Perceiving Learning at a Glance: A Systematic Literature Review of Learning Dashboard Research

Beat A. Schwendimann, María Jesús Rodríguez-Triana, Andrii Vozniuk, *Member, IEEE*,
Luis P. Prieto, *Member, IEEE*, Mina Shirvani Boroujeni, Adrian Holzer, Denis Gillet, and Pierre Dillenbourg

Abstract—This paper presents a systematic literature review of the state-of-the-art of research on learning dashboards in the fields of Learning Analytics and Educational Data Mining. Research on learning dashboards aims to identify what data is meaningful to different stakeholders and how data can be presented to support sense-making processes. Learning dashboards are becoming popular due to the increased use of educational technologies, such as Learning Management Systems (LMS) and Massive Open Online Courses (MOOCs). The initial search of five main academic databases and GScholar resulted in 346 papers out of which 55 papers were included in the final analysis. Our review distinguishes different kinds of research studies as well as various aspects of learning dashboards and their maturity regarding evaluation. As the research field is still relatively young, most studies are exploratory and proof-of-concept. The review concludes by offering a definition for learning dashboards and by outlining open issues and future lines of work in the area of learning dashboards. There is a need for longitudinal research in authentic settings and studies that systematically compare different dashboard designs.

Index Terms—Learning analytics, educational data mining, information visualization, dashboards, systematic review

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1 INTRODUCTION

THE amount of data collected through educational technologies, such as Learning Management Systems (LMS) and Massive Open Online Courses (MOOCs), is increasing rapidly in volume and complexity. Learning Analytics emerged as a consequence of the increasing number of online educational platforms [1] and the need to understand how technology-mediated learning happens. Once data has been gathered, data needs to be processed, analyzed and visualized [2]. Shemwell [3] suggested that visual displays are critical to sense-making as humans can process large amounts of data if presented in meaningful ways. Learning dashboards can show data through different visualizations, such as graphs, gauges, dials, and maps [4]. Fig. 1 shows a sample learning dashboard with four visualizations. The current big challenge is how data coming from learning platforms can be made actionable by analyzing and presenting it in ways meaningful to different stakeholders [5]. Learning dashboards build on research in Information Visualization, Learning Analytics and Educational Data Mining.

The interest in analysing student activities registered in technological learning environments is not new [6], [7]. As Romero & Ventura concluded in their state-of-the-art review [8], there have been several research approaches since 1995 dealing with the interpretation of educational data. However, the main work started in 2008 with the advent of the first Conference on Educational Data Mining (EDM), the Journal of EDM, and the establishment of the EDM Society. The field of Learning Analytics (LA) held the first conference on Learning Analytics and Knowledge (LAK) in 2011, followed one year later by the foundation of the Society for Learning Analytics (SoLAR). There has been extensive research on single information visualizations and dashboards in different settings. This review focuses on research on the effects of dashboards (see definition in Section 7) designed specifically for learning. The field of learning dashboards is still relatively young as indicated by Google Trends in Fig. 2. Nevertheless, enough work has already been done to conduct a review. Thus, this paper provides a systematic literature review of research on learning dashboards.

2 RELATED WORK

Several synonymous terms for learning dashboards are currently in use, including 'educational dashboard', 'dashboard for learning analytics', 'learning analytics dashboard', 'data dashboard', and 'web dashboard'. Similarly, different definitions for dashboards have been proposed. Stephen Few defined an information dashboard as "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" [9]. Brouns et al. [10] described dashboards as "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 organizations

- B.A. Schwendimann, L.P. Prieto, M.S. Boroujeni, and P. Dillenbourg are with the CHILI Lab, École Polytechnique Fédérale de Lausanne, Lausanne 1015, Switzerland. E-mail: beat.schwendimann@gmail.com, {luis.prieto, mina.shirvaniboroujeni, pierre.dillenbourg}@epfl.ch.
- M.J. Rodríguez-Triana, A. Vozniuk, A. Holzer, and D. Gillet are with the REACT Lab, École Polytechnique Fédérale de Lausanne, Lausanne 1015, Switzerland. E-mail:{maria.rodrigueztriana, andrii.vozniuk, adrian.holzer, denis.gillet}@epfl.ch.
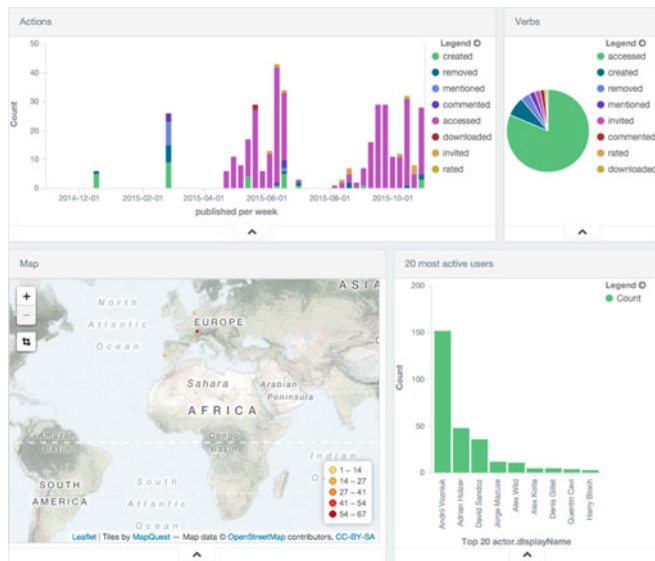
Fig. 1. A sample learning dashboard in Graasp.

