Adaptation in Learning Analytics Dashboards: A Systematic Review

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Abstract: Although learning analytics dashboards (LAD) grow in numbers, they often fail to improve learner awareness as they lack adaptation capabilities. This paper presents a systematic review following the PRISMA statement, about the adaptation capabilities of LADs based on new definitions for LADs and learning indicators. A detailed analysis of 23 articles selected among 426 articles retrieved from databases was conducted based on a coding scheme, centered on adaptation and its dimensions, namely: to whom, what, to what, who, and how. The main result of this study is that there is more evidence of adaptable LADs than adaptive LADs. As a result, the road to adaptivity is worth exploring. The analysis of LAD's common features led us to distinguish mainly 4 adaptable capabilities and 2 adaptive ones. Most of the adaptable capabilities consist of giving exploration power to the user and providing him with data filtering, zooming, or selection functionalities. In contrast, users have limited options when it comes to selecting indicators, their visualizations, and organization on the dashboard. Providing more flexible LADs could enhance their usability and increase learner awareness. Furthermore, the few adaptive features involve adaptations based on "if-then" rules and there are no reports of advanced computing techniques such as machine learning that could empower LAD's adaptation.

1 INTRODUCTION

Since the past years, the rise of hybrid learning activities and the higher disponibility of learning data have reinforced interest in learning analytics (LA) which is the measurement, collection, analysis, and reporting of data about learner and their contexts (Siemens, 2011), resulting from users' interactions with educational and information technologies (Gašević et al., 2015). Learning analytics dashboards, defined as a "single display that aggregates different indicators about learner (s), learning process(es) and/or learning context(s) into one or multiple visualizations" (Schwendimann et al., 2016, p. 37) are the most common tools used to report the results of learning analytics to many stakeholders such as teachers, learners or researchers. One of the major limitations of LADs is that they fail to improve learner awareness as they lack adaptation capabilities, resulting in less actionability (Jørnø and Gynther, 2018). This refers to some challenges pointed out in (Verbert et al., 2020) such as "one-size-does-not-fit-all" and the need to deal with data literacy. The adaptation capabilities we refer to have been in particular specified in the field of Adaptive Hypermedia Systems (AHS) (Brusilovsky, 2001), with Oppermann (2017) emphasizing the difference between adaptable systems (adaptability) and adaptive systems (adaptivity), saying that "Systems that allow the user to change certain system parameters, and thereby adapt the behavior of these systems, are called adaptable. Systems that adapt to users automatically based on monitoring the users' interaction during runtime are called adaptive".

Our main research goal is to explore the state of the art regarding adaptation capabilities of LADs. We identified two systematic reviews that are similar to what we propose. The first is from 2019 and reports on the tailoring capabilities of information dashboards (Vázquez-Ingelmo et al., 2019), while the second is from 2021 and is a replication of the previous one, centered on performance dashboards (Kruglov et al., 2021). The main similarity of these reviews with our study is the shared focus on the adaptation of the dashboards. However, this study focuses on LADs and analyzes LADs adaptation dimensions with a finer granularity, while the other studies adopt a more general analysis framework, not centered on

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learning. Moreover, in these studies a large range of vocabulary is employed knowing that there is in general a lack of agreement when speaking of adaptation: terms used do not always refer to the same concepts. For Vázquez-Ingelmo et al. (2019), ”A general term is necessary, because using “customizable,” “personalized” or “adaptive” indistinctly to refer to these solutions, could lead to misconceptions around these last terms, which, in the end, have different nuances”. In our study, we precise the terms we refer to, in connection with historical definitions grounded in the field of adaptive hypermedias.

We tackle the aforementioned challenges and retrieve research that focuses on the adaptation of LADs. First, we define the concepts of learning indicator, LAD, and adaptation dimensions before precising our analysis framework. Then, using a systematic review, we provide insights about the implementation of adaptable and/or adaptive learning dashboards.

In line with what we found in similar works, we map out such adaptation mechanisms with a level of detail allowing us to get a proper understanding of what has been made yet. As a result, this study addresses the following research questions:

- RQ1: What LADs since 2017 feature adaptability or adaptivity mechanisms?
- RQ2: What adaptation mechanisms are implemented into LAD, for what purposes?

