VLE, # resource/forum clicks per day (Hlosta et al., 2017) Class start date, course materials/resources access, materials access/purchase delay, # purchases/accesses, access period, # students, % students access materials since the start of semester, assignment/quiz scores, final/avg. scores (Agnihotri et al., 2017) # Clicks/views/downloads, time detection, views/downloads file prior to event start date, views/downloads file after event end date (Gruber, 2019) # Teams/team members, simulation interactions, explore/challenge activity modes, # explore/challenge questions, # questions/remaining questions, correct/incorrect answers/time spent, # students/student completed challenge questions, # challenge attempts/correctly answered questions, scores/points (Käser et al., 2017)

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TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		# Correctly/incorrectly solved assessment exercises, # correctly/incorrectly solved MCQs, # solutions requested for assessment item, course video views, reading material page views, dashboard views, schedule and learning objective page views (Jovanović et al., 2017) Formative assessment done correctly/incorrectly, requesting the solution for a formative assessment item, watching a course video, reading course content (Gasevic et al., 2017) # Forums/posts/views, # quiz attempts, time of assignment submission before the deadline, time of peer grading before deadline (Hart et al., 2017) # Successful compilations, successful compilations avg. complexity, # failed compilations, failed compilations avg. complexity, ratio btw. on-campus and off-campus connections, # connections, time spent on the platform, time spent on slides within the platform, time spent typing in platform, time idle in platform, slides coverage, # slides visited/opened, # transactions (activity), # transactions during/outside labs, # transactions in the platform (Casey, 2017) Course grades, # videos/video watched, frequently watched videos, # quizzes/assignments, # files/forums, clickstream (Chen et al., 2017) Age/gender, academic load, intervention attempt, study period/semester, # students, total enrolments, academic data (current course & semester outcome) (Dawson et al., 2017)
2018	Engagement and disengagement (multimodal) (Worsley, 2018) Presentation skills (multimodal) (Ochoa Xavier & Castells, 2018) Assignments quality, epistemic network (Fougt et al., 2018) Engagement and disengagement (Feild et al., 2018) Self-regulation, learning strategies, predict performance, procrastination (Davis et al., 2018) Course assessments (Cooper & Khosravi, 2018) Recommendations for successful course completion, self-regulation, timeline (status and goal) (Schumacher & Ifenthaler, 2018) Student interaction patterns (relation to performance) (Saqr et al., 2018) Performance rating, engagement rating, active reading rating, attendance rating (Majumdar et al., 2018) Online change detection (Shimada et al., 2018) Video engagements/analytics (der Zee et al., 2018)	# video segment/segments per participant, # left and right hand/wrist gestures/movements/gestures (Worsley, 2018) gaze tracking using camera, body posture using camera, pauses using audio sensor, volume using audio sensor, # movements/gestures (Ochoa Xavier & Castells, 2018) student essay keywords/all students essays keywords, # keywords (Fougt et al., 2018) Avg. grade, avg. time spent on assignments relative to class avg., % assignments submitted/submitted late/on time/not submitted, days since last submission, submission time relative to due date (Feild et al., 2018) clickstream, course/content/resource/exercise page interactions, quiz interactions, quiz points, questions/answers, time spent, # accesses/active days/sessions, avg. session duration/avg. clicks per session, avg. time until a student returns, active/inactive students (Davis et al., 2018) # students/topics/tags, students' backgrounds, course materials, competency among the students, achievements/grades, resources used, MCQs/questions/answers, ratings/discussions (Cooper & Khosravi, 2018) Time spent online, peers feedback, feedback for assignments, rating learning material, time to complete a task or read a text, comparison with fellow students, considering the students personal calendar for appropriate learning recommendations, newsfeed with relevant news matching the learning content revision of former learning content, reminder for deadlines, term scheduler (Schumacher & Ifenthaler, 2018)

TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		Time spent, # interactions, achievement (high or low), # early bird interactions, # early course interactions, grade (Saqr et al., 2018) Marker/memo count, time spent, reading completion/sequence, marker/memo content, engagement score/rating, active reading rating, performance/attendance/student/teacher rating, assessment scores (Majumdar et al., 2018) # Students/# clicks, avg. of quiz score, std. of quiz score, Avg. clicks, sd. of clicks, time duration (Shimada et al., 2018) Videos watched, in-video questions, summarize video content, questions/answers, correct/incorrect answers, weekly quizzes/tests, assignments, # students read/write summaries, grades (der Zee et al., 2018)
2019	Student performance, student comparison (Aljohani et al., 2019) Academic performance, learning strategies (Matcha et al., 2019) Student comparison, grade prediction, self-motivation (de Quincey et al., 2019) At-risk students, performance (Syed et al., 2019) Learning patterns (Wang et al., 2019) Perceived difficulty, self-efficacy, cognitive load (Jovanović et al., 2019) Reading analytics (Klebanov et al., 2019) Mediation analysis (Niaki et al., 2019) Dropout prediction (Manrique et al., 2019)	# student visits, avg. class visits, avg. of active students, highest visits, quiz results, # discussion forum/views/participations (Aljohani et al., 2019) Videos with MCQs, reading materials with MCQs, problem-solving activities (exercises), correct/incorrect exercises, correct/incorrect MCQs, solution requested for MCQs, play/pause/end the course video, reading materials visits, index page visits, project information page visits, dashboard visits, search for keyword, documents/files downloads (Matcha et al., 2019) # Clicks/views, # content views/clicks, lectures/practicals/coursework clicks, total/avg. time of content accesses, # days per week, avg. time btw. Content accesses, avg. group size of simultaneous content accesses, # clicks grouped by parent folder, # seen/unseen content, #/total lecture views, module grades, absences (practicals and lectures) (de Quincey et al., 2019) Login/logout, resource/video views/clicks, assignment submissions/attempts, time watching course videos, avg. views, most viewed video segments, video pauses, weekly prompt score, class participation score (Syed et al., 2019) # Videos watched, # students/assignment submissions, # forum posts/views/participants, # videos/video pauses/video-watching days, return to most recently watched video, return after a long time, return to previously skipped, overall grade, student education background, # student replies with strong education background, # student replies with college-level education background (Wang et al., 2019) Student engagement with the pre-class course activities, reading materials, # videos/quizzes/MCQs/exercises/questions, # correct/incorrect answers, request solutions, # clicks/views, timestamp, # evaluations per student/activity, final exam score (Jovanović et al., 2019) # Reading turns (mean, standard, min, max), # questions answered (mean, std, min, max), % answered correctly (mean, std, min, max), total audio time recorded (mean, std, min, max), avg. reading rate, timeline (Klebanov et al., 2019) Student gender, race, ethnicity, free and reduced lunch status, math scores/pre-score, a proxy for math preparedness, # logins/logouts, clickstream, questions/discussions, # videos/searched videos/video pauses, video views/videos watched, # attempts to solve problems, # sessions/wall posts/

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TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		comments/pages searched, # student/teacher, avg. # students per teacher (Niaki et al., 2019) # Courses/semesters, avg credits, # approved/failed courses, # failed courses (2nd attempt), # maximum courses attempts, grades mean/mean per semester, students grades mean difference, # courses in last semester, # credits completed/failed (Manrique et al., 2019)
2020	Assessment readiness prediction (Malekian et al., 2020) Predict student performance (Jovanović et al., 2020) Predicting learners' performance (Tuti et al., 2020) Predicting student success (Van Goidsenhoven et al., 2020) Predict students' choices (Faucon et al., 2020) Predicting learners' effortful behaviour (multimodal data LA) (Sharma et al., 2020) Predicting student performance (mouse movement) (Wei et al., 2020) Automated grading (mathematics) (Erickson et al., 2020) Reflections (automated assessment) (Jung & Wise, 2020) Perceived difficulty and discrimination of text (Benedetto et al., 2020) Epistemic network analysis of online discussions (Ferreira et al., 2020) Forum network analysis (Poquet & Jovanovic, 2020) Diffusion network analytics