Fig. 2. Interest in Learning Analytics (blue line), Educational Data Mining (red line), and Learning Dashboards (orange line) according to Google Trends (the *y*-axis indicates search interest relative to the highest point in the chart).
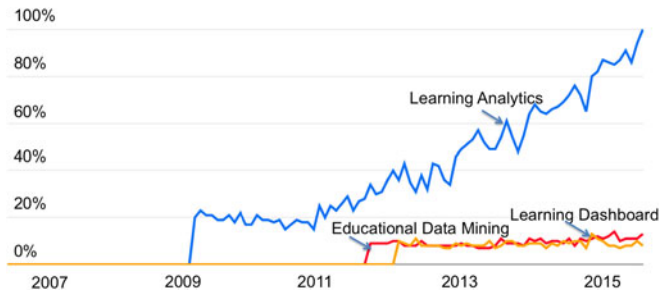
key performance indicators (KPIs) to enable instantaneous and informed decisions to be made at a glance". Others referred to dashboards as "a container of indicators" [11] or as "an emerging performance management system, for example, to monitor productivity, analyze cost-effectiveness and improve customer satisfaction" [12]. Regarding learning dashboards, Yoo et al. defined them as "a display which visualizes the results of educational data mining in a useful way" [13], while Steiner et al. referred to them as "visualisations of learning traces" [14]. The usage of different terms and definitions suggests that there is still no consensus on what constitutes a dashboard and, in particular, a learning dashboard. Based on our review, we will offer a definition of 'learning dashboards' in Section 7.

While learning dashboards are growing in popularity over the past few years (see Fig. 2), the question of what is the 'right' information displayed to different stakeholders and the question of how this information should be presented remain largely unresolved. Stephen Few points out that, although visually appealing, many dashboards lack the ability to provide truly useful information [15]. To make dashboards useful as decision-making and learning support tools, research is challenged to identify what and how information is displayed on dashboards in a timely and accurate way [4]. Existing reviews of learning dashboards focus on small case studies and on contrasting selected examples. For example, Duval et al. reviewed several data visualizations and dashboards as inspiration for their own learning dashboard development [16], [17]. Moissa et al. conducted a systematic review of research in learning analytics with a focus on MOOCs but mentioned dashboards only in passing [18]. Verbert et al. [19], [20] distinguished between three categories of dashboards: (1) for traditional face-to-face lectures, (2) for face-to-face group work, and (3) for awareness, reflection, sensemaking and behavior change in online or blended learning. Afterwards, they compared selected examples in each category. Yoo et al. [13] reviewed ten case studies of learning dashboards against Fews principles of dashboard design [15]. What is missing is a *systematic* review of the state-of-the-art of research in Learning Analytics and Educational Data Mining that focuses on learning dashboards.

3 RESEARCH QUESTIONS

This paper offers a systematic literature review of the state of research on learning dashboards in the areas of Learning Analytics and Educational Data Mining. The review focuses specifically on *dashboards* rather than visualizations in general. More specifically, the research questions[1] of this study are:

- RQ1: In which contexts are learning dashboards being applied, including educational settings, target users and learning activities?
- RQ2: What learning dashboards have been developed, including their purpose, indicators presented and technologies used?
- RQ3: How mature are such learning dashboards in terms of their evaluation?
- RQ4: What are important open issues and future lines of work in the field of learning dashboards?

4 METHODOLOGY

To answer the above research questions, we have performed a systematic literature review following the guidelines proposed by Kitchenham and Charters [22]. To conduct the review, we selected five main academic databases in Technology Enhanced Learning: ACM Digital Library,[2] IEEE Xplore,[3] SpringerLink,[4] Science Direct,[5] and Wiley.[6] Additionally, Google Scholar[7] was added in order to detect potentially relevant "grey literature" (i.e., technical reports and other research resources that are not normally indexed in most common literature databases, but can be relevant to assess the state of a research field, as noted by [22]).

To perform the search, we broke the query down into the object of study (dashboard) and the main research fields where dashboards have been applied in recent years (Learning Analytics or Educational Data Mining). The focus on the term 'dashboard' and these two emerging fields intended to

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1. In the sense of valuable inquiry that does not propose entirely new knowledge, but rather summarises and integrates existing knowledge [21].
2. ACM Digital Library: https://dl.acm.org
3. IEEE Xplore: http://ieeexplore.ieee.org
4. SpringerLink: http://link.springer.com
5. Science Direct: http://www.sciencedirect.com
6. Wiley: http://onlinelibrary.wiley.com
7. Google Scholar: https://scholar.google.ch

Query   Academic databases   Raw results   Analyzed papers

dashboard AND ("learning analytics" OR "educational data mining" OR "educational datamining")

246 results

First 100 results

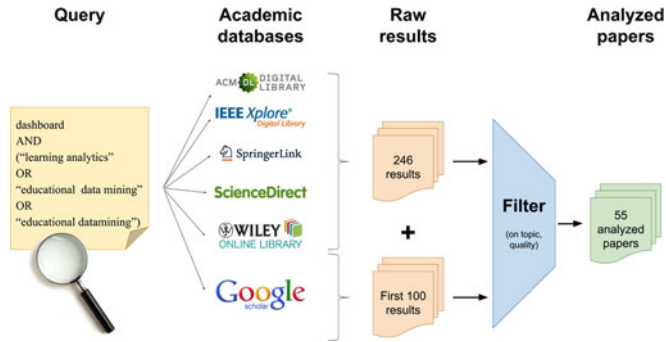Filter (on topic, quality)

55 analyzed papers

Fig. 3. Selection process.

capture the bulk of dashboard proposals for educational applications. The limitation of this approach is that our search might not have captured papers that did not explicitly use the term 'dashboard' or ascribe to the fields of Learning Analytics and Educational Data Mining. An example of such relevant but potentially not captured papers could be the well-established body of work on visualizations for educational applications, which were not labelled 'dashboard' at the time. After taking into account alternative spellings, the resulting search string was: *dashboard AND ("learning analytics" OR "educational data mining" OR "educational datamining")*. With this query, we searched the title, abstract, and keywords (whenever possible, or the closest that each database query engine allowed, since all of them differed). The literature search was conducted on 21st August 2015.