The remainder of the article is organized as follows. Firstly, we provide an overview of existing definitions for the key concepts of the study before deriving our own, to precise the theoretical background of the review. Secondly, we describe the method we applied to lead a systematic literature review, following the PRISMA statement (Page et al., 2021). We then jointly present and discuss the findings for each research question. Finally, we report the known limitations of our study before concluding.

2 KEY STUDY CONCEPTS DEFINITIONS AND RELATED LITERATURE

2.1 Learning Indicators (LI)

The term ”indicator” is commonly used across various scientific disciplines. Nonetheless, there is limited literature defining this term in the field of education. According to Muslim et al. (2017), an indicator can be defined as “a specific calculator with corresponding visualizations, tied to a specific question”. Ahmad et al. (2022) provided a comprehensive definition: “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 [...]”. For Dimitracopoulou (2004):

> The application of ‘data processing methods’ produces one or more ‘indicators’, that indicate something’ related to the ‘quality’ of individual activity, the mode or the quality of the collaboration, the quality of the collaborative product, or the appropriateness of its production process. These variables interpreted, taking into account, the learning activity, the profile of the participants and the context of interaction could support interaction participants on the level of awareness, or of the (self) assessment.

According to these definitions, we suggest that a learning indicator is a metric or latent variable that results from the analysis of data associated with a learning activity. To elaborate, we distinguish, in line with the metric concept defined by Ahmad et al. (2022), low-level indicators which are observable and calculated from the raw data of a learning activity, from higher-level indicators which are abstract variables derived from raw data and/or lower-level indicators.

2.2 Learning Analytics Dashboard (LAD)

Various fields integrate dashboards into their practices (e.g. Business Intelligence, Logistics, Healthcare). Few says that “A dashboard is a visual display of the most important information needed to achieve one or more objectives; consolidated and arranged on a single screen so the information can be monitored at a glance.” (Few, 2006). For Brouns et al. (2015), it’s ”An easy to read, often single page, real-time user interface, showing a graphical presentation of the current status (snapshot) and historical trends of an organization’s key performance indicators (KPIs) to enable instantaneous and informed decisions to be made at a glance.”. In the field of learning, LAD definitions share similarities with the previous ones. A recent definition is: “a learning dashboard is a single display that aggregates different indicators about learner (s), learning process(es) and/or learning context(s) into one or multiple visualizations.” (Schwendimann et al., 2016). Yoo et al. (2015) consider a dashboard as “a display which visualizes the results of educational data mining in a useful way”. Others see them as “visualisations of learning traces” (Steiner et al., 2014) and Podgorelec and Kuhar (2011) consider that "the Learning Analytics Dashboard (LAD) is an interactive, historical, personalized, and analytical monitoring display that reflects students' learning patterns, status, performance, and interactions. The outlook of LAD includes visual elements such as charts, graphs, indicators and alert mechanisms.".

Taking a closer look at each definition, it's noticeable that their authors do not place equal emphasis on dashboard characteristics. Some definitions complement each other, while others share traits such as the central concept of visualization, the use of learning traces, usability, and the objective of supporting awareness and decision-making. However, the concept of a single screen and/or display is to our mind ambiguous (e.g. is a window with several tabs considered as a single display or multiple display(s) ? Is a window split on multiple monitors considered as a single or multiple display(s) ?). To capitalize on these previous definitions and to clarify our study terms, we suggest a formal yet flexible definition of a LAD. We propose dropping the single display aspect and considering a LAD as an ordered aggregation of indicators - usually represented using visualizations - which support awareness, and decision-making in relation to one or more objectives related to learning.

2.3 Insights About Adaptation and Its Dimensions

In addition to adaptability and adaptivity, systems adaptation also refers to the development of systems tailored to meet specific user profiles. This study will not cover adapted LADs, as there is already extensive research utilizing participatory designs or user-centered methods during the conception of LADs. The focus of this study is primarily on adaptable and adaptive dashboards. Park et al. (2023) defined an adaptive learning analytics dashboard as "a specific learning environment where learners' learning progress, performance, and adaptive recommendations were provided on a real-time basis through their LAD.". In contrast, our study does not consider adaptive environments in general, but rather the adaptation capabilities of LADs themselves. Starting from the definitions given in (Brusilovsky, 2001; Brusilovsky and Millán, 2007; Oppermann, 2019), a reformulation is proposed to make these definitions, initially taken from AHS, applicable to LADs:

