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Categorizing learning analytics models according to their goals and identifying their relevant components: A review of the learning analytics literature from 2011 to 2019

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ABSTRACT

This study aimed to categorize learning analytics (LA) models and identify their relevant components by analyzing LA-related articles published between 2011 and 2019 in international journals. A total of 101 articles discussing various LA models were selected. These models were characterized according to their goals and components. A qualitative content analysis approach was used to develop a coding scheme for analyzing the aforementioned models. The results reveal that the studied LA models belong to five categories, namely performance, meta-cognitive, interactivity, communication, and data models. The majority of the selected LA-related articles were data models, followed by performance models. This review also identified 16 components that were commonly used in the studied models. The results indicate that analytics was the most common component in the studied models (used in 10 LA models). Furthermore, visualization was the most relevant component in the studied communication models.

1. Introduction

The learning analytics (LA) model took its current form around 2011. Since then, a steadily growing number of LA models have been developed in different fields, such as education (e.g., technology acceptance and academic resistance models, Herodotou et al., 2019; the student's control model, Rahimi et al., 2015; the online teaching–learning model, Torras-Virgili et al., 2018). In the field of education, LA models, including their foci, goals, and components, are regularly updated. The main purposes of LA models are to improve learning and examine the learning process through diverse instrumental investigations (Sengupta et al., 2020). Thus, researchers are becoming increasingly interested in investigating LA models that can be used in the context of education. In this review, an LA model is defined as the combination of two or more elements, with their functionality and techniques employed as cognitive tasks to achieve desired goals.

Numerous reasons may exist for developing models to achieve particular goals. For example, Mubarak et al. (2021) devolved a deep neural network (i.e., a long short-term memory network) comprising a recursive loop and constant-error carousel. These components are based on a set of implicit features extracted from video clickstream data to predict learners' weekly performance and enable instructors to set measures for timely intervention, improving the educational process. Jones (2019) developed a model by using the Platform for Privacy Preferences (P3P) technology and privacy dashboards such that student and institutional interests were balanced for establishing informed consent mechanisms to promote student privacy and autonomy. Shorfuzzaman et al. (2019) proposed a cloud-based mobile LA model with the components of data aggregation, data analytics, and decision support to use big data analytics techniques for extracting values from large volumes of mobile learners' data. Moreover, Bodily et al. (2017) developed the RISE Framework, which contains the components of resource inspection, selection, and enhancement, to identify resources, periods, and modules in a course for improvement of open educational resources. Thus, they could successfully identify course-level data rather than student-level data. As indicated by the aforementioned discussion, LA models must comprise relevant components to achieve the goals of LA studies (Chatti et al., 2012; Pinnell et al., 2017). To gain worthwhile outputs from LA research, an LA model must comprise appropriate goals, components, theories, and methods.

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Most LA-related studies have used LA models with specific or narrow goals. For example, Zou and Xie (2018) developed the "user model" by using different components (i.e., motivation, noticing, retrieval, generation, and retention) to facilitate effective word learning. Er et al. (2019) proposed two predictive models, namely a learning design (LD)–specific model that includes LD features and pedagogical intentions as well as a generic model that includes cumulative features. Their results indicated that the generic model outperformed the LD-specific model even though some LD features were powerful to predict. Such model comparisons help to identify LD problems.

However, limited research has examined more than one model with different goals. To address this gap, an optimum LA platform might need to be designed. Educators may need to apply multiple LA models with unique goals. Thus, the present review aimed to categorize all the LA models described in articles published in international journals. No systematic review has been conducted to categorize LA models with similar goals into groups or identify critical components of these models. Thus, an urgent need has arisen to categorize LA models according to their goals and to identify commonly used components of such models. Such a categorization would allow users to make decisions regarding which types of LA models containing which components are suitable for achieving desired goals. Therefore, the present review aimed to identify and categorize all the LA models described in articles published in international journals between 2011 and 2019. This review also aimed to investigate the most commonly used components of LA models. Specifically, this review intended to identify the most commonly used components in each category of LA models. Thus, the research questions of this review were as follows:

(1) How can all the LA models described in articles published in international journals between 2011 and 2019 be classified into meaningful categories?
(2) What are the relevant components of the LA models described in articles published in international journals between 2011 and 2019?

2. Literature review

Some LA-related review studies have provided empirical evidence of the effects of LA on successfully continuing with and completing university courses (Ifenthaler & Yau, 2020), education levels, and education stages; the use of LA in different vocational education and training contexts (Gedrimiene et al., 2019); and the use of different LA techniques (Leitner et al., 2017). Moreover, some studies have investigated factors related to how LA models engage learners (Pinnell et al., 2017). McKee (2017) described the limitations of available LA models and how to support instructors. Table 1 presents a description of some LA-related review studies, including their objectives, foci, major findings, and limitations.

Table 1
Review studies related to LA in education.

Author (year)	Ifenthaler and Yau (2020)	Gedrimiene et al. (2019)	Leitner et al. (2017)
Objectives/ foci of LA reviews	To focus on empirical evidence, demonstrating the success in facilitating study success in the continuation and completion of students' university courses.	To study the levels and stages of education that the reviewed LA literature examined.	To present an overview of the different techniques, limitations, potential stakeholders, and their categorization.
Identified articles	46 articles	60 articles	101 articles
Name of the methods	The key publications utilized data analytics methods, such as binary logistic regression, decision tree analysis, support vector machines, logistic regression, and classification systems.	Qualitative analysis	Mixed-method analysis
Major findings	There are a considerable number of LA approaches which utilize effective techniques for supporting study success and students at risk of dropping out.	The study found that most of the articles focus on the course level, followed by student and institution levels in higher education. Few empirical studies have addressed LA use during the VET stage, particularly at the governmental level.	This review successfully identified techniques, limitations, potential stakeholders, and their categorization.
Limitations	The systematic review does not reflect all research on LA and study success. The review included articles published in the English language.	Differences in educational systems across Europe and the world. More in-depth knowledge of each context could have changed some of the interpretations.	A change in the type of analysis is foreseeable.

