Learning analytics dashboards: the past, the present and the future

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ABSTRACT

Learning analytics dashboards are at the core of the LAK vision to involve the human into the decision-making process. The key focus of these dashboards is to support better human sense-making and decision-making by visualising data about learners to a variety of stakeholders. Early research on learning analytics dashboards focused on the use of visualisation and prediction techniques and demonstrates the rich potential of dashboards in a variety of learning settings. Present research increasingly uses participatory design methods to tailor dashboards to the needs of stakeholders, employs multimodal data acquisition techniques, and starts to research theoretical underpinnings of dashboards. In this paper, we present these past and present research efforts as well as the results of the VISLA19 workshop on "Visual approaches to Learning Analytics" that was held at LAK19 with experts in the domain to identify and articulate common practices and challenges for the domain. Based on an analysis of the results, we present a research agenda to help shape the future of learning analytics dashboards.

CCS CONCEPTS

• **Human-centered computing → Visualization design and evaluation methods**; *Interactive systems and tools*; • **Applied computing** → *Education.*

KEYWORDS

learning analytics dashboards, visualisation, interaction, evaluation

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1 INTRODUCTION

The field of Learning Analytics defines itself as the "measurement, collection, analysis and reporting of data" [31] to better understand and improve learning processes. While the first three components (measurement, collection and analysis) are shared with other learning technologies fields such as educational data mining, reporting the data and the results of the analysis directly back to the learning process' stakeholders is one of Learning Analytics distinctive features [30]. The most common way in which this reporting takes place is through learning analytics dashboards, defined by Schwendimann et al. [28] as "a single display that aggregates different indicators about learner (s), learning process(es) and/or learning context(s) into one or multiple visualisations."

Dashboards are the most visible face of what learning analytics is for the majority of the educational community. When vendors refer to their learning analytics solutions, they usually refer to some type of dashboard ready-made to serve administrators, teachers, students or parents. As important as they are, the process to design and evaluate dashboards has received very little attention from the Learning Analytics research community, usually focused on research level visualisations of data or new analytical methods [20].

To improve this current situation, this paper has three main objectives: 1) remembering the past: reviewing the existing research literature about the design of dashboards to better understand the state-of-the-art and position possible solutions; 2) be aware of the present: report on the joint reflection sessions that took place during the VISLA19 workshop at the Learning Analytics and Knowledge (LAK) conference 2019 to collect the current perceived successes, failures and areas of improvement in dashboards; and 3) charting the future: based on the previous two steps, proposing a research agenda for dashboards in general, from design patterns to how to make dashboards more transparent, configurable and dialog-based.

2 THE PAST

Over the past decade, several learning analytics dashboards have been elaborated that use a variety of data sources to support sense-making and decision-making. SAM [13] was one of the early dashboards developed on top of data from students and visualises time spent and resource use by students to support awareness for students and teachers. Other early examples presented at the LAK conference include SNAPP [7] that visualises the evolution of social interactions among learners in online forums to enable timely interventions by teachers, Step-up! [26] that visualises social media data of students to increase student engagement and Course Signals [2] that predicts and visualises learning outcomes based on grades, time spent and past performance. SLICE [10] visualises annotations of students on slides during face-to-face lectures. In addition, many researchers focused on the use of learning analytics dashboards to facilitate group work, including [27].

These early examples inspired the community by demonstrating the rich potential of learning analytics dashboards in a very broad range of applications, including raising awareness and self-reflection in blended learning settings for both students and teachers, e.g., [11], improving engagement of [1], and interaction with, students in face-to-face lectures [3, 25], predicting study outcomes and identifying at risk students [2, 23], facilitating group work [27], and enabling social comparison [6]. Most of these early examples relied on interaction data from learners with their learning environment captured from application logs [33]. In addition, the early examples typically supported either students or teachers, but other stakeholders were not often supported.