- Adaptable learning dashboard (adaptability): the adaptation of the dashboard is triggered by the user, following some of his interactions with the LAD
- Adaptive learning dashboard (adaptivity): the adaptation of the dashboard is automatically triggered by the system itself, without any user intervention

The adoption of the Five W's (Who, What, Where, When, Why) is a common practice in many fields to overview a system. In this study, we analyze the adaptation dimensions we want to describe by adapting and combining these questions:

- To whom (Who is the target of the adaptation ?): in most cases, the user is either a learner, a teacher, or a researcher.
- Who (Who initiates the adaptation ?): in adaptable cases, the user initiates the adaptation while in adaptive cases, the system itself triggers the adjustments.
- To what (on what data and/or knowledge about users are adaptations based ?): it's only relevant to monitor data involved in adaptive cases since it is always a user input in adaptable cases.
- What (What is adapted in LAD): describing the effects and changes occurring on the LADs.
- How (Which methods are involved in the adaptation process ?): from a system perspective, what are the steps in the decision-making process that lead to adapting one thing over another?

3 METHODS

This section describes the steps and methods used to conduct the review. A systematic review methodology was chosen due to its well-formalized framework outlined by the PRISMA statement (Page et al., 2021), and because this approach is becoming increasingly popular, not only in the LA research field. It consists of identifying academic databases to search into, formulating queries to effectively address our research questions, adding constraints to filter the abundant records collected, and then describing the process of analyzing the reports included in the study.

3.1 Identification of Databases

We first identified suitable databases for our study using previous systematic reviews which are grounded in the field of LA such as (Matcha et al., 2019; Bodily et al., 2018; Jivet et al., 2018; Papamitsiou and Economides, 2014). Then, we ranked our insights by popularity and compared the most frequently used databases (IEEE Xplore, ACM Digital Library, SpringerLink, ScienceDirect, ERIC) with the findings of Gusenbauer and Haddaway (2020), reporting well-suited academic search systems for systematic reviews. Lastly, we retained ACM Digital Library (ACM DL) as our principal data source and complemented it with IEEE Xplore (IEEE) and Web of Science (WoS). To complete records identification, we also searched specifically in conference proceedings and journals related to the LA research field. We scanned LAK (Learning Analytics and Knowledge) and L@S (Learning at Scale) proceedings because such conferences are related to learning, we also looked at UMAP (User Modeling, Adaptation and Personalization) proceedings for its focus on adaptation and personalization and we investigated in the Journal of Learning Analytics.

3.2 Search Terms and Requests

To answer our research questions, we designed a query to question the search engines and gather records in connection with LAD built around learner's data and any adaptation techniques. In a similar way to the academic databases identification, we selected relevant keywords from previous reviews. Then, we supplemented these with keywords we found through our readings to either restrict or extend the results to what interests us most. After iterative adjustments, we conducted searches within each database in the corpus using data from titles, abstracts, and keywords, structured around a query comprising four parts:

- (A) (dashboard OR visual*): restrict to papers explicitly mentioning a dashboard or something related to visualization.
- (B) ("LA" OR "learning analytics" OR "learning analytic" OR "educational data mining" OR "educational datamining"): restrict the application domain to learning analytics. We also included keywords for data mining because the boundary with the LA is thin.
- (C) (tailor* OR adapt* OR custom* OR intelligent OR individual* OR personal*): restrict to the main topic of our study, by including the words related to adaptation that are very often used by authors.
- (D) (learner OR student): restrict results to works based on learner data. We included "student" because it's a term often used in the field of education.

The resulting query combines all expressions and is adapted to the specifications of each search engine at search time. Finally, for searching in conferences and journals dedicated to learning, knowing that LA keywords are not necessarily employed, we used a simpler query by removing part (B) from Formula 1.

$$Query = (A) \; and \; (B) \; and \; (C) \; and \; (D) \tag{1}$$

3.3 Delimiting the Search

As we intend to complete the map of the existing adaptable or adaptive LADs, we take 2017 as a starting point, in line with the results achieved by (Vázquez-Ingelmo et al., 2019). We filtered the records by date using search engines' built-in functionalities. In addition, we systematically excluded records for which we were unable to obtain the report (it's a "document (paper or electronic), supplying information about a particular study. It could be a journal article, preprint, conference abstract, study register entry, clinical study report, dissertation, unpublished manuscript, government report, or any other document providing relevant information" (Page et al., 2021, p. 3)). A two-step filtering process was conducted on the resulting records, based on inclusion criteria (see Table 1). The first step involved excluding records after reading titles, abstracts, and keywords. The second step involved reading the entire texts of the remaining records.