2.1. LA models and their benefits in the field of education

Numerous studies have been conducted on LA models and frameworks (e.g., Adejo & Connolly, 2017; Lim et al., 2019; Reddick et al., 2017). Most of the developed LA models serve educators, learners, and educational institutions. Riquelme et al. (2019) proposed the "social network model" to analyze and visualize student discussion groups to accomplish a task. Adejo and Connolly (2017) designed the "multidimensional benefits framework" to improve students' learning experience and decision-making. This framework aims to improve administrative decision-making, which is a benefit of LA models. Vahldick et al. (2017) designed the Casual Serious Game for Computer Programming Learning model to identify students' progress in their performance of programming tasks. They found that most of the students in their study were good performers. Similarly, self-regulated learning (SRL) models (Lim et al., 2019) indicate how personalized feedback can improve students' SRL proficiency and academic performance. Lu et al. (2017) developed the LearnSense framework and wearable devices to capture students' activities and engagement status in class and found that the students' F1 score (i.e., the measure of the accuracy of the framework) was 0.9. The students were highly satisfied with the aforementioned framework. Thus, curricula evaluation is a crucial benefit that can be gained from LA models. Klašnja-Milićević et al. (2017) indicated that LA models can be used to evaluate typical grading techniques and instruments. Social media text mining analytics and visualization have been used to explain double-loop learning and e-participation (Reddick et al., 2017) for facilitating organizational learning and enhancing citizen-centric public service quality. Their study found the effective use of social media platform has a positive influence on public service quality. Moreover, the MOOC (i.e., massive open online courses) business model (Wulf et al., 2014) can be used by academic institutions to increase their administrative efficiency and productivity on the basis of the latest information.

2.2. Components of LA models

LA itself is insufficient for achieving inclusiveness (Chatti et al., 2012; Pinnell et al., 2017). To gain worthwhile outputs from LA models, suitable components must be incorporated into them. Suitable components should be selected for an LA model according to the goals to be achieved. For example, to improve students' learning experience and help them with decision-making, Adejo and Connolly (2017) developed a multidimensional benefits framework, which contains several components, such as government benefits, institutional benefits, operational benefits, and learner benefits. Alhadad and Thompson (2017) examined educators' inquiry process (as learners) in a professional learning workshop and proposed the ACAD model, which consists of the components of design time, learning time, and learning outcome. By contrast, the "complexity leadership model" of Tsai et al. (2019) contains the components of key action plans, prominent challenges, and considerations of policy development. This model is based on complexity leadership theory (i.e., entrepreneurial, operational, and enabling leadership behaviors) and enables higher education to shift toward more fluid and dynamic approaches for LA adoption, which confirms the scalability and sustainability of the model. Aguilar et al. (2019) developed a student learning model called the knowledge model, which includes the components of observation, analytics and decision-making, to improve the learning processes in smart classrooms.

3. Methods

Previous review studies have used a three-step process of search, selection, and data analysis to identify and process articles for review (Su & Zou, 2020; Zhang & Zou, 2021; Zou et al., 2020). The current review employed the same three-step process. The searching keywords search for LA research in education published between the years 2011 and 2019 consisted of "learning analytics" AND "models/frameworks." The original search returned 430 articles.

3.1. Article selection

The current review examined the Google Scholar, ACM Digital Library, Web of Science, ScienceDirect, and Scopus databases for journal articles related to LA models/frameworks. This review treated the model and framework as having a similar meaning. By selecting the articles belonging to the "Education Educational Research" and "Education Disciplines" (Hwang & Chang, 2021; Authors et al., 2020), "Educational Action Research" and "Educational Technology" categories, 23 articles were excluded. This review also excluded conference articles, books, unpublished articles, review articles, position articles, commentary notes, non-English articles, reflections, editorials, documentaries, and dissertations. This criterion excluded 302 articles. Then, we reviewed the abstract, method, and full text of each of the selected articles to confirm whether the article fit the requirement of presenting an LA model/framework. The current review excluded derived/borrowed LA models/frameworks. This criterion excluded 4 articles. Finally, 101 articles were selected for further review, as shown in Appendix 1. The process and methods of data searching and selection procedure in Zhang and Zou (2021) and Chen et al. (2020) were adopted, as shown in Fig. 1.

3.2. Data analysis

The qualitative content analysis approach was conducted with the typologies which are developed through grouping processes, where different elements are coded or identified according to shared characteristics (internal heterogeneity) (Kluge, 2000). The details of the coding scheme are presented in the following sub-section, "Coding scheme for categorizing LA models."

The key information corresponding to the two research questions was first identified from each LA study and then synthesized. The synthesis procedure had three main phases. Firstly, the studies were examined in terms of models which were applied in the field of LA research. Secondly, an inductive method was used to develop the coding categories and to identify the components in each study. Finally, commonly used components were identified from different models. A characterization of models involving a detailed description illustrating unique components and overlapping components with other models (Willis et al., 2016) is presented in this study. When dissimilarity appeared, the two reviewers from the research team discussed until they reached a consensus. As all of the decisions were reached by consensus during the process of categorization, it was considered unnecessary to perform a formal reliability check (Krippendorff, 2013).