After performing the searches, each candidate study passed through a set of stages until its eventual selection (see Fig. 3). First, we assessed the title and read the abstract, looking for papers that described either a dashboard, or its indicators, or architecture or model for building dashboards; papers unrelated to educational uses of dashboards in the context of Learning Analytics or Educational Data Mining were excluded. Second, we retrieved each study, read it entirely, and critically appraised it based on similar criteria as in the previous round. A paper was discarded if it was out of scope (e.g., the paper did not describe the dashboard or indicators in details or focused on isolated visualizations rather than a dashboard), or of no credibility, or of very low quality (e.g., papers of insufficient length, or low quality prose that prevented understanding and assessing the proposal/contribution). Then, a data extraction form was filled out for each selected study to gather evidence for the review goals.[8] Finally, we removed duplicate papers or preliminary versions of works already being analyzed (unless they described different aspects). In the first two stages of the review, the papers were randomly distributed among the six researchers to ensure that each paper was reviewed by at least two people. It is also noteworthy that conflicting views or unclear papers were discussed to reach consensus by the whole team of reviewers.

A total of 246 papers were obtained by running the query in the databases. Additionally, the top 100 papers from GScholar (from a total of 989) were added. Out of these 346 papers, 91 title/abstract/keywords passed the first stage, and

8. The review form is available online at https://goo.gl/forms/UuAeErZzR4

85 were thoroughly reviewed (certain papers were not accessible). After removing non-relevant papers, 66 papers were found to contain a dashboard proposal, and eight more were used as part of related work in Section 2 due to being review papers or general reflections about learning dashboards in the areas of Learning Analytics or Educational Data Mining (namely: [1], [13], [14], [16], [17], [18], [19], [20]). In the third stage, potential duplications or redundancies were detected by identifying the proposal papers written by the same author (s). For overlapping groups of papers written by the same authors on the same dashboard-related contribution, the reviewers chose *one paper per group* for the final review that described the contribution in most detail. Finally, 55 papers passed all the aforementioned filters and were included in the review presented in Section 5. The list of included papers as well as information about their contexts, data sources, and evaluation are presented in Table 2. Even though no temporal filter was applied when the queries were executed, all included papers were published between 2010 and 2015.

5 RESULTS

Below, we present an overview of the types of contributions made by the reviewed papers. We also describe the main results of the review, organized along our four research questions: the learning context for which the proposals were designed, the characteristics of the dashboards themselves, the maturity of the proposals, and the open issues detected by the studies.

5.1 Types of Contributions

The review distinguished between two types of contributions (see Table 2). First, papers that contributed a theoretical proposal or a framework (three papers; 5 percent). Richards [23] proposed the architecture for a personalized adaptive dashboard. Mottus et al. [24] proposed methods to measure and visualize student engagement. Vozniuk et al. [25] outlined an architecture to build and deploy learning dashboards in multiple learning environments through widgets. Second, the majority of papers (39 papers; 71 percent) described the implementation of a specific learning dashboard. 13 papers (5 percent) contributed a combination of a theoretical framework and a subsequent implementation. It is noteworthy that 93 percent of the papers did not provide a definition of the term 'dashboard'. Only 7 percent (four papers) defined 'dashboard', but each one offered a different definition.

5.2 Learning Context

To answer RQ1 ('In which contexts are learning dashboards being applied, including educational settings, target users and learning activities?'), we provide below a descriptive summary of the learning contexts discussed in the reviewed papers.

Target Users. Four types of target users were identified in the review: teachers, students, administrators and researchers (see Table 2). Teachers (41 papers; 75 percent) and students (28 papers; 51 percent) were clearly the main users of the dashboards, although administrators and researchers were not completely absent from the studies (as depicted in Fig. 4).

Learning Scenarios. We classified the papers regarding three types of learning scenarios typically considered [26]:

Fig. 4. Target users of the dashboards.

Fig. 5. Number of platforms data came from versus number of data source types. Zero denotes that the value was not specified. The size of a bubble represents the number of papers.
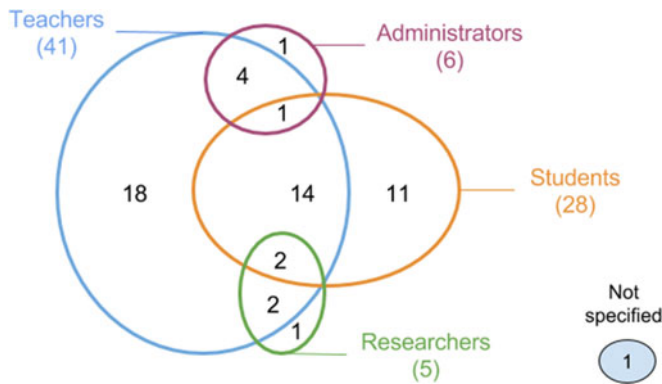
formal learning (intentional and structured learning framed in an education or training institution), non-formal (intentional and structured learning not provided by an education or training institution) and informal learning (mainly non-intentional and not structured learning not provided by an education or training institution). 91 percent of the papers (50 out of 55) targeted formal learning while the rest of the papers either addressed non-formal learning or did not specify the type of learning.

Educational Level. Regarding the educational level that the dashboards were applied in or designed for, 31 percent of the papers (17 out of 55) did not specify the learning context. It is noteworthy that 53 percent of the papers (29 out of 55) addressed university settings, as shown in Table 2.