3 THE PRESENT

In recent years, we can observe a few trends in learning analytics dashboard research. Increasingly, additional data from learners is being used and researched under the umbrella of multimodal learning analytics [24]. EMODA [9] is a recent example that supports teachers to monitor learners' emotions during an online learning session. Audio, video, self-reports and interaction traces are analysed to capture emotions, relying among others on facial expressions and voice analysis techniques. An additional recent trend is the use of participatory design methods to better address the actual needs and issues of end-users [8, 16, 21]. In addition, many researchers have been working on researching better pedagogical underpinning of learning analytics dashboards [18]. Furthermore, additional stakeholders such as study advisers are increasingly supported [23]. All these efforts have resulted in an increased uptake and scaling up of dashboards. Prominent recent examples are Student Explorer [22] and the LISSA dashboard [5] for study advisers. At the same time, some critical voices have also raised concerns about the evaluation of dashboards and the lack of acceptance, uptake and adoption [4, 19].

To analyse the best practices and pitfalls from present learning analytics dashboards, we organised a workshop with 16 experts (6 female) at LAK19. The main goal of the workshop was to collect the current perceived successes, failures and areas of improvement for dashboards as a basis to generate a list of good practices and common pitfalls, as well as to establish a research agenda. We first elaborate on the method and will then present a research agenda for the learning analytics community based on the results.

3.1 Method

First, based on eight predefined themes (see Table 1), ideas and opinions were generated by the participants. Participants were grouped into three teams/tables and each team covered all eights themes. As illustrated in Figure 1 and Figure 2, the eight themes were outlined together with their rationale and visualised using coloured paper. This first part took ca. 75 minutes, followed by a break. Afterwards, all ideas and comments were sorted and voted on through dot-voting (see Figure 2). Participants received five stickers they could use to endorse ideas. They also received one veto sticker for ideas they did not support. Finally, in the wrap-up phase, all voted ideas were discussed in group.

Table 1: The eight different themes

1	What data can be tracked? What are the challenges related to tracking different data sources?
2	What are the challenges to visualise the data, to clean up the data, to perform usability tests, to implement the technical design, etc.?
3	What are the challenges of using different visualisation techniques? Which interaction techniques are applied and what are their strengths and pitfalls?
4	What are the commonly encountered challenges and pitfalls during the visualisation process? What workflows and recipes can be used to develop the visualisation?
5	Which are the challenges when evaluating a LA visualisation?
6	What are the key success stories on the use of visualsations and learning dashboards?
7	What are the major pitfalls and limitations of current visual approaches to learning analytics?
8	How should we address disabilities in future LA visualisations?

Figure 1: Set-up of the workshop. Participants were divided into three larger groups/tables. On each table, the eight themes were visualised by using coloured papers.

3.2 Results

The results of the dot-voting are presented in Table 2. The table presents the top ideas resulting from the idea generation phase. The "+" column shows the number of endorsements, while the "-" column shows the number of vetoes. The most important challenges that emerged from the group discussion are presented in Table 3. These "top" challenges were selected by grouping the earlier ideas and counting the number of votes, as presented in Table 3. Based on the dot-voting and the discussion, we summarise and discuss

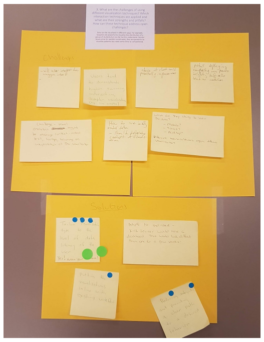

Figure 2: A picture taken after the dot-voting.

some of the key good practices, pitfalls and challenges in present dashboards identified by participants.

3.2.1 *Data acquisition.* Participants identified the rich data sources that are currently used by learning analytics dashboards, including interactions with learning content, tracing learning paths, time spent, eye tracking, location, and voice. Social interactions were identified as important, and include analysis of discussion forums, peer learning, social networking, and social media.

Participants highlighted challenges when working with click-stream data (4 vetoes). Privacy concerns and the lack of context were the main arguments. Participants identified the need to capture the emotions and feelings of students such as perceived engagement. One sticky-note questioned: "*Everything can be tracked, but should we track everything?*", which links to concerns expressed by other participants regarding data privacy, effectiveness of anonymisation techniques, and data ownership. Participants also questioned the risks and limitations of collecting and cleaning educational data, such as the possibility of introducing bias or even changing patterns during the cleaning process.