3.3. Coding scheme for categorizing LA models

LA models have unique foci, goals, objectives, and limitations (Barber & Sharkey, 2012) and comprise different components. In short, LA studies have focused on the components used to construct LA models. Pinnell et al. (2017) categorized LA models into groups according to

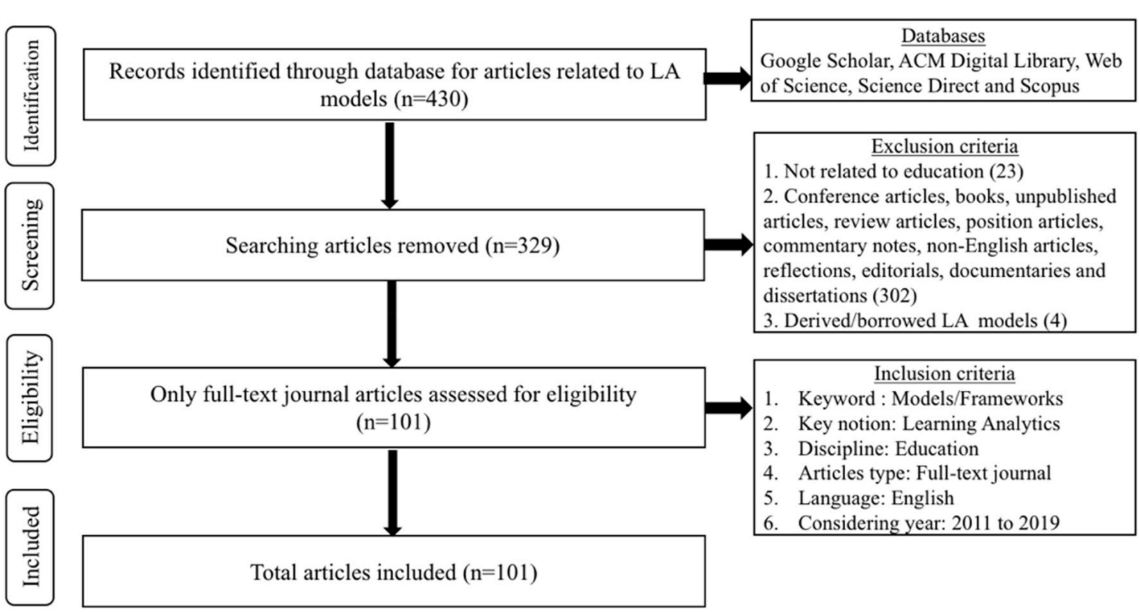

Fig. 1. The article selection procedure flowchart.

their overall goals. They identified six categories of LA models: ontology or meta-ontology, performance, meta-cognitive, communication, interactivity, and demographic models.

Several researchers have attempted to understand what motivates researchers to use the aforementioned models, which contain different components. For example, Spivey and McMillan (2013) conducted an effectively used a Blackboard course management system to investigate the relationship between student effort and performance. They found that frequent access of study resources and consistency had positive effects on student performance. Educators can obtain a clear idea of students' ability to follow and comprehend course content, the difficulties faced by them in understanding this content, their learning proficiency, and their academic performance by monitoring LA (Lim et al., 2019). Thus, LA models can be used to determine students' overall performance. Pinnell et al. (2017) explained that performance models include information about learning goals and long-term learning patterns. Therefore, performance models include a learner's progress, learning outcome or academic success, achievement goals, and formal and informal activities. These models also include some other components, such as teacher performance, instant response system performance, and university ranking.

Cognition is a crucial aspect related to learning. Pecari et al. (2017) discussed how the augmented collection and dynamic analysis of learning process data within a cognitive simulation can improve feedback and prompt more precise reflection on the accuracy of a novice clinician's skill development. Azevedo et al. (2017) proposed the CAMM (i.e., cognitive, affective, metacognitive, and motivational) SRL data visualizations model, which was designed to facilitate learners' monitoring and regulation of their emotions while learning with advanced learning technologies. Wise et al. (2016) proposed the Student Tuning Model, under which students engage in a continual cycle of planning, monitoring, and adjusting their learning practices on the basis of analytical information. Pinnell et al. (2017) stated that meta-cognitive models describe inferred mental states. They also argued that by observing behaviors, a sophisticated LA platform can be constructed to develop models that can accurately predict the cognitive states of learners (p. 134). The probabilistic graphical models of Saranti et al. (2019) provide insights into human learning competence and can be used to personalize tutoring according to a learner's knowledge level. The factors causing incorrect student responses and the weights of these factors provide valuable insight for teachers. Moreover, when a university introduces a new system, such as a technological instrument, or changes the learning management system, behavioral intention and past experience indicate students' acceptance of the factors of a meta-cognitive model.

Interactivity, which refers to learner–learner and learner–teacher interactions, is a crucial learning factor (Quadir et al., 2019) in a blog-based learning environment. An individual's learning process is influenced by their interactions with other learners (Kent et al., 2016). Many researchers have developed interactivity models that capture these complicated interactions (Shum & Ferguson, 2012). For example, Chatti et al. (2016) proposed the video-based learning (VBL) model to investigate effective VBL environment designs for teachers and learners to enable them to spend more time on discussions. According to Pinnell et al. (2017), in interactivity models, a strong relationship exists between how learners interact with each other within and outside the learning space and how they learn. Ma et al. (2015) demonstrated how the instructor's role affects students' engagement activities by using LA to track data related to teaching and learning activities for constructing an interactivity model. Interactivity models analyze the following factors: teachers, environments, stakeholders, interactions with learning resources, learner engagement, learning platforms, social learning platforms, interactive practice opportunities, and whole-class discussion tasks.

The main aims of communication models are to determine the meanings of messages that people send and the importance of the selected messaging medium (Teplovs & Fujita, 2013). Many communication channels exist, such as face-to-face speech, telephone, and social media (Pinnell et al., 2017). Communicative tools might influence the success of a course (Kent et al., 2016). These tools are used to remain focused on relevant tasks while attempting to improve students' learning outcomes (Yang et al., 2016). The study of Ullmann et al. (2019) provides one example of the use of discussion tools. These researchers developed the CI (i.e., collective intelligence) Dashboard to present several visual analytics that indicate crucial aspects of online debates facilitated by CCI discussion tools. Therefore, in the current review, communication media or channels, such as face-to-face speech, telephone, email, Twitter, forums, and other channels that provide considerable information on the content of sent messages and the choice and use of the channel, were considered to be factors within a communication model.