Pedagogical Approach. Concerning pedagogical approaches, we extracted those that were explicitly mentioned in the description of the learning activities provided in the papers. Although many of them did not include a specific reference to a pedagogical approach (31 papers; 56 percent), there is a noteworthy appearance of computer-supported collaborative learning-CSCL (seven papers; 13 percent), blended (five papers; 9 percent) and online learning (four papers; 7 percent). Additionally, we inferred the granularity of such activities from the learning activity descriptions. We found that 19 papers (35 percent) used dashboards to analyse individual sessions, three papers (5 percent) used them to visualize the outcome of multiple sessions, and 18 papers applied dashboards throughout a whole course (33 percent). It should be noted that this analysis may be imprecise as the learning activities were not described in sufficient detail in multiple papers.

5.3 Learning Dashboard Solutions

To answer RQ2 ('What learning dashboards have been developed, including their purpose, indicators presented and technologies used?'), we analysed not only the stated purpose and indicators but also the data sources used (and the platforms from which the data came) in the different dashboards. Furthermore, the types of visualizations used to present the indicators, and the concrete implementation technologies were also extracted from the paper descriptions.

Purpose. In terms of purpose, we mapped the learning dashboards into three groups: (1) self-monitoring (28 papers; 51 percent), (2) monitoring others (39 papers; 71 percent) and (3) administrative monitoring (one paper; 2 percent). Three papers (5 percent) did not explicitly state a purpose for their dashboard.
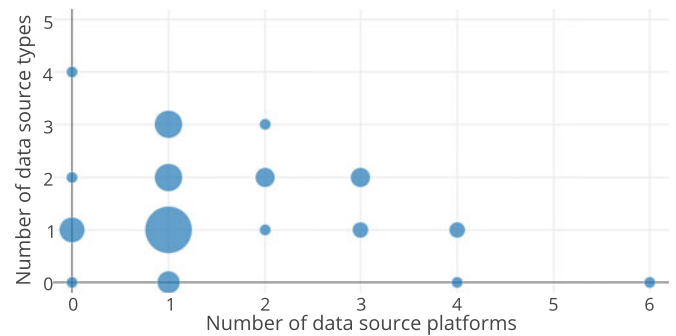
Types of Data Sources. We identified the following six main types of sources used to obtain data for the dashboards: (1) Logs used to track computer-mediated user activity, (2) Learning artefacts used or produced by the users (e.g., analysis of their contents), (3) Information asked directly from the users for analytics purposes (including questionnaires and interviews), (4) Institutional database records, (5) Physical user activity (tracked with physical sensors), and (6) external APIs (for collecting data from external platforms). The majority (47 papers; 85 percent) of papers mentioned logs as their data source for the dashboard. Learning artefacts were the second most frequently used data source (used in 16 papers; 29 percent), followed by information asked from the users (seven papers; 13 percent), institutional databases (five papers; 9 percent), physical user activity (four papers; 7 percent), and external APIs (three papers; 5 percent). Finally, four papers (7 percent) did not specify the data sources used. While most of the considered papers (27 papers, 49 percent) relied on a single data source, 13 papers (24 percent) combined two data sources, and nine papers (16 percent) combined three. Only two papers (4 percent) combined four data sources while one paper (2 percent) considered five distinct types of data sources for its dashboard.

Platforms. The solutions presented in the reviewed papers relied on data coming from a total of 51 distinct platforms (we will mention here only the ten most often encountered). Moodle was the single most popular platform for retrieving data (ten papers; 18 percent). In seven papers (13 percent), data was coming from an unidentified LMS. A number of papers mentioned aggregating data from external platforms. For instance, five papers (9 percent) used Twitter, four papers (8 percent) used Wikis, and three papers (5 percent) processed data from blogging platforms. Two papers used data from a MOOC platform (EdX, specifically), and two papers analysed data from a personal learning environment (PLE), Graasp. Other two papers relied on data from tools developed in the NEXT-TELL project. Most of the papers (33 papers; 60 percent) used data from a single platform while only a few papers aggregated data from several platforms: five papers combined data from two platforms, five papers from three platforms, three papers from four platforms, and one paper from six platforms.

Platforms versus Data Sources. To better understand the relation between the platforms and data sources used, the reader can refer to Fig. 5, where the size of the bubbles

TABLE 1
Overview of Indicator Types Presented in the Papers

Indicator group name	Question the indicators aim to answer	Examples of indicators in the group
Learner-related	Who are the learners?	Prior education, Competences, Age, Prior courses they took, University entrance grade
Action-related	What do they do while learning?	Number of page visits, Number of file downloads, Time spent on tasks, Login time, Timeline
Content-related	What is the content involved in their learning?	Sentiment of the messages, Topics covered and omitted in the report, Number of concepts and links in a concept map
Result-related	What is the result of their learning?	Average grade, Grades distribution in a group
Context-related	In which context does the learning take place?	Location of learners around a tabletop, Placement in a classroom, Geographical location
Social-related	How they interacts with others during learning?	Network showing communication with others in a group forum, Direction of interaction in a group around a tabletop

encodes the number of papers that use that amount of data sources and platforms. In general terms, most of the papers (33) involved a single platform and, among those, a majority collected only one data type (17 papers). However, there was a significant number of studies that involved integrated data, either as a result of combining multiple types of sources (21 papers; 38 percent) or several platforms (14 papers; 25 percent).

Indicator Types. During our analysis of the papers, we identified over 200 different indicators. These indicators can be categorized into six broad groups (shown in Table 1), depending on the questions they aim to answer (although an indicator may belong to more than one group). *Learner-related* indicators present information describing the learner (s). *Action-related* indicators present information about the actions performed by the learner(s), usually in an aggregated form. *Content-related* indicators provide information about the content that the learner(s) interacted with or produced. *Result-related* indicators give information about the outcome of learners' activities. *Context-related* indicators provide information about the context where the learning took place. *Social-related* indicators show how learners interacted with others. Noteworthy that most of the papers did not provide a detailed list of indicators used on the dashboard. To identify indicator types we often referred to the screenshots of dashboards presented in the papers, which makes it challenging to provide well-grounded conclusions regarding indicators distribution.

