Designing transparent learning analytics dashboards

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Abstract

With the rise of hybrid or distance learning, we can collect a large amount of data regarding learners, creating a significant opportunity to improve the identification of learning behaviors and assist teachers in their activities. However, since learning analytics deal with learning traces, it is mandatory to meet strict ethical criteria to foster these technologies' adoption. In that context, trustworthy learning analytics recently became a new concern. Learning analytics tools that can claim to be trustworthy should, among other things, be comprehensible, user-friendly, and transparent. We present a user study aiming at identifying the main qualities of a transparent learning dashboard and we contribute to the promotion of more trustworthy learning analytics tools.

Keywords

Trustworthy Learning Analytics, Learning Indicators, Dashboard, Co-design

1. Introduction

Learning Analytics Dashboards (LAD) are known to facilitate learning problem detection [1] and assessment of learner's effort level or learning progress [2]. However, while Learning Analytics (LA) is a promising field, adoption of these technologies is still limited [3]. This could be explained by their lack of trustworthiness and relation to users' needs [4]. To become more trustworthy, LA systems should meet, among other things, the transparency criterion by being "comprehensible, useful, user-friendly, and easily accessible" to teachers and by involving stakeholders in their conception [5]. That's why we ask ourselves **(RQ): How to design a learning analytics dashboard in order to meet the transparency dimension of trustworthy learning analytics?** To answer this question, we first assessed the comprehensibility of the LAD, by investigating teachers' social representations associated with the five learning indicators used to build visualizations. Then, we evaluated the LAD usability, and investigated its user-friendliness.

2. Related works

2.1. Learning behaviors and indicators

Description of learning behaviors through dashboards is related to the computation of learning indicators. Learning indicators are defined as "an observable that is pedagogically significant, computed or established with the help of observations, and testifying to the quality of interaction,

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activity, and learning. It is defined according to an observation objective and motivated by an educational objective" [6]. They are computed directly from the learning traces collected on virtual learning environments (VLE), and thus do not require explicit feedback from learners or teachers to be computed. In the educational field, a large number of learning indicators have been defined, in various contexts and answering various purposes. Chi and Wylie [7], for example, investigated deeply the engagement of learners and defined the ICAP model, describing four modes of engagement depending on the way learners behave during the learning process. Elsewhere, some researchers studied the temporal aspects of learning by quantifying the regularity and reactivity of learners [8]. To go further, other behavioral skills such as curiosity have been investigated, and seem to provide important information about learners' success in their learning task [9]. Often these indicators are supplemented by the calculation of student performance, which is a direct indicator of student success [10]. Altogether, these indicators have the power to provide valuable information to describe adopted learning behaviors in a specific context. However, when describing learners, transparency and comprehensibility seem to be the two aspects of trustworthiness that should be fulfilled, which means that every teacher should understand the descriptors in the same way. A shared social representation, defined as "the elaborating of a social object by the community for the purpose of behaving and communicating" [11], represents a common understanding as it refers to socially shared ideas that a social group (here teachers) develops about an object (here learning indicators and thus learners described by these indicators).

2.2. Dashboards

LAD serve various purposes including awareness and behavior change in online or blended learning [12]. In this case, LAD can report learning behaviors or predict learning outcomes based on data such as grades, time spent on learning tasks, and past performance, all collected on VLE. Thus, dashboards discussed here provide a display of digital learning traces based on learner's behaviors so that this information can be useful to the user, whether learner or teacher [13, 14]. When LAD are designed for the latter, information is presented in order to enable effective understanding, reasoning, and decision making by teachers [15, 16]. This is done by selecting appropriate visualizations based on the available data, so that they can be easily interpreted at a glance but also by taking into consideration cognitive psychology theories such as cognitive overload, attention processes, and data literacy [17, 18].