and clustering students' by roles (Saqr & Viberg, 2020) Self-regulated learning (Kia et al., 2020; Molenaar et al., 2020; Saint et al., 2020) Self-regulated learning (Kia et al., 2020; Molenaar et al., 2020; Saint et al., 2020) Self-regulated learning (Kia et al., 2020; Molenaar et al., 2020; Saint et al., 2020) Self-regulated learning (behavioural logs) (Quick et al., 2020) Self-assessment feedback (Delnoij et al., 2020) Self-directed learning and Student feedback (Yousuf et al., 2020) Teachers comparison (van Leeuwen & Rummel, 2020) Analysing performance behaviour (on learning record stores) (Labba et al., 2020) Procrastination (teacher email reminder intervention) (Nikolayeva et al., 2020) Student-controlled social comparison (Akhuseyinoglu et al., 2020) Course recommendation (Pardos & Jiang, 2020) Learning resource recommendations (Keyword extraction from videos) (Schulten et al., 2020) Learning path recommenders and students' activities (course and review periods) (Zhang et al., 2020) Writing analytics (Conijn et al., 2020; Southavilay et al., 2013) Teacher discourse analysis (Schlotterbeck et al., 2020) Time Management and Learning strategies/ tactics (Uzir et al., 2020) Learning strategies (trace data) (Quick et al., 2020) Game analytics (math classrooms) (Shabrina et al., 2020) Game analytics (curriculum sequencing) (Akintunde et al., 2020) Lecture videos thermal analytics (Srivastava et al., 2020) Collaborative engagement (Child robot Interaction) (Kim et al., 2020) Students engagement with personalized feedback (Iraj et al., 2020) Students consistency clusters (Sher et al., 2020)	Number of lectures viewed or downloaded, Number of lectures reviewed or redownloaded, Number of forums viewed, Number of failed submissions on the same assessment, Number of passed submissions on the other assessments, Number of failed submissions on the other assessments, Number of students enrolled, Number of assessments, Number of students engaged in assessments, Number of students dropping-out after assessment failure, Number of assessment submissions, Number of failed assessment submissions, Number of students completed (Malekian et al., 2020) User ID, Time (timestamp), Course, LMS module, Action (the action taken by the given student in the given module), Info (field with additional information about the action; its content depends on the type of action), URL (URL of the Web page within the course where the event occurred), Student final course marks, Number of assessments (and assessments submitted), Number of reexamined assessment requirements (and assignment-views), Number of quizzes (and quiz-attempts) Course views, Forum views, Number of forum posts, Number of forum posts updated, Forum subscribes, Student feedback views/quiz summary views (Jovanović et al., 2020) Learning sessions, Number of attempts they made at learning tasks, Number of questions answered/attempted, Time taken to complete the task Level of feedback provided on incorrect try, Cumulative count of opportunities at the specific learning task, Time since last attempt (Tuti et al., 2020) Time (the timestamp of the recorded event), Add a post (user creates new thread), Add user (user is added), Click bookmark (user used bookmark previously manually added), Click course tool heading (user clicks on link in the course tool heading), Click navigation bar (user selects any tab in the unit navigation bar to navigate through the course), Click resume (user resumes course where last left off), Load video (when video is fully rendered and ready to play), Next page (user clicks in navigation control to go to the next page), Page close (user closes the page), Pause video (user pauses the video), Play video (user starts to play the video), Previous page (user clicks in navigation control to go to the previous page), Reset problem (user resets the answer to a problem), Save answer of a problem (user saves the answer to a problem), Seek video (user seeks within a video), Select link (user clicks any hyperlink within the course content), Server grades submitted (server logs event when user submits and successfully saves an answer), Server problem checked (server logs event when user checks problem), Show answer of a problem (user clicks “Show answer” of a problem), Speed change video (user changes playing speed of video), Submit problem (user

TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		submits a problem), User enrollment (logged when user is successfully enrolled), Video completed (logged when user successfully finishes a video), View forum (user views a thread on the forum) (Van Goidsenhoven et al., 2020)
