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Investigating learning dashboards adaptation

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Abstract. Although there is a growing number of learning analytics dashboards (LADs), they often fail to improve learning and learners’ awareness due to their lack of adaptation capabilities. This paper presents a systematic review that follows the PRISMA statement and analyzes the adaptation features of LADs and their potential effects on learning. 24 of the 462 articles retrieved were scrutinized using an analysis framework centered on adaptation. The main finding is that there is more evidence of adaptable LADs than adaptive LADs, suggesting that adaptivity is worth exploring. The results mainly highlight 3 common LADs adaptable capabilities - most of which offer data exploration features - and 2 adaptive ones that change or refresh indicators on dashboards. Only a few articles investigate the adaptation of indicator visualizations or organization on dashboards. Currently, there is no work on the use of advanced computing techniques such as machine learning for LADs adaptation. Additionally, only 5 articles provide some evidence of dashboards adaptation features evaluation. As a result, a preliminary research agenda on LADs adaptation is suggested for enhancing LADs adoption and utility.

Keywords: Learning Analytics Dashboards · Systematic Review · Adaptation · Learning Indicators.

1 Introduction

Learning analytics (LA), which is the measurement, collection, analysis, and reporting of data about learner and their contexts [38], resulting from users’ interactions with educational and information technologies [13], has gained prominence with the increasing adoption of e-learning technologies and the need to make sense of the vast amount of learning data produced. Learning analytics dashboards (LADs) are commonly used to report LA results to stakeholders, but often suffer from a lack of adaptation capabilities, resulting in less actionability [22]. Consequently, challenges related to LADs’ adaptation capabilities persist, for instance, the “one-size-does-not-fit-all” challenge or the need to deal with different data literacy among users [45].

To gain a comprehensive insight of the current state of research concerning the adaptation capabilities of dashboards, two systematic reviews that report on adaptation capabilities of information dashboards [46] and of performance dashboards [25] were conducted. However, these studies employed a broad analysis framework that refers to adaptation using a sparse vocabulary (e.g. customizable, personalized, etc.), potentially leading to confusion and lacking specificity in the context of LADs. As a result, the present study complements and extends a previous work [4] that reviewed LADs that feature adaptation capabilities using a fine-grained analysis framework for describing adaptation in precise terms, grounded on top of two adaptation key concepts that originate from Adaptive Hypermedia Systems (AHS) [6]: adaptability and adaptivity. According to R. Oppermann [30], “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”.

As shown by the authors of [19], “most dashboard evaluations focus on assessing the tool’s usability and the impact on the behavioural competence”. This points to a real concern about whether LADs actually help to enhance learning outcomes. In line with this observation, this work presents the evaluation plans and evidence of learning impact drawn from the analyzed LADs featuring adaptation capabilities.

First, we define the key concepts of the study using related literature, and discuss the dimensions of learning analytics dashboards (LAD) adaptation to structure the first level of our analytical framework. Then, we detail the systematic literature review we conducted using the PRISMA statement [31], fulfilling our framework with a coding scheme we developed to address each of the following research questions :

- RQ1: What adaptation mechanisms are implemented into LAD over time, and for what purposes ?
- RQ2: How are adaptable or adaptive LADs evaluated ?

Lastly, we present and discuss the findings for each research question (results and discussion section), propose a research agenda upon adaptable and adaptive LADs, and report the known limitations of our study.

2 Key study concepts definitions and related literature

2.1 Learning Indicator and Learning Analytics Dashboard

To the best of our knowledge, there is limited literature defining the term indicator in digital learning. In general, it can be defined as “a specific calculator with corresponding visualizations, tied to a specific question” [29]; “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 [...]” [1]. According to these definitions, we suggest that a **Learning**

Indicator (LI) is a metric or latent variable that results from the analysis of data associated with a learning activity. We distinguish, in line with the metric concept [1], *low-level indicators which are observable and calculated from the raw data of a learning activity (metrics), from higher-level indicators which are abstract variables derived from raw data and/or lower-level indicator(s).*

Concerning LAD, the most recent definitions are: “a single display that aggregates different indicators about learner(s), learning process(es) and/or learning context(s) into one or multiple visualizations.” [37]; “a display which visualizes the results of educational data mining in a useful way” [48]; “visualisations of learning traces” [41] and “an interactive, historical, personalized, and analytical monitoring display that reflects students’ learning patterns, status, performance, and interactions.” [33].