Table 1: Inclusion criteria.

We added IC (inclusion criterion) 1-2-3 as criteria to guarantee a minimum quality of the publications to be included in our analysis	
IC1	The paper must be written in English
IC2	The paper must have been peer-reviewed
IC3	The paper must be a complete study, ie. we exclude everything which is a short paper (less than 5 pages), a review, a poster, an abstract, a work in progress, etc.)
We added IC4-5-6 to keep only records that could answer our topics	
IC4	The paper must describe a learning analytics dashboard (it must relate to learners)
IC5	The paper must describe one or more adaptation mechanisms of the dashboard
IC6	The paper must show evidence of an evaluation of the dashboard
We added IC7-8 to make sure we only study unique solutions or the most mature ones	
IC7	The paper must be the most mature solution of a series of research (duplicates removal)
IC8	The paper must not present an existing dashboard without proposing new features

The process up to the selection of the final pool of articles is illustrated in the PRISMA flow diagram (see Figure 1).

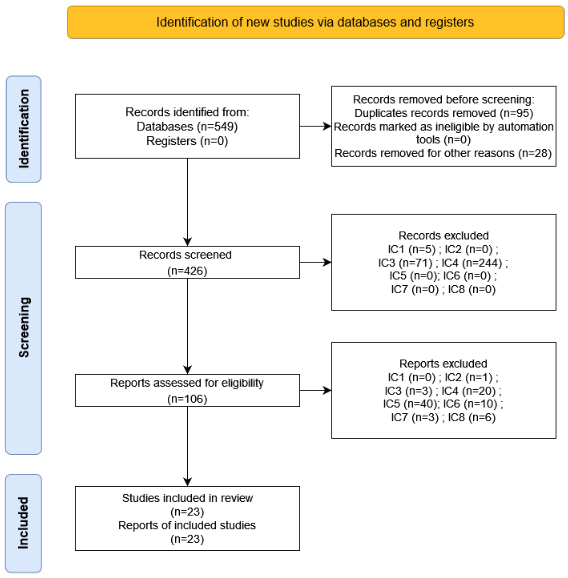

Figure 1: PRISMA inspired flow diagram.

3.4 Coding Scheme

The initial coding objective is to provide an overview of each LAD by identifying its target (to whom: learner, teacher, adviser, institutional...) and of the type of learning analytics presented by the indicators. The indicators are classified using the terms presented by Gartner, (2014) and the definitions in (Susnjak et al., 2022; Sirje Virkus, 2023):

Descriptive Indicators: indicators showing data about learner past actions. *e.g. An indicator showing how many modules a learner has completed yet*

Diagnostic Indicators: indicators giving in-depth insights about identified learner/learning state. *e.g. The dashboard shows that the learner didn't pass his year because of his lack of regularity*

Predictive Indicators: indicators showing estimation of future outcomes based on current and past data analysis. *e.g. An indicator showing the probability a student will pass a test*

Prescriptive Indicators: indicators aiming to recommend future actions. *e.g. An indicator showing a list of recommended learning material to work on to improve a point of weakness*

Note that we won't describe the nature of the data used to calculate the indicators, but the nature of the indicators themselves: whereas descriptive data are required to compute predictive data, there are no such relations for the indicators, which means that a dashboard can present predictive indicators only, without any descriptive ones.

The second coding goal is to describe the adaptation mechanisms present in the papers according to 4 dimensions of adaptation: "Who", "To what", "What", "How". As a result, we expanded our coding scheme for describing each dimension with the following codes:

<u>Dimension 1 - Who ?</u> Who initiated the adaptation process ? It's either the user or the system itself.

<u>Dimension 2 - To what ?</u> What data/knowledge about users are used to perform the adaptation ?