		Number of students, Student age, Student groups (younger/older), Exercises, Questions, Number of questions, Answers, Correct or incorrect answers, Number of answers, correct or incorrect, Sessions, Session time, Timestamp (Time taken answering), Number of topics, Number of sections (Faucon et al., 2020)
		Eye-tracking (record users' gaze), Fixations (the period of time where the eye is kept aligned with the target), Saccades (the type of eye movement used to move the fovea rapidly from one point of interest), Electroencephalography (a test that detects abnormalities in your brain waves), Face videos, Wristband data, Heart rate, Mean heart rate for a given question, Electrodermal Activity (EDA), Mean EDA for a given question, Body temperature (Skin temperature), Mean Temperature for a given question, Blood Volume Pulse (BVP), Mean BVP for a given question, Attention (Average fixation duration), Emotion intensity (based on Facial action Units), Cognitive load (Decreasing alpha and increasing theta band power), Mental workload (Alpha magnitude), Load on memory (theta band power) (Sharma et al., 2020)
		Score records, Number of Questions, Number of Trajectories (Mouse movement trajectories), Trace mouse events (mouse-move mouse-down mouse-drag mouse-up), Mouse movement Think-Time (Time-length Time-percent Event-length Event-percent), Mouse movement first-drag-and-drop (Time-length Time-percent Event-start-index Event-percent Event-end-index), Mouse movement first-attempt (event-end-index), Trace positions of the mouse during the whole problem-solving process, Number of Students, Grade, Timestamps, Number of Total submissions Number of 2nd submissions Percent of submissions (Wei et al., 2020)
		Number of unique students, Questions, Total student responses, Unique problems, Grades (Erickson et al., 2020)
		Total students, Reflective statements (student submitted text), Total statements, Personal id, Post id, Prompt type, Date of posting (Jung & Wise, 2020)
		Number of students, Number of interactions per student, Number of questions/items, Number of interactions per item, Timestamp of the interaction, Correctness per student, Correctness per item, Number of documents, Number of word occurrences per document, Number of most frequent keywords, Timestamps (Benedetto et al., 2020)
		Course grade, Number of messages, Word count (Word frequency), Number of threads, Number of apostrophes, Number of exclamation marks, Number of negative emotion, Number of negations, First person plural/singular, Second person, Number of question marks, Number of assent, Auxiliary verbs, Number of periods, Number all punctuation, Number of senses (core

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TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		meanings) of a word, Incidence score of pronouns, Dictionary words, Mean number of letters in the words within the text, Proportion of intersection tree nodes between all sentences, Total function words, Number of affiliations, Social processes, Number of clout-related words (Ferreira et al., 2020)
		Course forum, Discussion threads, Students enrolled, Students posts contributions, Post id, Author id, Target post id (that the current post was a response to), Thread id, Timestamp of post publication (Poquet & Jovanovic, 2020)
		Number of posts initiated, Number of students/teachers, Post ID, Subject, Content, Timestamp, Post author, Post target, Post replies, User IDs, User logs, User roles, Early posts, Number of posts, Total views of forums, Course grades, Group IDs, Outdegree centrality (total number of outcoming edges), Indegree centrality (total number of incoming edges), Degree centrality (sum of indegree and outdegree), Betweenness centrality (number of times a user has lied on the shortest paths between others), Closeness centrality (inverse distance between a course member and all others in the network), Diffusion centrality (probability that a person propagates information to contacts) (Saqr & Viberg, 2020)
		Total number of students, Student clicks/views Assignments, Tests, Quizzes, Reports, Average grade, Cumulative Grade Point Average/Final grade, Student groups (high mid-high mid-low and low performance groups), SRL survey constructs (i.e., motivation, planning, monitoring, and regulating) (Kia et al., 2020; Molenaar et al., 2020; Saint et al., 2020)
		Prior knowledge (Pre-test one-per-subskill), Post Knowledge (Post-test, one-per-subskill), Gain (Post-test pre-test per subskill), Process measures (Log file data), Unique problems (Number of unique problems completed per subskill), Accuracy unique problems (Correct unique problems/total unique problems completed), Score (Kia et al., 2020; Molenaar et al., 2020; Saint et al., 2020)