Pardo et al. (2018) designed a student–instructor-centered conceptual model consisting of six components (i.e., data warehouse, other data sources, data import, student data table, personalized learning support actions, and data mining/machine learning) to integrate the use of comprehensive data sources, instructor knowledge of the learning context, and a formal description of the connection between actions and personalized learning support actions (PLSAs). A data model can store students' overall performance as a range of values (Siemens & Baker, 2012). Therefore, in the current review, an LA platform, in-game and stealth measures, user modeling, adaptive control and visual analytics, maps of pedagogical patterns, in-game mechanics, the visual analytics area and generation of ideas, and the sorting of collected ideas into clusters were considered to be factors of a data model. The representation of contextualized attention metadata and idea ratings based on several parameters, such as importance and feasibility, were also considered as factors of a data model.

From the above analysis, it is clear that the aforementioned models along with their components are very important. Due to the growing interest in such models, the current review categorized all models published between 2011 and 2019 into particular categories depending on their overall goals. These categories are (1) performance models, (2) meta-cognitive models, (3) interactivity models, (4) communication models, and (5) data models. The definitions of each type of model with their features are given in Table 2.

4. Results

4.1. Overview of the analyzed articles

The study analyzed a total of 101 articles relating to LA models published as journal articles from 2011 to 2019. There was one article from 2011, six from 2012, three from 2013, eight from 2014, 15 from 2015, 14 from 2016, 16 from 2017, 17 from 2018 to 21 from 2019, as shown in Fig. 2. The number of research works regarding LA models has therefore shown an increasing trend.

4.2. Results of LA model categorization (RQ1)

These models were categorized based on their purposes and components as identified in the 101 articles (in Fig. 3). The study found that the highest number of articles (i.e., 47) discussed data models. This corresponds to 46.53% of the articles. The study also found a total of 26 and 18 articles which discussed, respectively, performance models and meta-cognitive models, corresponding to 25.74% and 17.82% of the articles, while interactivity models (6 articles) and communication models (4 articles) corresponded to 5.94% and 3.96%, respectively.

4.3. Results of LA models' relevant components (RQ2)

All components derived from each model are shown in Appendix 1. There were 384 components found in the 101 selected articles. The 16

Table 2
Coding scheme for categorizing LA models.

Model Name	Definition	References
Performance model	"Models of performance include those models that make statements about a learner's progress, level of skill, or some other statement regarding their competence in their learning objectives"	Pinnell et al. (2017), p. 133.
Meta-cognitive model	"Meta-cognition model holds that attitude objects can be linked in memory to both positive and negative evaluations that can vary in the degree to which they are endorsed or not"	Petty et al. (2007), p. 662.
	Refers to thoughts about thoughts or thought processes	Petty et al. (2007).
	Refers to an inferred mental state in the learning domain	Pinnell et al. (2017).
Interactivity model (Interaction between people and human-computer interaction)	Refers to a social exercise, conducted at the minimum between a learner and an educator (Pinnell et al., 2017) that resides inside a computational environment (Fischer, 2000).	Pinnell et al. (2017); Fischer (2000).
Communication model (Communication medium)	Refers to being largely interested in the importance of the choice of medium (Teplovs et al., 2011) including face-to-face speech, Google forms, social learning platforms, rating and semantic richness, and network learning (Pinnell et al., 2017).	Teplovs et al. (2011); Pinnell et al. (2017).
Data model	Refers to collecting all the required information as well as to being independent of each learning platform.	Lukarov et al. (2015).
	Includes a field to collect student feedback on their educational experience, for example degree of completion and success, progress measurement, and score.	Siemens and Baker (2012).

most commonly used components (i.e., those used at least three times) in the selected 101 published articles were also identified to present a picture of the current LA models, as shown in Fig. 4.

The most frequently used component is named analytics, and it has been used in 10 articles. This corresponds to 9.90% of the articles. Then, visualization, feedback, and performance have each been used in eight articles (7.92%), followed by behavior in seven articles (6.93%), while goal and environment constituted 4.95% each, intention, intervention, LMS, and stakeholders at 3.96% each, and engagement, ethics and privacy, objectiveness, knowledge, and usefulness/effectiveness accounting for 2.97% each. The remaining components constituted less than 2%, meaning that they were used in fewer than three models. More specifically, visualization is discussed in 50% of the communication models, performance is discussed in 19.23% of the performance models, and behavior is discussed in 16.66% of the meta-cognitive models. Details are given in Table 3. It should be noted that the number in the table represents the article ID from Appendix 1.

5. Discussion

Leitner et al. (2017) reviewed state-of-the-art LA models for higher education that are described in 101 articles and presented an overview of different techniques, limitations, potential stakeholders, and categorizations related to these models. The current study reviewed and categorized state-of-the-art LA models for education research that are described in 101 articles published between 2011 and 2019 in international journals. This review classified the identified models into five categories according to their overall goals: performance, meta-cognitive, interactivity, communication, and data models.

Data models were the most frequently discussed models in the reviewed articles (i.e., in 47 articles). As stated by Chatti et al. (2012), LA involves developing methods that connect educational datasets to support the learning process. The aforementioned authors explained that LA is a multidisciplinary field involving machine learning, artificial intelligence, information retrieval, statistical analysis, visualization, academic analytics, action analytics, and educational data mining. Performance models were the second most frequently discussed models in the reviewed articles (i.e., in 26 articles). The model of Lim et al. (2019) was categorized as a performance model because it aims to use an LA-based system of personalized feedback to improve students' SRL proficiency and academic performance. Meta-cognitive models (18 models) were the third most frequently discussed models. The purpose of the model of Ali et al. (2013) is to identify how LA tools are perceived by educators, which is a mental state in the learning domain. The components of this model (i.e., ease of use, usefulness, and behavioral intention) are influenced by meta-cognitive characteristics; thus, the aforementioned model is categorized into the meta-cognitive category.