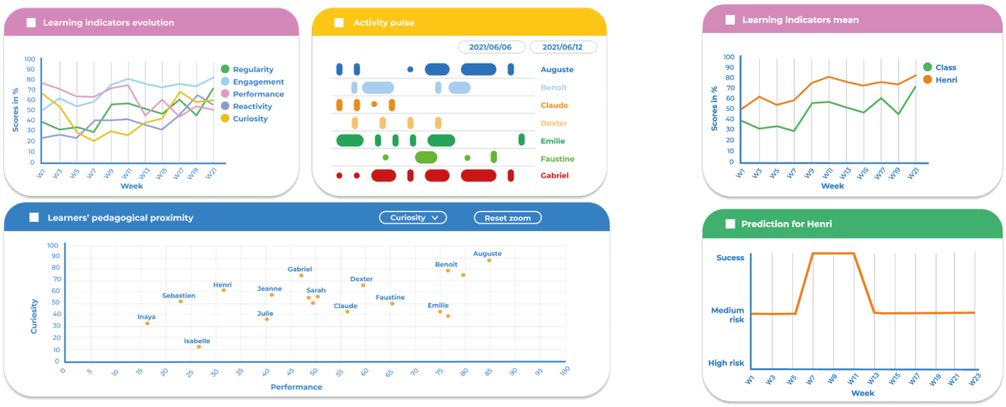
To report learning traces, a dashboard seems to be an efficient solution since it is known to be a facilitator for learning problem detection [1] and satisfies its users [2, 19]. Among the information that seems relevant to include in a dashboard are six categories: learner demographics (such as age or previous education), learner actions or artifacts (for instance, number of visited pages or the number of downloaded documents), information related to pedagogical content (for example, the topic or academic results), context (like the place in the classroom) and finally social links between forum users for example [15, 2]. Dashboards are a tool of great interest. On one hand, visualization displaying learners' use of resources is reported to be useful by teachers as it helps them assess learners' level of effort or even resources relevance. On the other hand, time spent on activities as well as learner's results allow teachers to estimate the latter's learning progress [2].

3. User study method

We conducted a user study with thirty french volunteer teachers. Twenty-four worked in higher education (sixteen males and eight females) while six were high school teachers (three males and three females). As the recruitment of our participants mostly took place in a computer science department, 50% of the teachers in our sample taught computer sciences or related subjects, 30% taught sciences-related fields such as Neuroscience, Physics, Chemistry, or Biology and we also recruited Languages and Art teachers representing the last 20% of our sample. We first identified teachers' representations associated with five common learning indicators [6]: (1) curiosity (individual's intrinsic motivation [9]), (2) engagement (learners' involvement in their learning process [20]), (3) reactivity (delay of response for different course-related events [21]), (4) performance (individual's level of learning), (5) regularity (investment in the learning task at regular and close time intervals [21]). Social representations can be collected using word association tasks [22]. Thus, to assess representations, we conducted semi-structured interviews during which we asked questions such as "*What is a curious learner to you ?*", "*How does a learner's curiosity manifest itself ?*", or "*Could you describe a situation that you have experienced in your professional experience, which embodies the curiosity of a learner?*". The questions were repeated for each learning indicator.

Second, we assessed the dashboard's comprehensibility and usability. The evaluated LAD was designed during a previous project [23] through participatory co-design with French high school and middle school teachers. Teachers' representations and values in terms of education were collected through qualitative methods regarding student assessment and monitoring, digital tools, and finally, about dashboards in general [23]. Then, a co-design session on the LAD data visualisation was carried out, resulting in the design of a LAD mock-up. The LAD is divided into two parts: visualization of learners' overall activity (See Fig 1a) with a focus on effort in completing the educational tasks, and an individual visualization of learners' activity (See Fig 1b). The global activity layout is organized into three frames which include: the class learning indicators weekly evolution, the activity frequency of each learner in the class, and a final visualization of what we called "pedagogical proximity" which allows teachers to compare learners to each other. The individual activity layout includes the evolution of learning indicators for the selected learner measured in terms of percentage score by week, a visualization of a percentage score computed by averaging all indicators scores of the selected learner providing a comparison of the latter with the class, and finally, a graph showing a prediction of the learner's risk of failure. This prediction is computed by a machine learning algorithm on the basis of learning indicators scores. The risk is expressed in three levels: high, medium, or success.