		Correctly solving a summative assessment item, Incorrectly attempted summative assessment item, Correctly solved formative assessment item (MCQ), Incorrectly attempted formative assessment item (MCQ), Solution request for an MCQ, Course video load, Course video play, Course video pause, Course video end, Reading materials access, Dashboard access, Index page access, Project page access, Accessing the schedule and the learning objective pages (Kia et al., 2020; Molenaar et al., 2020; Saint et al., 2020)
		The average amount of time (secs.) spent on assignment pages within Canvas, The average time (hours) between a participants first access of an assignment and its submission, The average length of time per web session within Canvas where an assignment is accessed, The average number of HTTP requests (page views) in sessions in which an assignment is accessed within Canvas, The average time (minutes) between first access of an assignment and its submission, Submissions, The number of assignment submissions created, The total count of views of assignments occurring prior to the deadline of the assignment, The total count of views of assignments

TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		occurring after the deadline of an assignment, The total count of web sessions in which an assignment was accessed, The total number of calendar page views, The longest period (in hours) between sessions within Canvas, The average time (minutes) between the submission and deadline for assignments, Course enrollments, Questionnaire, Assignment submission, Assignment due date, Assignment submission method, Assignment grade (Quick et al., 2020)
		Students, Valid responses, Explanation of the test (what was measured), Advice on further preparation for (a) course(s) or study, Indication of chances of completing a course, Comparison of obtained score to scores of other test-takers, Comparison of obtained score to scores of successful students (Delnoij et al., 2020)
		Student-logged data, All students interactions, Time spent on the various components of the course, MCQs, Uploading resources, Attempting and reattempting the synopses, Answering the assessment questions, Gathering of students' responses to a post-course questionnaire and their opinions (Yousuf et al., 2020)
		Teacher age, Teacher sex, Teacher experience, Teacher total clicks, Teacher clickstream, Teacher group page clicks, Teacher time spent on the dashboard, Teacher indicator clicks, Teacher (student) groups visits (van Leeuwen & Rummel, 2020)
		Student interactions with Moodle content, Time intervals, Number of events generated by students, Students number, Statements per Student, Total statement/req, Iteration duration (s), Iterations number, Response time, Number of users, Number of requests/iteration, Break time request (s), # Statement for all requests, # Iterations, Break time iteration (s), Total execution time (Min), Number of statements, Error rate (%), Average response time (ms), Minimum response time (ms), Maximum response time (ms) (Labba et al., 2020)
		Students, Number of students, Students groups, Course content, Exercises/quizzes (in course content), Students' final grades, Pre-test scores, Pre-test completion rate Email intervention (results-summary advice/feedback auto-evaluation) (Nikolayeva et al., 2020)
		Total activity access, Number of sessions, Unique questions attempted, Unique parsons attempted, Unique challenges attempted, Unique animated examples viewed, Unique examples viewed, Number of social comparison events, Total comparison group changes, Change to lower group, Change to average group, Change to higher group, Ranked list views, Timestamp (Akhuseyinoglu et al., 2020)
		Length of the number of unique words, Non-zero value if the word in the vocabulary, Term weight, Term frequency, Courses, Number of courses (Pardos & Jiang, 2020)
		Separation of the audio track from the video, Segmentation of audio track, Transcription (speech-to-text), Keyword extraction (keyword spotting), Keywords, Important keywords in relation to the topic, Suitable keywords

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TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		but not important, Irrelevant keywords to the topic, Suitable and helpful resources, Suitable but not helpful resources, Unsuitable resources, Learning resources (Schulten et al., 2020)