3.2.2 *The visualisation design process.* A recurrent topic related to the development of visualisations was the need to involve stakeholders in the design process as early as possible through **participatory design**. Participants identified several recent success stories, including the RISE network for Connecticut schools, four initiatives in the University of Michigan, the Advising Tool at ESPOL, and the Oregon state Canvas faculty dashboard. They highlighted the importance of input from stakeholders throughout the design process, including in early needs analysis, concept generation, and concept validation. Focus groups, pilot studies, eye tracking, simulated recall, and interviews were cited as possible strategies to achieve this goal. Other good practices include the assessment of users' data analytics skills prior to development, replication of results through open anonymised datasets, open source code, the use of standards, and learning from successful visualisations.

Pitfalls in the design process include starting from the visualisation instead of a research question and building visualisations without conducting any validation analysis on the data. Participants also indicated that researchers and practitioners might be neglecting the **psychological research on how humans understand graphs (visual communication)** and identified the need

Table 2: Top notes resulting from the idea generation phase and group discussion. The + column shows the number of endorsements, while the - column shows the number of vetoes.

Note	+	-
(1) Data acquisition		
Only capture click-stream data	0	4
Integration of data from different systems	2	0
Difficult to track engagement	1	1
Everything can be tracked, but should we track everything?	1	0
Social interactions: discussion fora, peer learning, social networking, social media analysis	1	0
Tracing learning paths: the sequence/order of a student; time spent in materials, watching videos; number of interactions, views, clicks; returning to materials, or returning content	0	0
Danger of introducing bias/changing patterns through cleaning	0	0
...		
(2) The visualisation design process		
Integrate psychological research on visual literacy	2	1
Involve all actors in the design	3	0
Lack of actionability	1	0
When to provide information and intersection with motivation	3	0
Linking the visualisation to pedagogy	2	1
Common educational data standards	1	0
Integrate into existing workflows	1	0
Adding stakeholder input as early as possible; focus groups, eyetracking studies, simulated recall, interviews	1	0
Start with research question, not the visualisation itself. What are you trying to show?	1	0
Using inappropriate visualisations (e.g. pie charts)	1	0
...		
(3) Visualisation complexity and personalisation		
Tailor the visualisation type to level of data literacy	3	2
Complexity vs. needed simplicity	3	0
Misinterpretation of the data	2	1
One-size-does-not-fit-all	3	1
...		
(4) Evaluation		
What do we evaluate? Usable? Actionable? Change behaviour?	1	0
Successful for who? In which conditions?	1	0
Integrate lessons learned from previous failures	1	0
Report how short-term data can link to long-term learning process	1	0
Use existing tools that assess graphics	1	0
Difficult to find participants	1	0
...		

Table 3: Most important challenges that emerged from the group discussion. The participants returned to their original table, and reported the results from each Table; Column A, B, and C report the number of votes from each table.

Challenge	A	B	C	Total
One-size-does-not-fit-all	5	5	/	**10**
Tailor to data literacy	5	2	/	**7**
Integrate psychological research on visual literacy	4	1	1	**6**
Participatory design	3	1	1	**5**
Personalisation (e.g., impact on age, gender, race, etc.)	/	4	/	**4**
Misinterpretation	1	3	/	**4**
Actionability	4	/	/	**4**
Theoretical underpinning	/	/	3	**3**

to integrate domain knowledge and visual science/graphic design principles. Another important pitfall was the lack **actionability** of current learning analytics dashboards: often users need to be explained how to enact upon the information given. In addition, the lack of **theoretical grounding** in learning sciences was identified.

3.2.3 Visualisation complexity and personalisation. The **one-size-does-not-fit-all** principle was a recurrent topic when the group was discussing the involvement of the user. However, they made a distinction between the overall principle of one-size-does-not-fit-all (e.g., a dashboard that works in Europe does not necessarily work in other cultures; or a dashboard that is designed for learners is not always useful for teachers) and its subdomain of personalisation (e.g., dynamically adapting a dashboard on the literacy or needs of an individual user). There was a consensus between participants that it is important to clearly outline who will be the end-user of a dashboard, as different user groups have different needs, but also different levels of **data literacy**.