To assess the dashboard's comprehensibility and usability, participants were asked to interact with the LAD according to four scenarios we created corresponding to the LAD main functionalities (teachers confirmed that they met some of their needs): (1) Find a learner who had not been consistent lately; (2) Build a group of three learners with various levels of curiosity; (3) Find a learner who had not performed well at the start of the course but whose performances increased with time; (4) Identify a week during which the majority of learners failed a test. Then, participants completed the System Usability Scale (SUS) [24], used to evaluate users' satisfaction by measuring the system usability.



(a) Global view visualizations

(b) Individual view visualizations

Figure 1: Evaluated dashboard global and individual layout

4. Results

We conducted a lexical analysis of the interviews and completed this process with qualitative content analysis, identifying shared social representations when themes were present in more than 50% of the interviews. To this end, we first performed a similarity analysis based on the co-occurrence of words, which allows us to identify groups of words that are frequently quoted together. To proceed, we performed divisive hierarchical clustering using word classification. For example, when it comes to the curiosity learning indicator, the similarity tree displays two clusters. The first one contains words like "go", "search" and "beyond" when the second includes "ask" "question", "understanding" and "thing" for example. This first analysis step allows us to have an idea of the representation related to curiosity which is the idea of going beyond the lesson, searching, and asking questions. These findings were supported by the clusterization which shows four classes : one that includes "beyond" and "course/lesson", one that relates to "interest" and "thing", one with "go" and "search", and finally the last class corresponding to "ask" and "question".

To conduct the qualitative content analysis, we reread the interviews, identified the recurring themes, and counted the occurrences based on the previous lexical analysis. If the theme appeared in more than 50% of the interviews, we concluded that it was a representation shared by the majority of teachers in our sample regarding the learning indicator. The results show that engagement, achievement, and curiosity are well understood and related to shared representations. Curiosity seems to be related to the idea that learners go beyond the course content, search for information on their own, and ask questions. Engagement refers to learners participating in class with seriousness and commitment and doing the required work correctly. Finally, performance refers to the attainment of good grades and good results on assessments. We could not find representations for the other two indicators. They need to be explicitly defined on the website LAD.

The four scenarios were easily completed by participants. Participants were able to identify learners on the basis of a learning indicator (scenarios 1 and 3) very quickly (1 min 37s on average). They either started with the global view to identify learners of interest, then moved to the individual page of the learners to verify their hypothesis, or, in a less efficient way, went through each individual view to assess learners' behavior. To complete the second scenario, the majority of teachers naturally used "pedagogical proximity" by selecting the learning indicator of interest to compare learners, and the task was done in 1 min 27s on average. Finally, to identify an element concerning the whole group of learners (scenario 4), participants used the global view and needed less than 1 minute on average. The speed at which each task was completed, coupled with a high SUS score of 70,8 (SD = 13,5) out of 100, suggests the good usability and user-friendliness of the evaluated dashboard.

5. Conclusion

The purpose of this user study was to determine how to design a LAD according to the transparency dimension of trustworthiness. To achieve this goal, stakeholders were engaged in each step of the conception: identification of users' needs, design of the visualizations, user experience evaluation, and investigation of the understanding of the indicators. From participants' feedback and the barriers they met while interacting with the LAD, we proposed an enhanced version of the LAD dashboard (See Figure 2). The good acceptability of the LAD, coupled with its user-friendly interface shows that the system is comprehensible and useful, thus meeting the transparency criterion. Our user study thus highlights key elements enabling the design of trustworthy and transparent LAD: learning indicators must be well understood by the users and match the group social representations. Otherwise, the definition of the terms used will need to be made explicit to ensure a good understanding. Also, the LAD functionality should be built on the basis of users' needs, and the user experience should be assessed with target users.

(a) Global view visualizations

(b) Individual view visualizations

Figure 2: Enhanced version of the dashboard

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