Chatti et al. (2016) developed the VBL model to enhance interactions between teachers and learners in the discussion of issues in a learning course. According to its purpose and interaction-related components, the VBL model is categorized as an interactivity model in this review. Six of the reviewed articles, which represent 5.94% of all the reviewed articles, discussed interactivity models. Ali et al. (2012) proposed the

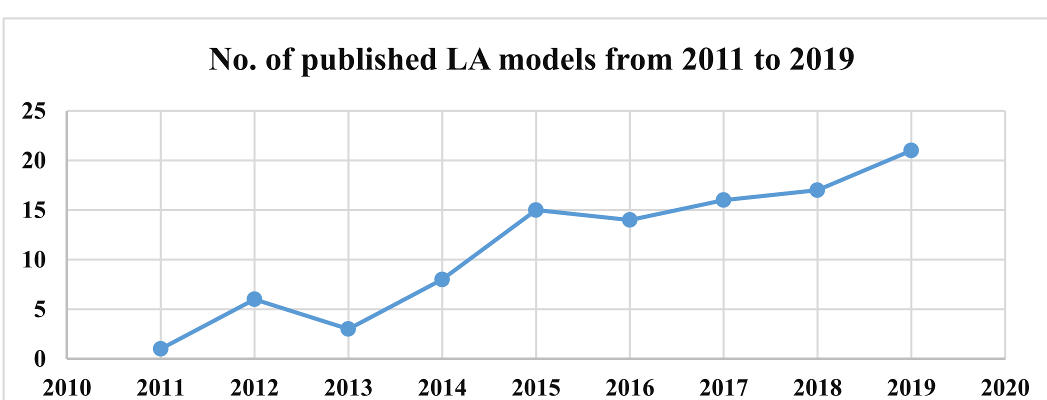

Fig. 2. Trend of LA models published from 2011 to 2019.

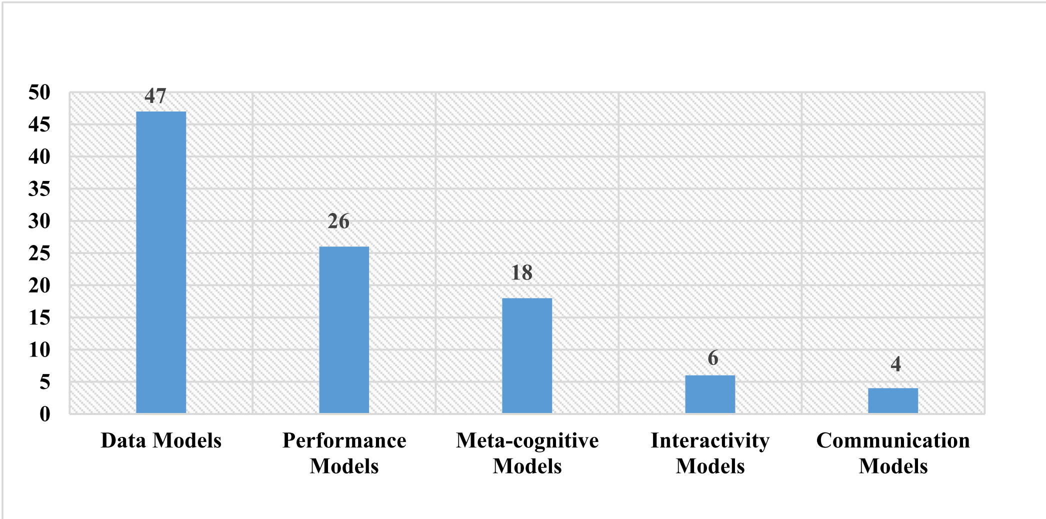

Fig. 3. The category distribution of all of the LA models published from 2011 to 2019.

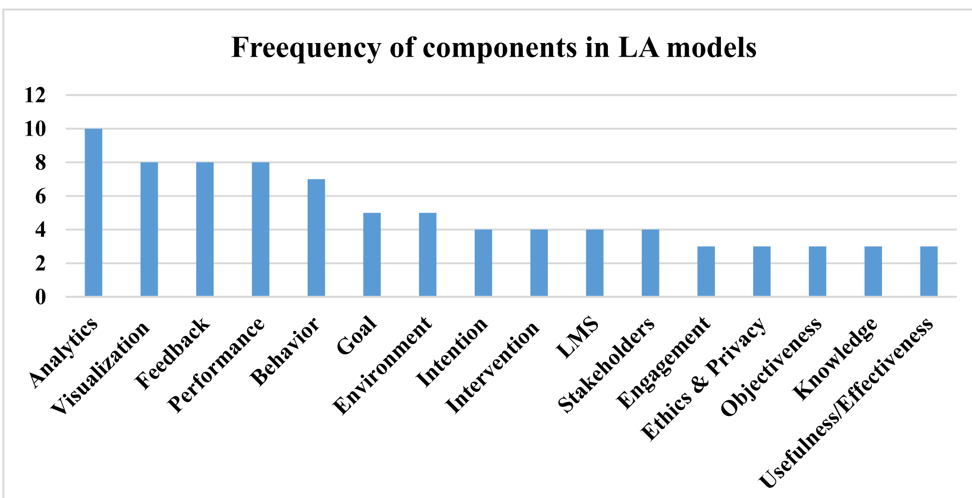

Fig. 4. The distribution of relevant components in the proposed LA models published from 2011 to 2019.

Table 3
Most commonly used components in different models published from 2011 to 2019.