There was no consensus among participants on whether visualisations should be tailored to the user's data literacy level or not (3 endorsements, 2 vetoes). Several participants endorsed the claim that visualisations created by researchers may be too complex if we take into account users' average data literacy level. On the other hand, two participants who used their veto sticker argued that we should also be careful with treating data literacy as a given. Also, most participants agreed that we should consider the **impact of visualisations on users of different ages, genders, races, etc**. **Possible misinterpretations** of the data displayed in visualisations was another issue endorsed by several participants. Participants also indicated that many dashboards are overwhelming, presenting too much data and options.

3.2.4 Evaluating Dashboards. Participants identified the following needs when evaluating learning analytics dashboards: i) choosing what to evaluate (e.g. usability, actionability, changes in learner behaviour/performance, change in teacher practice, acceptance of a new technology, etc.); ii) how to evaluate "success": success for who? In which conditions?; iii) theoretical assessment: what are the theoretical arguments for using the dashboard?

Participants did not reach a consensus regarding which evaluation methods should be used by default. One group argued for randomised controlled trials (RCTs), while the other group argued for smaller incremental studies, focusing on the user experience. The main argument for RCT studies was that universities have sparse resources and evidence is needed before dashboards are deployed on an institution wide scale. Counter arguments were that impact may be achieved in a later stage and is difficult to measure, and that using a control group is often not allowed.

Participants identified several challenges in evaluating dashboards, including finding users to participate in evaluations and avoiding a skewed sample of students who are already engaged.

4 THE FUTURE: A RESEARCH AGENDA

4.1 Design Patterns

To resolve the mentioned issues on data literacy, misinterpretation and lack of theoretical underpinning, it is important to extract and group successful patterns from existing learning analytics dashboards and visualisation literature. For example, it would be useful to come up with a list of designs linked to specific objectives, including designs that have been shown to be effective ways to show course progress, designs for reflection of own performance compared with others, designs for showing predictions, etc. In this way, new dashboards should not have to be designed from scratch, but they will reuse tried and theory-grounded solutions in innovative combinations. Initial work in this area has been done by Sedrakyan et al. [29], proposing a conceptual model that links design principles with learning process and feedback concepts.

Future work should further elaborate such mapping exercises and present recommendations to guide the choice of visual representations of data in learning dashboards based on empirical research studies. Such studies should also assess the utility of different visualisations for different end-users to infer design guidelines that can be used for different user groups. Design patterns and guidelines should be elaborated to better inform the community about key visualisation principles that need to be taken into account when designing dashboards. Although some initial awareness about misleading visualisations, such as 3D pie charts, has been raised by researchers in the field [20], there is a need to research and present principles from visual sciences and infer design patterns based on existing learning analytics dashboards.

4.2 Evaluation Methodology

Many researchers have argued that the evaluation of dashboards should move from simplistic usability testing to a more holistic impact evaluation. The purpose of dashboards is not only to make participants aware of the data, but to help them reflect on that data and improve their own learning process as a result [19]. Evaluation should be directed to tracing changes in behaviour to information obtained from dashboards. Developing such an evaluation strategy should be one of the key goals of the Learning Analytics community.

Results of our workshop indicate that there is a need to better articulate the evaluation goals of dashboards. Jivet et al. [19] also identified a mismatch between the goal of the dashboard and its evaluation. Both in the literature as well as in the results of our workshop we can observe some differences with respect to evaluation of learning analytics dashboards. Jivet et al. argue that "dashboard evaluation should focus (primarily) on whether its goals are fulfilled, (secondarily) on the impact on learners' affect and motivation, and (finally) on the usability of the tool". Bodily and Verbert [4], on the other hand, also critique approaches where impact is measured, without evaluating the usability of dashboards. Participants of our workshop also voiced concerns about misinterpretations of visualisations and the need to evaluate the understanding of data and visualisations.

Several participants argued to use iterative user-centered approaches that first focus on the user experience before conducting impact evaluations in order to avoid bias in the results, to better tailor dashboards to the needs of stakeholders and to increase acceptance. In addition, an evaluation framework is needed that is grounded in both learning and visual sciences and that makes use of validated instruments. Several review papers of learning analytics dashboards [4, 19, 35] provide a good starting point for such an evaluation framework that should outline different goals of dashboards and how these goals can be evaluated with validated instruments. Finally, there is a need to elaborate a practitioner guide that outlines different human-computer interaction methods that can be used for evaluating dashboards with end-users.