		Slides, Exercises for lab sessions, Quizzes, Final exam, Student ID, Timestamp of the interaction, Type of access (view, submit), Resource ID, Score (for quizzes and exam), Number of students/resources, Number of learning records, Median number of students' learning records, Average number of learning records (Zhang et al., 2020)
		Students, Writing assignment, Students' assignment final text, Number of revisions, Number of correct revisions, Number of incorrect revisions, Number of words, Time spent on quizzes/assignments, Total time spent, number of learning sessions, students' language background (Conijn et al., 2020; Southavilay et al., 2013)
		Total number of students, Videotaped transcripts (Automatic speech recognition), Pre- and Post-test items, Keywords (Text mining - physics textbook), Word frequency (Schlotterbeck et al., 2020)
		Students' interactions with the online course activities, Students' assessments grades, Students' quizzes grades, Timestamp of each event, Assignment/quiz/resource/forum views, Assignment/quiz/ resource/forum attempts, Assignment/quiz/resource/forum update, Forum discussion post, Course views, Overall course score, Anonymous user IDs, Course module IDs, Description of the learning action (Uzir et al., 2020)
		Discussion_answer (Answer to the discussion), Discussion_AUnvote (Undo the vote for the answer to the discussion), Discussion_AVote (Vote for the answer to the discussion), Discussion_QFollow (Follow the discussion question), Discussion_QUnfollow (Unfollow the discussion question), Discussion_QVote (Vote for the question posted in the forum), Exam (Work on practical exam questions), Exam_begin (Begin working on the practical exam), Exam_complete (Complete the practical exam question), Exam_correct (Correctly solve the practical exam question), Exam_incorrect (Incorrectly solve the practical exam question), Quiz (work on the quiz), Quiz_begin (Begin working on the quiz), Quiz_complete (Complete the quiz), Quiz_correct (Correctly solve the quiz), Quiz_incorrect (Incorrectly solve the quiz), Supplement_start (Access the extra reading materials), Supplement_complete (Complete the access to the extra reading materials), Video_begin (Begin the video), Video_download (Download the video), Video_end (End the video), Video_pause (Pause the video), Video_play (Play the video), Video_playback_rate (Change the playback rate of the video), Video_seek (Seek the video), Video_subtitle_change (Change the subtitle of the video), Video_subtitle_download (Download the subtitle), Video_volume_change (Change the volume), Video_wait (Wait for the video to load), Page_preload (Load the page for the first time), Page_view (View the page) (Quick et al., 2020)
		Student identifier, Student grade, Timestamp indicating level attempt completion, Login session identifier (When students log in to the system to

TABLE A2 (Continued)

Year	Indicators (sorted yearly 2011–2019)	Metrics
		play this id is recorded against each level played before logging out), Login place, Objective number, Game number, Level number, Count of prior attempts for that level, Count of previously passed levels, Number of puzzles passed, Number of total puzzles in that level (Shabrina et al., 2020)
		Total number of students, Total objectives (levels and puzzles), Number of objectives played, Highest number of students that completed the first N objective in the same order, Total retries by students, Districts, Percentage of retries by districts (Akintunde et al., 2020)
		Number of students, Student age, Students' background (previous knowledge about neuroscience), Video materials (video lectures), Lecture topics, Text-based data, Animation-based data (slides, annotated images), Questionnaire Student facial expressions (facial temperature), Average/mean change in forehead temperature, Average/mean change in nose temperature, Timestamps, eye movements (Srivastava et al., 2020)
		Video recordings, Sessions, Voice frequency, Speech recognition, Kinesics, Eye contact, Gaze orientation (looking at the robot), Body orientation (facing peer or robot), Posture (leaning forward), Gestures or enactments of ideas (representing a concept), Facial expressions, Responding to the robot's question, Extending or elaborating talks by the peer or the robot, Initiating a talk related to the current topic, Self-talk and talk or mumbling unrelated to prior robot/peer (Kim et al., 2020)
		Demographic variables (Study-program Attendance Gender age Previous-attainment), Quiz, Quiz score, Student clicks, Students' final course grades, Group interview with students (Iraj et al., 2020)
		Student id, Course id, Type of learning action, User-agent (used for extracting the type of device used for the action), Action URL, Session number, Start time, End time (Sher et al., 2020)