User's Configuration: user actions to trigger a specific system behavior. *e.g. The user selects a date range or some data to "zoom in/out". The user modifies the font size.*

Prior Knowledge, Knowledge Growth: any data related to a learner model that can be used to report on its progress in terms of knowledge or skills. *e.g. The history of what a learner has learned or mastered since he enrolled in the online course.*

Learning Paths: any data reporting the learning paths or sequences of a learner within a learning application *e.g. The learner first read the course materials and then tried the quizzes.*

Performance: any data related to an evaluation and/or an assessment task which indicates a learner's performance at a given time. *e.g. The learner's grades for the semester.*

Engagement, Motivation: any data or data aggregation which can be used to monitor the engagement of a learner (activity logs, emotional or expressive data...). *e.g. The learner's engagement is in line with his login frequency.*

Metacognition: any data related to the learner's metacognitive state such as his self-regulated learning level, the learning strategies or the methods he uses to learn or solve problems... *e.g. Learning objectives formulated by the learner.*

Collaboration: any data that highlights collaboration or interactions between the stakeholders during a learning activity/process. *e.g. The number of times a specific learner asked his teacher for help.*

Socio-Demographic Data: any data related to the socio-demographic profile of a learner. *e.g. The learner is twenty years old and he is funded by a scholarship.*

Data Availability: when the data usually used to compute some indicator is not available yet. It is similar to a cold start. *eg. The dashboard can't compute Adam performance metrics because he hasn't passed any test yet.*

User's Preferences: any data inferred from previous user configurations and/or log analysis. These data

are a product of past user-system interactions. *e.g. The system has learned from the logs that the user has a preference for line charts*
<u>Dimension 3 - What ?</u> Which elements of the LAD are adapted ?
Indicators Set: the combination of indicators within the LAD is changed. In particular, indicators can be added, removed, or re-calculated to change the meaning of the feedback conveyed by the dashboard. *e.g. A new indicator appears in the LAD*
Indicators Importance: an indicator or a sub-set of indicators can be highlighted. The degree of importance could be modified using for instance visual tricks or by changing indicator relative positions. *e.g. Indicator 1 is now the most important and its visualization size increased.*
Indicators Visualization: a visualization can be associated with one or more learning indicators. Sometimes, visualizations can change while the indicators remain the same. *e.g. The data are now presented with a bar chart instead of a pie chart.*
Indicators Timing: an indicator can be presented after a delay or at a given time, which can be configured. *e.g. The feedback was presented after each learning session but is now presented only one session out of two.*
Indicators Source Data: when the data used to compute the indicator is changed (filtered, modified...), the indicator remains the same as long as the data model is unchanged. *e.g. The indicator is now showing Adam's grades instead of Collin's grades.*

<u>Dimension 4 - How ?</u>
How is the adaptation decided ?
Rules Engine: the adaptation is realized following simple 'if-then" rules. *e.g. The alert box is shown only if the learner underperformed his test.*
Algorithms: the adaptation is realized following more advanced programming concepts which are more complex than 'if-then" rules (e.g. loops). *e.g. Heavy calculation is needed before deciding if the dashboard must include a particular indicator.*
Machine Learning: to go further than "if-then" rules and advanced programming concepts, the adaptation is realized using machine learning. *e.g. A prediction machine learning algorithm is used to decide whether or not it's good to visualize a set of indicators with a bar chart instead of a pie chart.*
How is the adaptation performed ?
Activation/Deactivation: action to activate or deactivate an indicator, to make a component appear or not... *e.g. A new indicator is now shown in the dashboard.*
Refine Data: action often associated with the fact to filter, select, or brush the data. The output value of the indicator is actualized but the indicator remains the same. *e.g. The indicator showing Adam's grades for week 2 is now showing Adam's grades for week 5.*

This coding scheme is the result of several iterations of analysis of samples of articles and associated discussions. Each iteration enabled us to refine/improve the previous version of the coding scheme until we obtained a coding scheme that we consider stable and complete. Finally, coding was carried out by a unique coder to ensure homogeneity.

4 RESULTS & DISCUSSIONS

In this part, we jointly present the analysis results and discuss them regarding our research questions. Raw data, resulting from our analysis, are shown in Table 2 where we conveniently removed empty columns for visualization purposes. The systematic process we followed led us to review 426 papers to determine if they described adaptable or adaptive LADs. After two screening steps and applying inclusion criteria, we ended up with 23 papers integrating adaptation mechanisms to analyze (see Figure 1). As there is only one LAD per report read, we assume that saying report, publication, LAD, or paper refers to the same thing.