Components/Models	Performance models (26)	Meta-Cognitive models (18)	Interactivity models (6)	Communication models (4)	Data models (47)
Analytics	3.85%	5.55%	16.66%	–	14.89%
Visualization	3.85%	5.55%	–	50%	6.38%
Feedback	23.08%	–	–	–	4.08%
Performance	19.23%	11.11%	–	–	2.12%
Behavior	3.85%	16.66%	–	–	4.25%
Goal	3.85%	11.11%	–	–	4.25%
Environment	–	5.55%	–	–	6.38%
Intention	3.85%	16.6%	–	–	–
Intervention	3.85%	5.55%	–	–	4.25%
LMS	7.69%	–	–	–	4.25%
Stakeholders	–	–	–	–	8.51%
Engagement	3.85%	5.55%	–	–	2.12%
Ethics and privacy	7.69%	5.55%	–	–	4.25%
Objectiveness	–	–	–	–	6.38%
Knowledge	7.69%	5.55%	–	–	
Usefulness/effectiveness	3.85%	11.11%	–	–	–

Ontology LOCO (i.e., learning object context ontology) framework for enabling the use of existing knowledge from human–computer interaction to improve the effectiveness of LA for educators, learners, and institutions. Their study identified that interaction is the most crucial factor in education. Finally, Ullmann et al. (2019) designed the Architecture of the CI Dashboard to improve sense-making and participation in online debates, and found that students with little experience in using analytics visualizations performed better than the students with no experience on given tasks. Because the CI Dashboard is used as a communication medium, this dashboard is categorized as a communication model. Models that meet the aforementioned criteria were considered communication models in this review.

The current review identified the components of all the LA models described in the 101 reviewed articles. Then, an analysis was conducted to identify commonly used model components. Alonso-Fernandez et al. (2019) identified commonly used techniques in LA studies. The most frequently used component in the analyzed models is analytics, which was used in 10 studies. Moreover, visualization is the second most frequently used model component. Reddick et al. (2017) used the component of social media text mining analytics and visualization to facilitate organizational learning and enhance public service quality. Moreover, Ali et al. (2012) identified that visualization techniques are among most crucial factors in education. Alonso-Fernandez et al. (2019) found that some studies have used visualization as a supervised technique and unsupervised technique. Feedback and performance are the third most frequently used model components (used in eight studies). The studies in which these components were used include those of Ali et al. (2013), Taraghi et al. (2015), Hadhrami (2017), and Zhang and Liu (2019). “Ethics and privacy” were used as model components in 2.97% of the reviewed articles; however, the results of Banihashem et al. (2018) indicate that ethics and privacy are major challenges in the application of LA in education.

6. Conclusions

This study reviewed all the LA models described in LA-related articles published between 2011 and 2019 in international journals. The reviewed models were classified into five categories. Moreover, each component of all the reviewed models was examined to identify the most commonly used model components.

Educators who wish to develop LA models can refer to the results of the current study to identify which category their model belongs to according to its foci and goals. They can examine the features of the relevant category and consider these features in their proposed model. Thus, an overview of all LA models can be obtained and a new LA model can be developed easily, effectively, and efficiently. An implication of the results of this study is that to gain the optimum benefits of LA, educators should create LA platforms by using multiple LA models with unique goals. For example, researchers, practitioners, data scientists, and social science scholars should collaborate to ensure the long-term success of the application of LA models. They can combine performance models with meta-cognitive models because such a combination may enable the achievement of a complete set of goals and objectives and provide an avenue for obtaining promising results. Researchers can also consider using the most commonly used model components identified in this review to develop their LA model. The results of this study might help researchers obtain an overview of LA model components as well as select and prioritize relevant and popular components in their designed LA model.

This study had certain limitations. First, the literature review was limited to articles describing the use of LA in education that were published in international journals between 2011 and 2019. Moreover, these articles were selected on the basis of the following keywords: learning analytics and models/frameworks. Second, the current study did not analyze LA models derived from or related to those described in the selected articles. Third, relevant articles written in other languages and related to non educational contexts were not considered in this review. Future research should include academic databases that cover literature from additional fields related to LA models or frameworks, such as business or psychology.

The results of the current study suggest that LA models from different categories, which have different relevant components, can be combined to achieve various goals. None of the LA models examined in this study were classified as ontology, meta-ontology, or demographic models; however, these models can be highly useful (Pinnell et al., 2017). Because of the demand for ontology or meta-ontology models (in which concepts are arranged into a network of relationships) and demographic models (which consider individuals’ information) as well as the related components of these models in the context of LA research, such models are recommended to be developed in future studies. Moreover, future research can identify commonly used techniques in existing LA models to validate LA models or frameworks. Therefore, deeply examining LA models, their components, the techniques that they use, how they can be integrated with suitable components, and how they can be widely used in different fields are worthwhile directions for future research.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix B. Supplementary data

Supplementary data related to this article can be found at https://doi.org/10.1016/j.caeai.2021.100034.

Appendix 1. LA models and their respective components in the published LA Articles

Performance models	
Name of the models/frameworks	Components
1.Ontology LOCO framework (Ali et al., 2012)	Tool’s data visualization, user interface, supported feedback
2.Relational model (Ali et al., 2014)	Learning strategies, achievement goals
3. Probabilistic model (Lacave et al., 2018)	Qualitative component, quantitative component
4. A new tool for visualization of student learning model (Minović et al., 2015)	Knowledge, learning path
5 The polyphonic social knowledge building model (Nistor et al., 2015)	Reader bench, important moments
6. Learners’ profile model (Taraghi et al., 2015)	Learners’ profile, answering behavior
7. Blended learning model (Gaševic, Dawson, Rogers, & Gasevic, 2016)	LMS usage, academic success
8. Design Framework (Lin & Hwang, 2018)	Performance, participation, perception and interactive
9. Course-specific models (Smith, 2012)	Course outcome, linkage between instructors and at-risk students, online environment
10. The lens of a cognitive model of radiograph interpretation (Pecaric et al., 2017)	Orientation, searching, feature detection, decision making
11. Student experience (Borden & Coates, 2017)	