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 notion of display is not clear to our minds (e.g., is a window with several tabs and/or split on multiple monitors considered as a single or multiple display(s) ?). To clarify and capitalize on previous definitions, we suggest defining a **Learning Analytics Dashboard (LAD)** as *an ordered aggregation of indicators, usually represented using visualizations, which support awareness, decision-making in relation to one or more objectives related to learning.*

When focusing about learners, Open Learner Model (OLM) and LAD are two related concepts [5]. While they share similarities, such as encouraging learners’ awareness or help them regulate their learning, they originate from different communities and have parallel lines of research. In a broader sense, one difference lies in the fact that LADs are not only aimed at learners, but also at all stakeholders who could benefit from such a reporting tool.

2.2 Insights about adaptation and its dimensions

Adapted LADs, i.e., LADs specifically designed for dedicated user profiles, are out of the scope of this study. This study considers the adaptation capabilities of LADs and covers adaptable and adaptive LADs. For **adaptable LAD** (*adaptability*), dashboard adaptation is triggered by the user, following some of his interactions with the LAD. For **adaptive LAD** (*adaptivity*), the dashboard adaptation is automatically triggered by the system itself, without any user intervention.

We use an adaptation of the commonly used Five W’s (Who, What, Where, When, Why) as dimensions for first-level structuring our analysis framework: **To whom** (*Who is the target of the adaptation ?* In most cases, a learner, a teacher, or a researcher); **Who** (*Who initiates the adaptation ?* The user for adaptability, the system for adaptivity.); **To what** (*On what data and/or knowledge about users are adaptations based ?* Only relevant for adaptivity, since it is always user input for adaptability.); **What** (*What is adapted in LAD ?* To describe the effects and changes occurring on LAD.); **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

The PRISMA statement [31] was used as a guideline for reporting the systematic review. This section outlines the academic databases, queries, filters, and analysis framework we used on the remaining reports to address the research questions.

3.1 Identification of databases, search terms/requests, delimitation

Previous systematic reviews grounded in LA [5, 19, 26, 32] were used to identify candidate databases. These candidate databases were ranked by popularity and compared with the findings of [14] that reports suited academic search systems for systematic reviews: we selected as general sources the ACM Digital Library, IEEE Xplore and Web of Science. We have also included specialized sources that consist of searchable conferences proceedings and journals, dedicated to LA, user modeling or adaptation: Learning Analytics and Knowledge (LAK), Learning at Scale (L@S), User Modeling, Adaptation and Personalization (UMAP), Artificial Intelligence in Education (AIED), as well as the Journal of Learning Analytics.

Query keywords were extracted from previous reviews and supplemented with keywords taken from our readings to refine the resulting records. We ran upon data from titles, abstracts and keywords, queries composed of 3 or 4 parts:

- (1) (dashboard OR visual* OR “Open Learner Model*” OR “Open Social Learner Model*” OR “Open Student Model*” OR “Open Social Student Model*”): study subject (use of ‘*’ was adjusted to meet the specifications of each search engine).
- (2) (tailor* OR adapt* OR custom* OR intelligent OR individual* OR personal*): adaptation dimension.
- (3) (learner OR student): to keep records related to learner data.
- (4) (“LA” OR “learning analytics” OR “learning analytic” OR “educational data mining” OR “educational datamining”): general research field.

More precisely, we ran a version of “Query 1:= (1) AND (2) AND (3) AND (4)” adapted to each search engine specification on databases belonging to the general sources. Finally, based on the observation that LA/EDM keywords are not necessarily written in papers coming from the specialized sources, we ran a simpler query on it by removing (4) : “Query 2:= (1) AND (2) AND (3)”.

In line with the results achieved by [46], we took 2017 as a starting point and excluded records for which we were unable to obtain the document. We then conducted a two-step filtering process based on inclusion criteria. Firstly, we excluded records by reviewing the titles, abstracts, keywords and, secondly, for the remaining records, by reviewing the entire texts. Inclusion criteria are : (IC3) document must be a complete study (not a short paper, a review, etc.), (IC1) written in English and (IC2) peer-reviewed ; (IC4) document must describe a

learning analytics dashboard, (IC5) one or more dashboard adaptation mechanisms, and (IC6) provide evidences of a dashboard evaluation ; (IC7) document must be the most mature one if there exist several related articles (duplicates removal), (IC8) must not present an existing dashboard without describing new features.

The whole process is illustrated by the PRISMA flow diagram (cf. Figure 1).