Indicator Targets. Most of the papers (47 papers; 85 percent) presented indicators about individuals. 25 papers (45 percent) contained indicators related the whole classes, eight papers (15 percent) had indicators about groups or pairs, and five papers (9 percent) presented indicators regarding large groups, for instance in the case of MOOCs.

Visualization Types. The reviewed papers described 29 distinct types of visualisations integrated into the learning dashboards. Fig. 6 displays the 15 most frequently employed visualizations. The most popular representations were bar charts (33 papers; 60 percent), line graphs (24 papers; 44 percent), tables (21 papers; 38 percent), pie charts (15 papers; 27 percent), and network graphs (ten papers; 18 percent). We have analyzed the co-occurrence of visualization types and target users (since one could intuitively expect that dashboards targeting students would employ

simpler visualizations compared to the ones targeting researchers or administrator)s). However, as Fig. 7 illustrates, the most common types of visualizations have been used across all target user groups. In a similar way, the visualization types used did not vary significantly for different educational settings (e.g., university, secondary).

Technology. When presenting the dashboard, most of the papers (29; 53 percent) did not specify the technology used to build it. In 20 papers (36 percent), it was possible to identify that the dashboard was a web application. Some papers mentioned specific technologies (frameworks and libraries) used to build the dashboard. For instance, three papers used Google Charts, two papers mentioned D3.js, and two papers highlighted the Next-TELL toolset. Other technologies mentioned at least once in the papers include QlikView, Google App Engine, Google Maps, Learning Log Dashboard (L2D), GLASS tool, iGoogle widgets, Navi Badgeboard, Navi Surface, LARAe, JsCharts, Highcharts, R, and Java.

5.4 Evaluation

To answer RQ3 ('How mature are such learning dashboards in terms of their evaluation?'), we examined the methods and scale of the learning dashboard evaluations. The maturity of current learning dashboard solutions, regarding the evaluation presented in the papers, is rather unequal: a majority of papers (58 percent) contained no evaluation whatsoever (see Table 2). On the positive side, it is commendable that 33 of the analyzed papers (60 percent) used data gathered from authentic educational situations (e.g.,
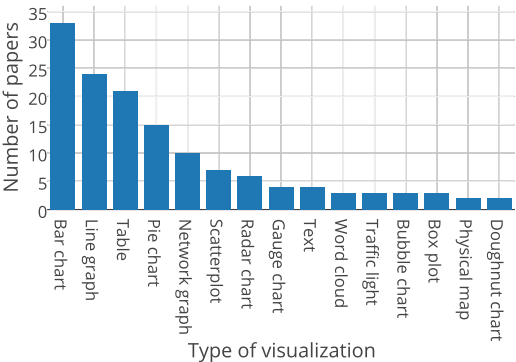
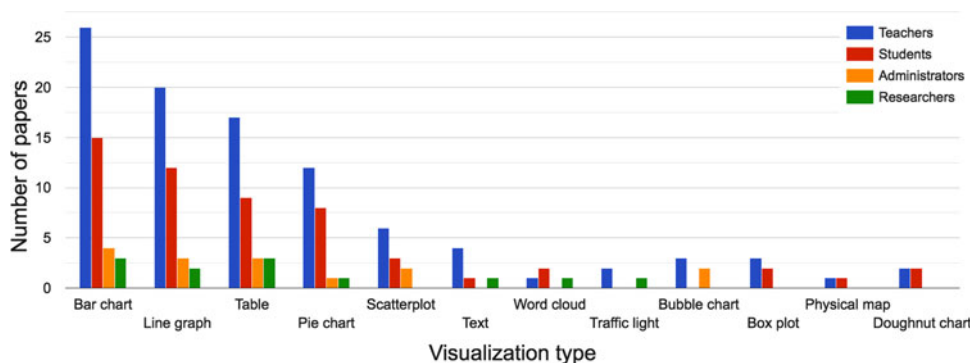Fig. 6. Most frequently used visualization types.

Fig. 7. Visualization type used depending on target user.

past or present courses) to build analyses and visualizations presented in the dashboards. This indicates that the concrete features of authentic data are of major importance to understand the usefulness of data visualizations. However, the overall evaluation state of the dashboard proposals was relatively weak, with only 15 of them (29 percent) portraying actual evaluations of the dashboard in authentic educational situations (i.e., the dashboard was shown to stakeholders and data were gathered about their use in real courses or sessions). Aside from these authentic evaluations, we found several instances where the dashboard contribution was evaluated through controlled lab studies (four papers), with only one paper referring to evaluation methods like expert panels or simulation. The rest (another four papers) only mentioned evaluations done informally, without providing much detail.

Regarding the methodologies used in the evaluations, the evaluated contributions were most commonly evaluated using mixed methods [27] that combined qualitative and quantitative techniques (15 papers; 65 percent of the papers portraying evaluations), as opposed to purely qualitative (four papers) or purely quantitative evaluations (only two papers). In these evaluations, a wide variety of data sources were used (see Fig. 8), with questionnaires and interviews being the most popular.

The evaluation studies varied regarding the targeted stakeholders (for example, teachers versus students), with only six evaluations gathering evaluation data from *both* teachers and students (see Table 2). In total, ten papers gathered information from teachers while 19 papers focused on students as informants in the evaluation. Regarding the scale of the evaluations, they typically included 30-150 students, and/or 3-9 teachers (except for [28] and [29], which gathered data from hundreds of students and teachers, respectively).