4.1 RQ1: What Dashboards Since 2017 Feature Adaptability or Adaptivity Mechanisms?

As shown in Figure 2, we reported publications including adaptable features every year since 2017, with a total of 19 LADs. In contrast, publications embedding adaptive features were only found in 2018 (n=1), 2019 (n=3), 2020 (n=2), and 2021 (n=1), with a total of 7 LADs. As a result, we have found more evidence of adaptability than evidence of adaptivity (19 against 7). We assume our sample size is too limited to discuss any trend. We report and discuss below the nature of indicators involved in adaptable and adaptive LADs respectively. Descriptive indicators are found in all papers and are the most commonly used (n=19; n=7), followed by diagnostic indicators (n=8; n=6), then predictive and prescriptive indicators (n=1; n=2). Table 3 shows for each adaptation category the percentage ratio of the number of LADs including descriptive, diagnostic, predictive, and prescriptive indicators respectively, over the number of LADs re-

Table 2: Analysis findings.

Authors	End user	Indicators nature				To what								What				How		
		Descriptive	Diagnostic	Predictive	Prescriptive	User's configuration	Knowledge	Paths	Performance	Engagement, motivation	Metacognition	Data availability	Preferences	Selection	Importance	Visualization	Source data	Rules	Activation	Refine
(Hasnine et al., 2023)	T	•	•			•								•			•		•	•
(Hou et al., 2022)	L	•				•											•			•
(J. A. Ruipérez-Valiente et al., 2021)	T	•	•			•											•			•
(Al-Doulat et al., 2020)	A	•				•											•			•
(Mohseni et al., 2022)	T	•	•			•										•	•		•	•
(Chaudy and Connolly, 2018)	T, D, R	•	•			•							•				•	•		•
(Zamecnik et al., 2022)	L	•				•								•			•			•
(van der Stappen, 2018)	I	•				•								•	•	•		•	•	
(D. Pérez-Berenguer et al., 2020)	L, T	•	•			•		•	•					•				•	•	
(Şahin and Yurdugül, 2019)	L	•	•	•					•					•				•	•	
(Aslan et al., 2019)	T	•	•							•				•				•	•	
(Molenaar et al., 2020)	L	•	•		•		•				•			•				•	•	
(Jivet et al., 2021)	L	•				•								•					•	
(de Quincey et al., 2019)	L	•	•	•	•	•								•		•			•	
(T. Rohloff et al., 2019)	L	•		•	•							•		•				•	•	
(Chen et al., 2018)	T	•				•								•			•		•	•
(Scheffel et al., 2017)	L	•				•											•			•
(Jonathan et al., 2017)	L	•				•											•			•
(Smith, 2020)	L	•				•											•			•
(Taibi. et al., 2018)	L	•				•											•			•
(Ez-zaouia and Lavoué, 2017)	T	•	•			•											•			•
(Torre et al., 2020)	P	•				•											•			•
(Dickler, 2021)	T	•	•			•	•										•			•

Light gray = Adaptive ; Dark gray = Adaptable

L=Learner; T=Teacher; A=Advisor; R=Researcher ; D=Developer; I=Institutional; P=Practitioner.

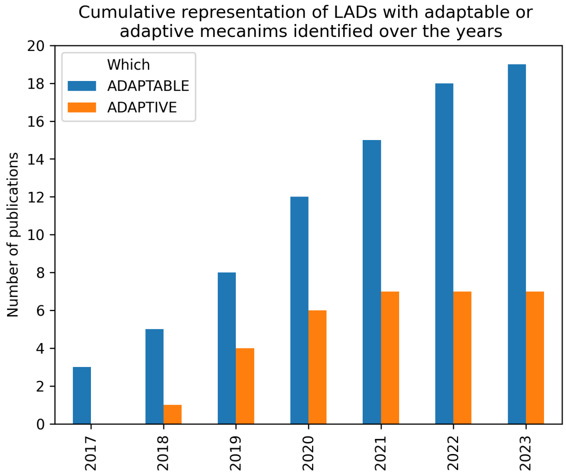

Figure 2: Cumulative publications since 2017.

spectively. As a result, there are always descriptive indicators in both adaptable and adaptive LADs and the ratio is increasing between adaptable and adaptive LADs for other types of indicators. Based on this analysis, we hypothesize that adaptive LADs embed more complex indicator natures, such as diagnostic, predictive, and prescriptive than adaptable LADs.