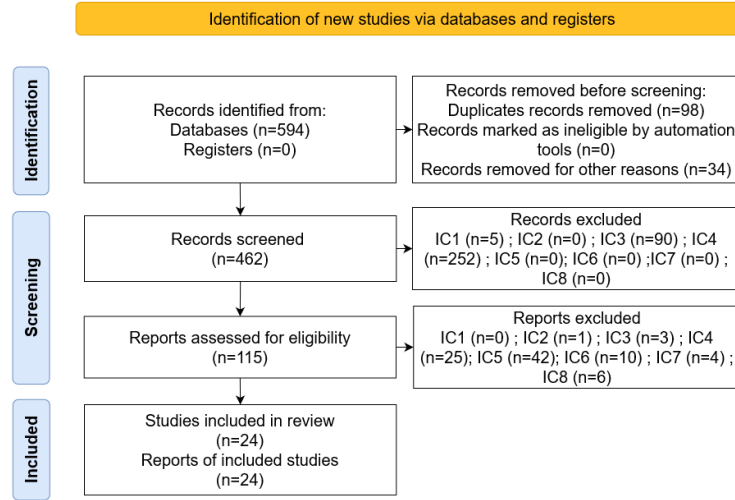


Fig. 1. PRISMA inspired flow diagram.

3.2 Analysis framework and coding scheme

A coding scheme centered on adaptation and its dimensions was iteratively refined. The authors utilized their knowledge of LA and systems adaptation to design the first version, which was further refined through the reading of the articles included in the review. The coding process and code book's comprehensiveness and consistency were estimated through two coding steps, using two different article subsamples (n=3). Each author independently coded the article subsamples, and any divergences were discussed after the first step. A Krippendorff's alpha (an inter-reliability metric) of 0.76 was obtained after the coding of the second article subsamples. One author coded all the articles and, any uncertainties doubts or exceptional cases were discussed. Alongside with adaptation capabilities, the scheme described below was completed to provide an overview of LADs learning indicators and to code LADs evaluation using the evaluation recommendations of the checklist described in [23].

LI: LAD Learning Indicators Description

Descriptive: indicators showing data about learner past actions; *Diagnostic*: indicators giving in-depth insights about identified learner/learning states; *Predictive*: indicators showing estimation of future outcomes; *Prescriptive*: indicators aiming to recommend future actions.

LAD Adaptation features

To what? What data/knowledge about users are used to perform the adaptation? *User's configuration*: user actions to trigger a specific system behavior; *Knowledge*: any data related to a learner model that can be used to report on its progress in terms of knowledge or skills; *Paths*: any data reporting the learning paths or sequences of a learner; *Performance*: any data related to an evaluation/assessment task indicating a learner's performance at a given time; *Engagement, motivation*: any data or data aggregation which can be used to monitor the engagement of a learner; *Metacognition*: any data related to the learner's metacognitive state such as his self-regulated learning level, the learning strategies, etc.; *Data availability*: when data usually used to compute some indicator is not available yet (i.e., cold start); *Preferences*: any data inferred from previous user configurations and/or log analysis; *Collaboration*: any data that highlights collaboration or interactions between the stakeholders during a learning activity/process; *Socio-Demographic data*: any data related to the socio-demographic profile of a learner.

What? Which elements of the LAD are adapted? *Selection*: combination of indicators within the LAD is changed; *Importance*: an indicator or a sub-set of indicators can be highlighted, using for instance visual tricks or by changing indicator relative positions; *Visualization*: a change in visualization(s) associated with one or more Learning 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; *Indicators timing*: an indicator can be presented after a delay or at a given time, which can be configured.

How?

How is the adaptation decided? *Rules*: adaptation is realized following 'if-then' rules; *Algorithms*: the adaptation is realized following more advanced programming concepts (e.g., loops); *Machine learning*: to go further than 'if-then' rules and advanced programming concepts, the adaptation is realized using machine learning methods.

How is the adaptation performed? *Activation*: action to activate/deactivate an indicator; *Refine*: 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.

LAD evaluation

Methods? How is it evaluated? *Surveys*; *Interviews*; *Log analysis*; *Observation*; *Pre-/post-test*; *Focus group*; *Case study*

Focus? What is evaluated? *Reaction*: Evaluation of the user's impression of a particular LAD; *Learning*: What have the learners learned in terms of knowledge and/or skills? Have the learners improved? *Behavior*: How do the learners use

their new skills after learning it ? Can the users apply/re-use their new competencies? *Usage*: Evaluation or exploration of the usage the learners (or any stakeholder/user) have with the dashboard/functionalities.

Adaptation? Has a specific evaluation of an adaptation feature been conducted?

For the coding scheme including examples, visit <http://tinyurl.com/yu23jrv7>

4 Results & Discussions

This section presents the analysis results and jointly discusses them regarding our research questions. Results for RQ1 and RQ2 are shown in Table 1 where we conveniently removed empty columns for visualization purposes. 24 articles matching the inclusion criterion were analyzed among the 462 initial reports retrieved from academic databases. As there is only one LAD per report read, we assume that saying report, publication, LAD, article, or paper refer to the same thing.