Mirroring the opinions given by the experts during the workshop, these evaluations should have three main characteristics: 1) they should clearly articulate the goals and target end-users as well as personal characteristics of these end-users; 2) they should be based on empirical data, not only on expert opinions; 3) they should be part of the dashboard deployment as it is often not feasible to deny access to the information to a control group. Prominent examples of such evaluations were done by [17, 34].

4.3 Beyond the Dashboard Towards Visual Analytics Tools

To resolve the mentioned issues of one-size-does-not-fit-all, actionability, data literacy and theorethical underpinning, interaction with learning analytics dashboards needs to move beyond the current incarnations of dashboards as a one-way information route. Users receive information that dashboards are presenting. In the best cases, users are able to interact with the visualisations to filter or provide details on a given data point. The field needs to move from these one-way dashboards towards conversational systems where human and dashboard work together with a common goal (improving learning). These movements require the user to be able to trust the dashboard (by understanding how the dashboard works - transparency), modify how the dashboard works (by changing what data that is feed into the model, changing the model parameters or by changing the model itself) and to interact with the dashboard on a regular basis (the dashboard monitors the progress of the student and it is able to start the conversation).

Also, dashboards should be better embedded into the learning process to not only present data to reflect, but also to offer actionable suggestions that users could take to improve their current situation. Finally, dashboards should also react differently to different students at different points in time during the course. The information that is presented to a struggling students at the beginning of the course should not be the same than that to a student that is improving after mid-terms or that that is presented to a high-performing students at the end of the course. This new bread of explainable, configurable, interactive, integrated and personalised dashboards is the next evolutionary step for Learning Analytics. First examples of such dashboards have been elaborated at KU Leuven [5, 23].

To address these challenges, research efforts on Explainable AI [14] and model steering with input from end-users [32] conducted by the visual analytics community is of key interest. As in work of Gutierrez et al. [15], it will be essential to tailor existing solutions to the needs and the level of expertise of the end-user. Most current and past visual analytics work has been tailored to machine learning experts: a key challenge is to come up with interaction paradigms that will work for non-expert users in data processing and data analysis, and to enable such users to steer the analytics process.

4.4 Responsible Learning Analytics

The collection of click-stream data only received the highest number of veto stickers (4). As in other domains, there is a need to consider ethical implications of predictive systems and bias that may be present in the data. Learning analytics dashboards offer a great promise to address these challenges, as by visualising the data used by predictive models end-users can potentially be made aware of underlying biases. An important future line of research is to investigate the fairness, accountability and transparency of predictive models used by dashboards. We believe the LAK community and particularly researchers working on dashboards should take up this challenge, as the use of data visualisation can explain the reasoning behind predictive models and address these crucial challenges.

Although researchers have addressed the fairness of predictive student models [12], ethical implications of dashboards need further research. All of the previous avenues for improvement require heavy access to data that is sensible and when used incorrectly could lead to harm in the users of the tool. For example, predictions could discourage students, and students' progress could be used wrongly used to evaluate and fire instructors. A strong ethical framework should be developed in parallel to the more powerful dashboards. Issues like data ownership, keeping humans in the analytics loop and bias-prevention should be explored not only in theory, but in practical workable schemas.

5 CONCLUSION

Dashboards are the main representation of Learning Analytics and as such their correct design and evaluation should be an important component in the Learning Analytics research agenda. While there has been extensive implementation efforts, several researchers have critiqued the evaluation of dashboards [4, 19]. This leads to uncertainty in the design of new dashboards were there are no lessons learned and effort is waisted on rebuilding from scratch. Current experts think that the field is not mature enough for adoption.

A research agenda is proposed to solve most of the identified issues, from the creation of design patterns, advancing dashboard evaluation methodologies, a new paradigm for dashboards as visual analytics tools and finally the creation of ethical guidelines to avoid harm. We hope that this reflection paper on learning analytics dashboards will inspire many researchers and practitioners and help shape a next generation of dashboards that are actionable, tailored to the needs of end-users, responsible, configurable, interactive, integrated and embedded in learning and visual sciences.

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