Table 3: Indicator's nature ratio.

%	Desc.	Diag.	Pred.	Pres.
Adaptable (n=19)	100	42	5.2	5.2
Adaptive (n=7)	100	86	29	29

Last but not least, we mostly report dashboards for learners (n=11) and teachers (n=8), one targeting both learners and teachers and three others for advisers, institutional, and practitioners. There is no noticeable trend or evolution of the targeted end users over time.

4.2 RQ2: What Adaptation Mechanisms Are Implemented into LAD, for What Purposes?

4.2.1 Adaptive LADs

Most of the expected data types have been found, except for collaboration data and socio-demographic data. Additionally, during the adaptive process, two out of seven LADs use two types of data instead of one. The adaptive capabilities can be grouped into two main categories, based on similarities shared across "What" and "How" dimensions.

The first category (n=5) concerns LADs that can activate and/or deactivate certain indicators on their own, thereby altering the resulting set of indicators. Two publications include "all or nothing" indicators as contextual notifications are displayed to the user. For instance, in (Molenaar et al., 2020), indicators are added to the screen to notify the learner that he has completed the learning goals he set. In (Aslan et al., 2019), a red bell appears on the corresponding learner's avatar when he is highly disengaged, indicating that he is off the learning platform. In (de Quincey et al., 2019) the authors insist on the use of empty states to enhance the learning process: some indicators are replaced with other learning materials, such as basic recommendations, when there is not enough data to compute them. Replacement indicators show personalized recommendations or various descriptive data. The LAD of D. Pérez-Berenguer et al. (2020) is adaptive due to the dynamic selection of the indicators displayed on the screen. The decision process is based on rules that can be edited by the teacher and the rule engine can be fed either by performance or event sequences data of the learners. Finally, the LAD in (Şahin and Yurdugül, 2019) can complement the set of indicators by activating additional feedback to learners who have been classified as poor performers by the system.

The second adaptivity category includes LADs that automatically update their indicators when the corresponding source data is changing (n=2). In (Chaudy and Connolly, 2018), the LAD automatically restricts the data accessible to a user based on their role upon login. Teachers are limited to monitoring their students while administrators of the system, such as developers or researchers, have access to data from all the students. In (Dickler, 2021), the LAD computes and triggers alerts from student data. We consider this LAD to be adaptive because each alert, whether it's focused on a student in particular or a group of students, pre-defines the data that the teacher can consult after clicking on one of the notifications. The teacher navigates through the data automatically selected by the LAD and doesn't know in advance what he will be able to monitor.

Table 2 data highlights that the use of rules predominates to activate or deactivate learning indicators. It's important to notice that no complex algorithms or machine learning were reported in the adaptation/decision process, leaving research on these questions open. As previously reported, the two adaptivity capabilities only involve changes in the set of indicators of the LAD or changes in the available source data. Our analysis didn't reveal any adaptation from the system that focuses on changing the relative importance (order) of indicators, visualizations that support the reporting of data, or any delay that could be considered before presenting one or more indicators to a user.

4.2.2 Adaptable LADs

There is not much to discuss regarding the "To what" dimension as all reported functionalities correspond to a user input (User's configuration). In this section, we organize and discuss the results according to the "What" and "How" dimensions. Adaptable capabilities are grouped into four categories based on shared configurations.

Most of the LADs (n=15) are featured with the functionality that consists in updating the dashboard indicators when the user selects a new subset of data, such as changing the date range (Hou et al., 2022; Zamecnik et al., 2022; Scheffel et al., 2017; Mohseni et al., 2022; Taibi. et al., 2018), subgroup or subdata to monitor (Hasnine et al., 2023; J. A. Ruipérez-Valiente et al., 2021; Torre et al., 2020; Chaudy and Connolly, 2018; Chen et al., 2018; Al-Doulat et al., 2020; Dickler, 2021; Jonathan et al., 2017; Taibi. et al., 2018; Ez-zaouia and Lavoué, 2017; Smith, 2020). This functionality mainly corresponds to filter, select, and zoom actions. It is worth noting that the codes "Refine data" and "Indicator data" are strongly correlated. Note that the nature of the indicators remains the same, even if the values they return change. This is because the indicators still answer the same initial question.