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Performance models	
Name of the models/frameworks	Components
	People analytics, education informatics, learner analytics, learning analytics, and a host of other forms of institutional, governmental analysis of reporting
12. LEARNSense (Lu et al., 2017)	Student activities, engagement status
13. ACAD model (Alhadad & Thompson, 2017)	Design time, learn time, learning outcome
14. Predictive model (Vera, 2017)	LMS, socio-demographic variables
15. RISE framework (Bodily et al., 2017)	Resource inspection, selection, enhancement
16. Multi dimensional benefits framework. (Adejo & Connolly, 2017)	Government benefits, institutional benefits, operational benefits, learner benefits
17. Self-regulated learning (SRL) (Jovanović et al., 2017)	Well thought of, planned and employed for the purposes of learning new skills and knowledge.
18. Casual Serious Game for Computer Programming Learning (Vahldick et al., 2017)	Students performance, rating system, feedback
19. Self-regulated learning SRL (Lim et al., 2019)	LA-based feedback, performance
20. Framework of expectations (Whitelock- Wainwright et al., 2019)	Ethical and privacy expectations, agency expectations, intervention expectations, meaning- fullness expectations
21. Technology Acceptance and Academic Resistance models (Herodotou et al., 2019)	Easy of using OUA, perceived OUA effectiveness, feelings towards OUA, future intentions
22. Performance analysis learning model (computer based learning model) (Srimani & Kamath, 2012)	Pathway, curriculum, implementation strategies, assessment, tracking student progress, identification of learning abilities, Feedback.
23. TAN Model (Goggins et al., 2015)	Learning, performance
24. Predictive model (Nouri et al., 2019)	Early-warning systems, formative feedback mechanisms, teachers monitoring practices
25. EduOpen MOOC (Dipace et al., 2019)	Key performance Indicators (KPI), data hierarchy, dashboard design, filters,
26. Model of learning analytics, digital badges, and generic skills (Mah, 2016)	Predictive models and algorithms, learning support recommendations and feedback, data privacy, ethical issues.
Meta-cognitive models	
1. Learning analytics acceptance model (Ali et al., 2013)	Ease of use, usefulness, past experience, behavioral intention
2. Student progress model (Blikstein et al., 2014)	Code from instructors, writes code to instruct, code to create a single row, two rows, a solution.
3. SQL-Tutor open learner model (Epp & Bull, 2015)	Learner's beliefs, goals, knowledge, intentions, or cognitive state.
4. An integrated model of learning characteristics of the MOOC type X with type C, with adaptive learning and knowledge management (Fidalgo-Blanco et al., 2015)	Integration of formal and informal activities, integration of instructionism and connectivism, creation of sustainable products: the learning communities
5. A combined research model including the UTAUT and the CoP model (Nistor et al., 2014)	Performance expectancy, effort expectancy, social influence facilitating conditions, computer anxiety, use intention
6. Psycho-pedagogical framework is the domain model (Nussbaumer et al., 2015)	A self-regulated learning model, a psychological model, an open learner model, learning analytics approach.
7. The Assurance of Learning for Graduate Employability framework iPortfolio (Oliver & Whelan, 2011)	Plan enhancement, determine capabilities, map inputs, outcomes
8. The student's control model (Rahimi et al., 2015)	Capability, support autonomy
9. Learning analytics process model. (Verbert et al., 2013)	Awareness, reflection, sense making, impact
10. Student Tuning Model (Wise et al., 2016)	A self-regulatory cycle of grounding, goal-setting, action, reflection
11. Critical learning analytics (Scott & Nichols, 2017)	Technical assemblage, designed assemblage, socio cognitive assemblage
12. Learning Analytics Techniques to Improve Students' Performance and Success (Hadhrami, 2017)	Information usefulness, effective visualization, ease of use understanding level reflective use behavioral engagement, perceived effectiveness
13. CAMM SRL data visualizations (Azevedo et al., 2017)	Eye-movement behaviors, facial expressions of emotions, physiological arousal
14. Research Model (Zhang & Liu, 2019)	Motivation, behavior, performance, environment factors.
15. Framework for utilizing a method (Kondo & Hatanaka, 2019)	Unmodifiable personal attribute, learning outcome, action result or state, intervention
16. Model (Zhu et al., 2019)	Context authenticity, task motivation, focused immersion, process satisfaction, outcome satisfaction
17. A model (Jones, 2019)	Consent mechanisms and privacy dashboards, and institutional interests.
18. User model (Zou & Xie, 2018)	Motivation, noticing, retrieval, generation, retention.
Interactivity models	
1. Lifecycle of interactions with learning resources (Dix & Leavesley, 2015)	Learning resource creation, use, management
2. Networked learning (Joksimovic et al., 2014)	Quantitative methods of (SNA) content analysis, qualitative methods of contextual analysis
3.Video-Based Learning (Chatti et al., 2016)	Discussion about difficulties, problems, practical aspects of the learning course
4. Using social media text mining analytics and visualization to explain double-loop learning and e-participation (Reddick et al., 2017)	Single-loop learning, Double-loop learning, social media text mining
5. Social network model (Riquelme et al., 2019)	Complex decision-making processes, SNA techniques
6. Course-adapted student learning analytics framework (Aljohani et al., 2019)	Instructor level, data level, data analytics level, presentation level
Communication models	
1. Teacher Inquiry into Student Learning (TISL) (Avramides et al., 2015)	Trigger, refine question, collect data, analyze, enact change
2. A model of instructors' process of analytics use (Wise & Jung, 2019)	Sense making, pedagogical response
3. Prototypes Direwolf and SWEVA (Koren & Klamma, 2018)	Data sources, processing pipelines, visualization
4 Architecture of the CI Dashboard (Ullmann et al., 2019)	Data layer, transformation layer, visualization layer
Data models	
1. A reference model (Chatti et al., 2012)	Environments, stake holders, objectives, methods.
2. Data governance models (Elouazizi, 2014)	Uni-Cameral, Bi-Cameral, Tri-Cameral, Hybrid
3. A learning analytics framework (Ifenthaler & Widanapathirana, 2014)	Stakeholders, objectives, data, instruments, internal and external constraints.
4. The evidence-centered-design (ECD) framework (Reese et al., 2015)	Selene accretion data, static goals, the timed report
5. Structural topic models (Reich et al., 2015)	Find syntactic patterns with semantic meaning in unstructured text, identify variation in those patterns across covariates, and uncover archetypal texts that exemplify the documents within a topical pattern.
6. Analytics4Action Evaluation Framework (A4AEF) (Rienties et al., 2016)	Key metrics and drill-downs, menu of response actions, menu of protocols, institutional sharing of evidence, deep dive analysis and strategic insight, outcome analysis and evaluation
7. A framework of quality indicators for learning analytics (Scheffel et al., 2014)	Generation of ideas, sorting of the collected ideas into clusters, and rating of the ideas