4.1 RQ1: What adaptation mechanisms are implemented into LAD, for what purposes ?

Figure 2 depicted over years publications describing adaptable LADs (n=20) and/or adaptive LADs (n=8), resulting in more evidence of adaptability than adaptivity (see Table 1). Moreover, most LADs target learners (n=10) or teachers (n=8), both (n=2), three others target advisers (n=1), institutional (n=1) and practitioners (n=1) and one targets teachers, developers and researchers. Generally speaking, there are over years fewer works on LADs for learners than on LADs for teachers, regardless of whether they are adaptable or adaptive. Observing the occurrences of indicators' natures over the years shows that descriptive indicators are more prevalent in adaptable LADs than in adaptive LADs.

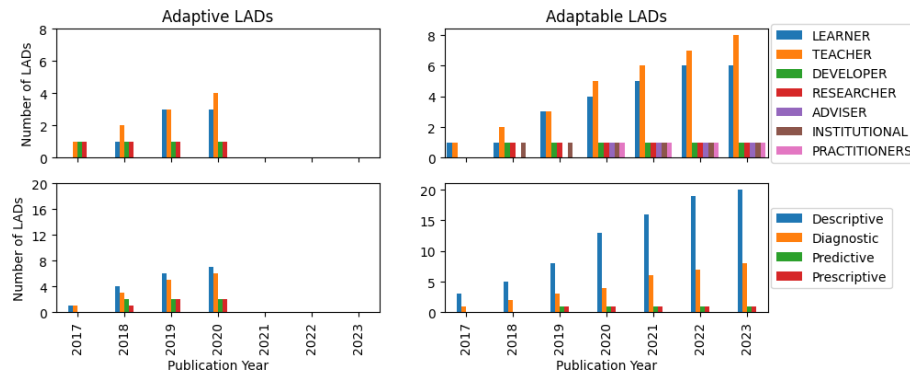


Fig. 2. Cumulative publications since 2017

While all reported adaptable LADs result from a user input, five adaptive LADs are based on one of the data types presented in the coding scheme and two LADs use two types. Collaboration and socio-demographic data are not represented. In the following section, we present adaptation functionalities, grouped by their shared similarities across “What” and “How” dimensions.

Two categories of adaptive LADs can be distinguished. The first category (n=6) covers LADs that can modify on their own the set of indicators presented by activating or deactivating some indicators. In [3, 16, 28], indicators follow an “all or nothing” attitude and are either displayed or invisible, depending on the input data. These indicators most likely act as alerts or notifications. In [42], indicators are replaced by alternative and default learning materials to solve the cold start problem (lack of available data). Indicators of [9] are automatically selected according to editable rules, based on performance or events data. Finally, the LAD in [35] can complement the set of indicators by activating additional feedback to learners who have been classified as poor performers by the system. The second category includes LADs that refresh their indicators, changing the source data used for calculation (n=2). Available data of [7] is automatically restricted according to the role of the user logged in (teacher or administrator). The LAD of [11] automatically determines the data a teacher can navigate into according to the alerts triggered by the system.

Three categories of adaptable LADs stand out. Firstly, numerous LADs (n=15) are provided with filtering, selecting or zooming controls that allow the users to change the source data producing indicators values, such as the date range to monitor [17, 27, 36, 43, 49] or the subgroup of data to consider [2, 7, 8, 11, 12, 15, 18, 21, 39, 43, 44]. Indicators are consequently updated without changing their initial nature. Secondly, the analysis highlighted LADs (n=6) in which users can configure what is presented. In [20, 34, 40], learners select the indicators they want to see. LAD in [34] offers numerous adaptation options as learners. They can select their preferred visualizations from bar, line or pie charts, and activate a tooltip when hovering over a particular score. This provides better insight into how the score value was calculated. LAD in [40] provides many possibilities for users to create their own indicators by writing SQL queries, selecting associated visualizations, and modifying the order in which indicators are displayed. In [16], the teacher can request additional indicators from the dashboard to gain better insights into a particular student’s struggles. In [15], teachers can activate overview indicators, summarizing real time learners’ indicators of a work session. In [8], specific teacher’ inputs will result in the apparition of contextual indicators. Finally, there are LADs (n=2) that grant the user the possibility to configure the indicators he wishes on the basis of the addition of rules. In [40], the rules are the result of SQL queries and in [9], a specific domain language can be used to determine which indicators will be shown at execution time, depending on the input learning traces.