It is also noteworthy that most of the evaluations in the reviewed set of papers (74 percent of the 23 that had evaluation) addressed general constructs such as usability, usefulness, or user satisfaction—often with the intention of gathering formative feedback to improve the dashboard itself. Several evaluations (seven) targeted whether the dashboard improved awareness (of students, by teachers or other peers) while five others tried to evaluate changes in motivation and behavior prompted by the use of the dashboards; others evaluated the impact of dashboard usage on collaboration (three papers). Very few studies actually looked at (and provided evidence for) the impact of these technologies on *learning* [12], [30], [31], [32]. Indeed, the

only study that attempted measuring learning gains empirically in a controlled manner did not find statistically significant learning effects [12].

Finally, it is interesting to note that few of the evaluations specified the device through which the dashboard was being accessed (only eight of them did, wherein six of them mentioned access from a desktop, two from tabletops, and one through both shared displays and desktop). This may denote a lack of concern with the subtleties of how to best provide different kinds of information (and of visualization), depending on the context and device being used.

5.5 Open Issues

To answer RQ4 ('What are important open issues and future lines of work in the field of learning dashboards?'), we analyzed future work and open issues sections of the papers. Most papers mentioned extending their proposal by conducting evaluations with larger or different user groups as their future work. Considering the open issues in the field of learning dashboards, ethics and data privacy concerns appear to be of particular importance as mentioned by five papers (9 percent). Namely, learners should be made aware that their learning traces are being captured and analyzed as well as by whom and for what purpose this information is being used.

User experiences and usability issues are another challenge while implementing learning dashboards (four papers, 7 percent). This includes investigating particular requirements for different user groups (learners, instructors, etc), determining the granularity level of information being displayed on the dashboard, and adopting proper visualization techniques, as users could get overwhelmed by the amount of information presented to them or confused by visualizations type. Moreover, some studies such as [33] indicated that although high level indicators are easier to perceive than more detailed information, they will not be useful if they cannot be trusted by users to be complete and accurate. Additionally, making interpretations based on the presented information could be challenging for users. In this regard, two papers (4 percent) proposed to integrate mechanisms to automatically analyze information and provide feedback or warnings to educators and learners.

6 MAIN FINDINGS AND INSIGHTS

From all the results described above, we can extract several main responses to our four research questions. Most of the

TABLE 2
Overview of the Reviewed Papers, Including: Contribution (I=Implementation, T=Theoretical), Users (A=Administrators, R=Researchers, S=Students, T=Teachers), Educational Settings (A=Adult Education, C=Corporate Learning, M=MOOCs, S=Secondary School, U=University), Data Sources (DB=Institutional Records, I=Information Asked from Users, L=Logs, LA=Learning Artefacts, P=Physical Activity, E=External APIs), and Evaluation Type
(A=Authentic, C=Controlled, E=Experts, I=Informal, S=Simulation)

| Ref. | Context | | | Data Source | | Evaluation | | |
	Contribution	Users	Edu. setting	Type	# of platforms	Type	# of teachers	# of students
[37]	I	T	S	L, I	-	A	9	219
[38]	T, I	T, S	-	L	1	-	-	-
[10]	T, I	T, S	U	L, I, LA, DB	4	-	-	-
[39]	T, I	T, S	-	-	3	-	-	-
[28]	T, I	T, S	-	L, I, LA	3	A	-	1,169
[40]	I	T, S	U	L, E	2	A	-	22
[41]	I	T	U	L, E	3	C	6	-
[42]	I	T, S, R	S	L, LA	1	-	-	-
[43]	I	T	U	L, LA	2	-	-	-
[32]	I	S	U	L	1	A	-	28
[44]	I	T	U	L	2	C	4	-
[45]	I	T	-	L	1	-	-	-
[46]	I	T	U	L	1	-	-	-
[47]	T, I	S	U	L, LA	1	-	-	-
[48]	I	T, S	U	-	1	C	-	20
[49]	T, I	T	S	L, P, LA	1	-	-	-
[50]	I	S	U	L, LA	1	-	-	-
[51]	I	T, S	U	-	1	-	-	-
[52]	I	R	-	L	1	-	-	-
[53]	I	T, S	U	L, LA	1	A	10	30
[54]	I	S	-	L, LA, DB	1	A	-	123
[55]	I	T, A	U	L, LA, DB	1	-	-	-
[11]	I	S	-	L, I, LA	1	-	-	-
[56]	I	A	C	L, LA, DB	2	-	-	-
[57]	I	T, S	-	L	-	-	-	-
[33]	T, I	T	U	L	4	-	-	-
[58]	I	T	U	L	1	A	4	150
[59]	T, I	T	U	L, P	1	A, S	7	203
[60]	I	T, A	U	L	1	-	-	-
[29]	T, I	T, A	S	L, LA	1	E	210	-
[24]	T	T	-	L	-	-	-	-
[61]	I	S	S	L	1	A	-	209
[62]	I	S	-	L, P, LA, DB	1	-	-	-
[63]	T, I	T, A	S, U	L	-	-	-	-
[64]	I	T, R	M	L	1	-	-	-
[12]	I	S	U	L	1	A	-	37
[65]	I	T, S, R	U	L	1	A	-	85
[66]	I	T	U	L	1	-	-	-
[67]	I	T	U	L	6	-	-	-
[23]	T	T, S, A	U	L, DB	-	-	-	-
[68]	I	S	A	I	-	A	3	82
[69]	T, I	T, S	-	L	1	-	-	-
[70]	I	T	M	L	1	-	-	-
[30]	I	S	-	L, I, LA, E	3	A	-	69
[71]	I	S	-	L, I, LA	2	A	-	57
[35]	T, I	T, S	S, U	L	3	-	-	-
[31]	I	T, S	-	L	1	I	-	80
[72]	I	T, S	U	L, I	1	C	-	4
[73]	I	T, S	-	L	4	-	-	-
[74]	T, I	T, R	-	L	-	I	-	56
[75]	I	T	U	-	-	-	-	-
[76]	I	T	U	P	1	A	1	49
[77]	I	T	U	L, LA	1	-	-	-
[78]	I	T	S, U	L	1	A	2	-
[25]	I	-	-	-	1	-	-	-
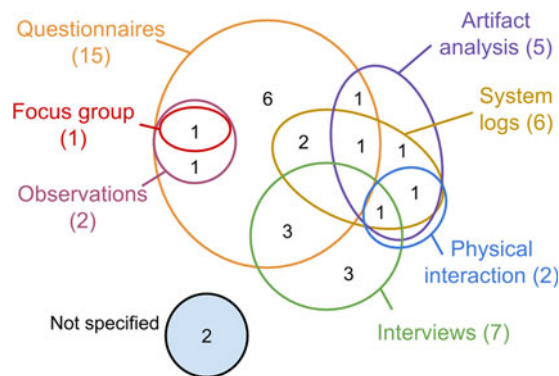
Fig. 8. Data sources used in the evaluation of the reviewed dashboards.