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Performance models	
Name of the models/frameworks	Components
8. Multimodal learning analytics (MMLA) techniques (Schneider & Blikstein, 2015)	Information retrieval techniques, the tangible interface logs, predict learning gains, KinectTM, tabletop by using clustering algorithms, a machine-learning classifier.
9. An integrated, socio critical ethical framework (Slade & Prinsloo, 2013)	Learning analytics as moral practice, students as agents, student identity and performance are temporal dynamic constructs, student success is a complex and multidimensional phenomenon transparency, higher education cannot afford to not use data
10. A conceptual framework for positioning analytics within a business and academic domain (Van Barneveld et al., 2012)	Business analytics, academic analytics, learning analytics, predictive analytics, actionable intelligence, decision making
11. Educational dataset framework (Verbert et al., 2012)	Dataset properties, data properties, LAK objectives
12. MOOC business models (Wulf et al., 2014)	Direct, provider and third party model
13. A student performance prediction model (Xing et al., 2015)	Subject, rules, tools, division of labor, community, and object
14. Artificial intelligence and data analysis (AIDA) (Kitto & Knight, 2019)	Consequentialism, deontological, virtue ethic
15. A Privacy and Data Protection Framework (Steiner et al., 2016)	Existing guidelines, approaches, regulations
16. Learner activity model (Ji et al., 2016)	Learning content data, learning activity data, operational data, career data and profile data
17. Hypercube Model (Fuchs et al., 2016)	a learner's progress, learning history, capabilities, the learning environment.
18. The conceptual model (ecosystem and architecture) (Hauge et al., 2015)	LA platform, in-game and stealth measures, user modelling, adaptive control, visual analytics, map of pedagogical patterns.
19. The proposed conceptual de-identification–learning analytics framework (Khalila & Ebner, 2016)	Learning environment, Immersive Learning Simulations, mobile learning, and Personalized Learning Environments
20. Development of a code of practice model (Sclater, 2016)	Expert consultation, expert and public consultation, public release and institutional piloting and use
21. MOLAC framework (Drachsler & Kalz, 2016)	Teaching and learning innovation, intervention identification, data repository, meta data standards, MOOC directory
22. A new two-stage ethical framework (Cormack, 2016)	Analysis, intervention
23. Predictive model (Gursoy et al., 2016)	Data analysts, data publishing, anonymizer, ϵ-differential privacy mechanism, data access layer, SDR database
24. SHEILA framework (Tsai et al., 2018)	Map political context, key stakeholders, behavior changes, develop engagement strategy, analyze internal capacity to effect change, establish monitoring and learning frameworks
25. Moodle LMS (Fenu et al., 2017)	Usability score visualization, graph visualization, temporal data visualization.
26. Instructor Learning Analytics Implementation Model (McKee, 2017)	Adoption, caution
27. The machine-learning based framework (Amigud et al., 2017)	Students' patterns of language use, student identities and student-produced content.
28. LA process model (Hoel & Chen, 2018)	Learning activity, data collection, data storing and processing, analyzing, visualization, feedback actions
29. Personalization and Learning Analytics (PERLA) (Chatti & Muslim, 2019)	Goal setting, executing and evaluating
30. Business intelligence framework for AE-LS (Janati et al., 2019)	Open educational data sets, E-learning platform, Learning Management Systems, Intelligent Tutoring Systems, and Hypermedia Systems.
31. Mobile learning analytic model (Shorfuzzaman et al., 2019)	Data aggregation, data analytics and decision support
32. A complexity leadership model (Tsai et al., 2019)	key action plans, prominent challenges, and considerations of policy development
33. Knowledge models (Aguilar et al., 2019)	Observation, analysis, decision making
34. Integrated methodological framework (Jan & Vlachopoulos, 2019)	SNA parameters, application, adaptation and interpretation
35. Predictive model (LD-specific model & Generic model) (Er et al., 2019)	Meeting notes, survey responses, students log, interview transcripts
36. Student behaviors model (Paquette & Baker, 2019)	Accuracy on the original data used to create them, model interpretability, model generalizability to new data and new contexts.
37. A student–instructor centered conceptual model (Pardo et al., 2018)	Data warehouse, other data sources, data import, name, personalized learning support action, data mining machine learning
38. LA Platform Framework (Flanagan & Ogata, 2018)	LMS, behavior sensors, LRS, and analysis and results
39. Multi-stage prediction model (Choi et al., 2018)	Attend, clicker, exam
40. Proposed Model (Lau et al., 2018)	Global, series, video, and feedback
41. The analytics layers for learning design (AL4LD) framework (Hernández-Leo et al., 2019)	Learning analytics, design analytics and community analytics
42. Analytics framework (Muslim et al., 2018)	Analytics engine, visualizer, analytics module, analytics methods
43. VASCORLL 2.0 framework (Mouri, Uosaki, & Ogata, 2018)	E-Book learning structure and real-life learning structure
44. Multimodal Learning Analytics Model (MLeAM) (Di Mitri et al., 2018)	Physical world, digital world, input space, hypothesis space
45. Integrated multimodal framework for learning analytics (IMFLA) (Wang & Chen, 2018)	The stakeholders, data, audio-video, instruments
46. Learning analytics model for e-book logs (Mouri, Uosaki, & Yin, 2018)	Collection, evaluation, cleansing and analytics
47. Experimentation strategies in design (Vieira et al., 2016)	Experimentation strategies

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