No advanced or machine learning algorithms were reported in the adaptation process of adaptive or adaptable LADs, leaving research on these questions open.

In addition, there is no adaptive feature that implies a change in the relative importance of indicators or their visualizations. In both adaptive and adaptable analyzed LADs, there are no dashboards that delay the feedback conveyed by the indicators (indicators timing) : could it be beneficial in some situations that LADs observe a delay before giving some feedbacks ?

4.2 RQ2: How are adaptable or adaptive LADs evaluated ?

According to Table 1, evaluations tend to focus on measuring quantitatively or qualitatively the users' dashboard usages and perception. The effects of the dashboard utilization on the stakeholders' behavior or on the learning performance are less measured, probably because it's a more complex process requiring longitudinal studies. Reaction, usage, behavior, and learning are respectively evaluated in 17, 9, 7, and 5 articles over a total of 24 papers. The evaluation purposes of [15] couldn't be clearly retrieved. Moreover, 10 articles have a single evaluation purpose, while 13 articles have two or more.

Evaluation methods of [17] were not retrieved. Commonly used evaluation methods have been employed: surveys (11 articles), log analysis (9), case studies (6), interviews (6), focus groups (4), pre-/post-tests (4) and observations (2).

Only 5 papers out of 24 include evidence about evaluation of the benefits of some adaptation functionalities. Two articles provide insights on how the users used the provided functionalities. In their evaluations, the authors collect the choices made by the learners for customizing their dashboard and compute statistics. The experiments and analysis of [20] monitor the combination of indicators the learners wanted to see, according to the course they are enrolled in. Notably, some common selected indicators emerged and, according to the results, content progress indicators seem to be preferred to learning behavior indicators. In [34], preferences of students regarding whether they choose one kind of representation over another and their favorite motivators (acting as indicators) are reported with a frequency of use. In [3], we have found indirect evidence of the effect of an adaptive alert, displayed when a student is disengaged, that modify a teacher' behavior since he wouldn't have intervened without this notification. Finally, the evaluation proposed in [11] has shown evidence of some effects of the dashboard use on student learning performance. Indeed, authors have found that, thanks to alerts automatically computed for the teachers to provide them with some indicators on a particular student, the student who benefited of feedback from their teacher better maintained their performance across various activities than the other students. To go further, evaluations of the augmented reality dashboard [16] have shown that it helped increase learning gain. Although there is no explicit evaluation of its adaptive features (learner-level indicators), this aspect is predominant in the dashboard and has therefore been indirectly evaluated.

5 Research agenda

The findings of this review, based on our analysis framework, indicate a limited number of works focusing on adaptable or adaptive LADs.

Identifying such LADs capabilities across various works is challenging. Providing more detailed/standardized reports and using unambiguous vocabulary could be of great value to improve research efforts on LADs adaptation. For instance, such reports could rely on the proposed analysis framework.

A lot of works consist in developing new indicators, tailored to specific learning contexts, but only a few works attempt to reuse existing indicators and conduct experiments to fully propose adaptable or adaptive LADs. In this regard, it could be beneficial to multiply studies that report user needs and preferences regarding indicators selection in various learning and social contexts. Systematically reporting such work could help establish a reliable knowledge base, which could be used, for instance, to support the development of dashboard generation tools.

Last but not least, since research on adaptive LADs is still not at a sufficient level of maturity, developing a bunch of research works on adaptive LADs that include rigorous evaluations should be a priority. This is crucial to determine more precisely the potential impacts on LADs adoption and, at the end, on learning.

6 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 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.

7 Conclusions

This article presents a systematic review of the adaptability and adaptivity capabilities of LADs since 2017. To achieve this, we propose an analysis framework to clarify and reduce the sparse vocabulary often used when reporting on LADs adaptation capabilities. Our findings reveal that there are fewer works on adaptive dashboards than on adaptable dashboards. The analysis of the coding performed on articles reveals several categories of adaptation capabilities and provides insights into the learner data used for adaptivity. Currently, there is limited attention given to the adaptation functionalities of LADs, and there may not be sufficient evidence to support their benefits at this time. Future research should investigate the effects of such adaptations on users' perception,

behavior, and learning. Additionally, the analysis points 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 could be integrated on dashboards, such as the adaptation of the indicators relative importance or time-delayed presentation of indicators according to learners' needs.

To provide more context for this review, we have identified several papers that were not included in the analysis but are representative of some of the work on LADs. One body of research focuses on the development of intelligent learning indicators (e.g., [24]) that could be associated by transition with works on intelligent LADs. Another body of research, such as [10, 47], focuses on the development of "meta dashboards" instead of a particular intelligent LAD.

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