proposed learning dashboards still follow the traditional paradigm in which the teacher is the main user monitoring students. So far, dashboards have been studied mostly in formal, higher education contexts (as those are the contexts most accessible to many researchers). However, more and more studies are starting to experiment with providing dashboards to students; we expect to see an increase in this trend, as well as in the application of dashboards in secondary education and lifelong learning. It was also striking that many proposals did not explicitly mention a target educational level or a pedagogical approach. This may indicate that these proposals try to be applicable in a wide variety of contexts, but it could also signal a disregard for the peculiarities of specific groups of users (e.g., regarding data literacy), which can be fatal for the adoption of this kind of technology.

Dashboard solutions are (still) heavily based on log analysis, often using a single platform as their source of data. However, the fact that learning is becoming more blended and more distributed across different tools and contexts, more and more dashboards are experimenting with multiple kinds of data sources and platforms to get a complete view of learning processes. This also highlights the importance of proposals regarding data integration in learning analytics and the need for future researchers and dashboard developers to understand and adopt interoperable standards and specifications like Caliper or xAPI.

There is a rich variety of indicators being used to build current learning dashboards. However, there is comparatively little work on comparing which indicators (and which visualizations) are most suitable for the different user data literacy levels.

In terms of evaluation, many of the proposals are still exploratory, but this area is slowly veering towards more evaluations in real courses and other authentic settings. Indeed, there is a general acknowledgement of the importance of authentic data to make a meaningful dashboard proposal (most proposals, even those that lack evaluation, work with authentic data for their analyses and demonstrations of the value of the dashboard). The relative scarcity of long-term evaluations is noteworthy, especially for users considering the adoption of this kind of solutions in everyday practice (once the researcher team goes away). Nevertheless, perhaps the most striking finding of this review is the fact that very few studies look directly into student learning gains or learning-related constructs. Although the very nature of dashboards and how they are used (normally

designed either to support the teaching process or to facilitate reflection and motivation) makes it difficult to isolate the impact of dashboards on learning, this is a limitation of most existing studies that should be addressed in the future.

Overall, the 55 studies depicted in Table 2 paint the picture of an area of research which has been unequally explored[9]: A large majority of studies (around two-thirds) describe the implementation of a specific learning dashboard, relying on logs as the main data source. Among these, a large group of studies (21) targeted teachers as the main user group and provided no evaluation at all. The remaining 14 studies in this group addressed university settings and included an authentic or controlled evaluations of the proposed dashboard, mostly (albeit not invariably) aimed at students. There was also a quite large group of papers (11) that described dashboard implementations combining the analysis of logs and learning artefacts, but which provided no evaluation of their proposals either. A much smaller group (four papers) described dashboards targeting students, used multiple data sources (including logs, learning artefacts and other sources), and performed authentic evaluations of the dashboard with students. Another small group of papers (four papers) described theoretical proposals of dashboards for teachers and other user categories (often considering logs as the main data source and without an evaluation). Beyond these groups, there lay only a few outliers that provided larger-scale evaluations (e.g., more than 100 students/teachers) using multiple methods (e.g., through simulations and in authentic settings).

7 CONCLUSION AND FUTURE STUDIES ON LEARNING DASHBOARDS

The results from our analysis of the 55 learning dashboard publications enable us to draw several conclusions about this area within the fields of Learning Analytics and Educational Data Mining. A first insight would be that the field would benefit from a shared definition of what a 'learning dashboard' is and agree on the terminology. Based on our review, we suggest using the term 'learning dashboard' and propose the following definition: *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.* These criteria allow distinguishing a learning dashboard from a single information visualization that presents a single indicator. Additionally, these criteria offer starting points for further systematic research on learning dashboards.

More than half of the papers focused on university settings, which highlights a need for learning dashboard studies in other settings, such as K-12 as well as non-formal settings where students can follow their own pathways.

The fact that dashboards have been proposed for a variety of learning activity granularities seems to indicate that there is no consensus yet regarding the frequency and patterns of use of the learning dashboards and that the recording and proposing of (teaching and learning) practices for

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9. This description has been extracted from the application of a k-means clustering algorithm on the four principal components of the data depicted in Table 2.

learning *around* dashboards are another promising field for future research in the area.

It is also noteworthy that the kinds of visualizations chosen in most cases are rather similar to those in other areas of dashboard applications (e.g., web analytics), which highlights the lack of specific visualizations and visual metaphors that address the activities of learning and teaching (another potential area for future research).

Dashboards presented in the analyzed papers mainly used logs of user activities as their data source and only a few used external APIs, user physical activity, or institutional databases. With the development of distributed learning environments, it will become more important to be able to aggregate learning-related data across platforms. Some recent proposals, including [34] and [35], already move in this direction. To track learning across physical and digital boundaries in blended learning, it will become necessary to capture several data sources at the same time to be able to record and analyze learning activities happening in a physical (recorded with sensors or cameras) and technology-mediated environments (recorded through logs).