It seems that some LADs (n=4) allow the user to change/choose the indicators presented in the dashboard through activation/deactivation. Among them, two LADs enable the user to select their visualizations. Jivet et al. (2021) allowed learners to select up to six indicators from a choice of twelve to be displayed on a radar chart. The learners could change their choices at any time. Three distinct functionalities were identified in the LAD developed by de Quincey et al. (2019). The first allows the learner to choose between a professional visualization with common charts and diagrams or a personified theme that represents indicators with visual metaphors: icons and images representing the concepts are used instead of bar, line, or pie charts. The second allows the learner to select the indicators he prefers to monitor. The third consists of displaying a contextual indicator (a tooltip) when the learner requests it, providing additional explanations on how the current score is calculated. The LAD presented in (Hasnine et al., 2023) enables the user to access a session summary on demand. It presents a more general set of learning indicators than the real-time indicators presented during the session. The analysis dashboard, as presented in (Chen et al., 2018) allows the teacher to progressively drill down into student data, and some actions or specific inputs of the teacher will result in the apparition of contextual indicators.

The following LADs (n=2) seem to feature adaptation capabilities, which involve recomputing the indicators to fit a new subset of data, along with other effects on the set of indicators or their relative importance. In (Zamecnik et al., 2022), the learner has filtering functionalities, but the indicator set is also likely to change since the learner can remove certain types of information, which alters the nature of the indicators. In (van der Stappen, 2018) the authors propose a customizable LAD. It's mentioned that the users can personalize the order in which visualizations are displayed.

Finally, there are two dashboards (n=2) that allow the user to configure the indicators he wishes based on the edition of rules. The design proposed by van der Stappen (2018) includes adaptation mechanisms, such as the capability for the user to customize the indicators on the LAD using SQL queries and select their associated visualizations. Similarly, teachers can set adaptation rules using a specific domain language as presented in (D. Pérez-Berenguer et al., 2020) to determine which indicators will be present at execution time, depending on the input learning traces.

Neither algorithms nor machine learning power the adaptability mechanism after the user triggers the adaptation. It's important to note that we are referring to the decision step of the adaptation and not to the steps used to compute the learning indicators. Additionally, as reported for adaptivity mechanisms, no features allow the user to configure a delay that the LAD should respect before presenting one or more indicators.

5 LIMITATIONS

The study has some limitations. Firstly, we examined the proceedings of specialized conferences, namely LAK, L@S, and UMAP but we were unable to do so for the Educational Data Mining conference (EDM) due to restrictions upon the EDM proceedings search engine. Secondly, our study could benefit from the integration of more data sources, notably LADs identified by other means than academic databases. Thirdly, it could be difficult to deal with the analysis step as adaptation mechanisms were not always clearly described by the authors. Concerned papers have been discussed by experts until a consensus was reached. To improve the analysis step, it could be beneficial to involve multiple coders and calculate an inter-rater reliability metric.

6 CONCLUSIONS

A systematic review was conducted to investigate the adaptation capabilities of LADs in terms of adaptability and adaptivity. An analysis framework was designed to reduce the diversity of the vocabulary used when reporting on adaptation capabilities. Our findings highlighted less work on adaptive dashboards than on adaptable dashboards since 2017. Our detailed coding scheme helped us to identify categories of adaptation capabilities and gave us more insights about the learner data used for adaptivity. There is currently little focus on the adaptation functionalities of LADs, and there is likely insufficient evidence to support their benefits at this time. Going further, it could be profitable to investigate the effects of such adaptations on user's perception, behavior, and learning in future research. Additionally, the analysis has pointed out paths that could be explored further. These include the utilization of advanced computing techniques in the adaptation process, adaptive capabilities that could be based on more, or new types of data, and functionalities that show up differently on the dashboard, such as the adaptation of the indicator's relative importance or time-delayed presentation of indicators according to learners' needs.

To nuance this review, we have identified several papers that were not included in the analysis but which are representative of some of the work on LADs. One body of research focuses on the development of intelligent learning indicators (e.g. (Khosravi et al., 2021)) which could be associated by transition with work on intelligent LAD. Another body of research, such as (Dabbebi et al., 2017; Vázquez-Ingelmo et al., 2020), focuses on the development of "meta dashboards" instead of a particular intelligent LAD.

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