From our analysis of the paper's evaluations, we can observe that research on the impact of learning dashboards is still young. While there has been a considerable amount of research on information visualizations, research on the effects of learning dashboards is still in its early stages-as indicated by the considerable amount of exploratory work and small proof-of-concept studies, which very often do not reach the stage of being used (and evaluated) in authentic settings. Large-scale studies with a focus on evaluating dashboards regarding adoption and learning impact are probably the most important yet under-explored aspect of research regarding learning dashboards.

On the positive side, even at this early stage, learning dashboard research considers the use authentic data important (even on first prototypes). There is a certain abundance of mixed method studies triangulating multiple data sources (in accordance with many methodological recommendations from the learning sciences [36]), even if the techniques used very often veer towards "low-effort, low-detail" (e.g., short questionnaires or brief interviews).

Another hallmark of younger fields is the lack of comparative studies among different dashboards or dashboard design options (in part due to the difficulty in achieving controlled yet relatively authentic conditions, but also due to a lack of widely-accepted, specific evaluative constructs, beyond general ones like usability or usefulness). Regarding the ecological validity of the proposals, the lack of longitudinal evaluations of learning dashboards in authentic conditions may make transferring these technologies to more widespread educational practice a challenging issue. Clearly, more studies on the long-term impact and affordances of learning dashboards are needed if these technologies are to be part of the common toolbox of teachers and learners in the years to come.

Based on the reviewed papers, we offer the following checklist for papers on learning dashboards: a) provide a definition of 'learning dashboard' (or references to the one they ascribe to); b) provide details about the technologies used; c) provide details about the educational context for which the dashboard is deemed appropriate; d) evaluate and clearly denote the impact regarding learning (or, at least, describe what other constructs were the target of the evaluation); pointing to new instruments and methods, if applicable; e) provide details about the (learner and/or teacher) practices that developed (or are expected) using the dashboard.

Addressing these elements in future studies on learning dashboards can further develop the field and support comparison between studies. Learning dashboards are quickly moving towards maturity, and the field needs to demonstrate the benefits for learning and teaching, to drive long-term adoption.

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Beat A. Schwendimann is a post-doctoral researcher in the CHILI Group, Swiss Federal Institute of Technology in Lausanne (EPFL). He conducted his PhD research as a Fulbright scholar at the University of California, Berkeley, exploring how collaborative knowledge visualization activities, embedded in a technology-enhanced science learning environment, can foster a more coherent understanding of biology. At EPFL, he is the coordinator of the Leading House DUAL-T that develops and implements innovative learning technologies that support vocational students by bridging the skill gap between what they learn in school and in their workspaces.

María Jesús Rodríguez-Triana is a post-doctoral researcher in the Coordination and Interaction Systems Group (REACT), École Polytechnique Fédérale de Lausanne (EPFL). Her research lines address blended and collaborative learning, classroom orchestration, learning design, learning analytics, and distributed learning environments. Currently, she is investigating the synergies between learning design and learning analytics when using pedagogical approaches such as inquiry based learning and computer-supported collaborative learning.

Andrii Vozniuk is currently working toward the PhD degree in computer science from the Coordination and Interaction Systems Group (REACT), Swiss Federal Institute of Technology in Lausanne (EPFL). His research and software engineering interests include learning analytics, learning dashboards and more broadly approaches and tools supporting knowledge sharing in the educational and the humanitarian domains. In the course of the PhD studies, he has proposed and developed tools that visualize and analyze students' activities to support awareness and reflection. He is a member of the IEEE and the ACM.

Luis P. Prieto received the PhD degree in information and communication technologies from the University of Valladolid. He is a Marie Curie fellow in the CHILI Lab, École Polytechnique Fédérale de Lausanne (EPFL). His research interests include classroom orchestration, distributed and augmented paper learning technologies, and the use of wearable technologies to capture and understand complex practice with ICT and use it for reflection. He has authored more than 50 academic publications on these topics. He is a member of the IEEE and the ACM.

Mina Shirvani Boroujeni is currently working toward the PhD degree in computer science from the Computer Human Interaction for Learning and Instruction Group (CHILI), Swiss Federal Institute of Technology in Lausanne (EPFL). Her research focus is on learning analytics, time series analysis, social networks analysis and learning dashboards to support awareness, and reflection in blended learning settings.

Adrian Holzer received the PhD degree in information systems from the University of Lausanne, Switzerland. He is a research associate in Ecole Polytechnique Fédérale de Lausanne (EPFL), Coordination & Interaction Systems Group (REACT). His research and teaching activities focus on mobile social media interaction in the learning and humanitarian contexts.

Denis Gillet received the PhD degree in information systems from the Swiss Federal Institute of Technology in Lausanne (EPFL), in 1995. He is currently an associate professor with EPFL School of Engineering, where he leads the REACT multi-disciplinary research group. He is an associate editor of the *IEEE Transactions on Learning Technologies* and the *International Journal of Technology Enhanced Learning*. His current research interests include technologies enhanced learning, human computer interaction, human devices interaction and optimal coordination of complex, and distributed systems.

Pierre Dillenbourg received the PhD degree in computer science from the University of Lancaster, United Kingdom, in the domain of artificial intelligence applications for educational software. He is a full professor of learning technologies with the School of Computer & Communication Sciences, where he is the head of the CHILI Lab: "Computer-Human Interaction for Learning & Instruction. He is also the academic director of the Center for Digital Education, which implements the MOOC strategy of EPFL. A former teacher in elementary school, he graduated in educational science (University of Mons, Belgium). He started his research on learning technologies in 1984. He has been an assistant professor with the University of Geneva.