Awareness is not enough. Pitfalls of learning analytics dashboards in the educational practice

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Abstract. It has been long argued that learning analytics has the potential to act as a "middle space" between the learning sciences and data analytics, creating technical possibilities for exploring the vast amount of data generated in online learning environments. One common learning analytics intervention is the learning dashboard, a support tool for teachers and learners alike that allows them to gain insight into the learning process. Although several related works have scrutinised the state-of-the-art in the field of learning dashboards, none have addressed the theoretical foundation that should inform the design of such interventions. In this systematic literature review, we analyse the extent to which theories and models from learning sciences have been integrated into the development of learning dashboards aimed at learners. Our critical examination reveals the most common educational concepts and the context in which they have been applied. We find evidence that current designs foster competition between learners rather than knowledge mastery, offering misguided frames of reference for comparison.

Keywords: learning dashboards, learning theory, learning analytics, systematic review, learning science, social comparison, competition

1 Introduction

Learning Analytics (LA) emerged from the need to harness the potential of the increasingly large data sets describing learner data generated by the widespread use of online leaning environments and it has been defined as "the measurement, collection, analysis, and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" [37]. Ferguson [13] identified two main challenges when it comes to learning analytics: (i) building strong connections to learning sciences and (ii) focusing on the perspectives of learners.

There is a common notion in the LA community that learning analytics research should be deeply grounded in learning sciences [28, 29]. Suthers & Verbert [38] labelled LA the "middle space" as it lies at the intersection between technology and learning sciences. Moreover, LA should be seen as an educational approach guided by pedagogy and not the other way around [19]. However, there is a strong emphasis on the "analytics", i.e. computation of the data and creation of predictive models, and not so much on the "learning", i.e. applying and researching LA in the learning context where student outcomes can be improved [17].

One of the focuses of LA research is to empower teachers and learners to make informed decisions about the learning process, mainly by visualising the collected learner data through dashboards [9]. Learning analytics dashboards are "single displays that aggregate different indicators about learner (s), learning process(es) and/or learning context(s) into one or multiple visualizations" [35]. Dashboards have been developed for different stakeholder groups, including learners, teachers, researchers or administrative staff [35]. Charleer et al. [5] suggest that LA dashboards could be used as powerful metacognitive tools for learners, triggering them to reason about the effort invested in the learning activities and learning outcomes. However, a large majority of dashboards are still aimed at teachers, or at both teachers and learners [35]. Moreover, there has been very little research in terms of what effects such tools have on learning [26].

As a first step towards building effective dashboards for learners, we need to understand how learning sciences can be considered in the design and pedagogical use of learning dashboards. Following Suther and Verbert's [38] position that learning analytics research should be explicit about the theory or conception of learning underlying the work, we sought out to investigate which educational concepts constitute the theoretical foundation for the development of learning dashboards aimed at learners.

A number of previous works reviewed LA dashboards from different perspectives, including their design and evaluation. Verbert et al. [42] introduced a conceptual framework for analysing LA applications and reviewed 15 dashboards based on the target users, displayed data and the focus of the evaluation. A follow-up review [43] extended this analysis to 24 dashboards, examining the context in which the dashboards had been deployed, the data sources, the devices used and the evaluation methodology. Yoo et al. [47] reviewed the design and evaluation of 10 educational dashboards for teachers and students through their proposed evaluative tool based on Few's principles of dashboard design [15] and Kirkpatrick's four-level evaluation model [25]. A more recent systematic review by Schwendimann et al. [35] of 55 dashboards looked at the context in which dashboards had been deployed, their purpose, the displayed indicators, the technologies used, the maturity of the evaluation and open issues.

The scope of all these reviews included learning analytics dashboards, regardless of their target users. Focusing on the challenges identified by Ferguson [13], we narrow down our scope to LA dashboards aimed at learners in order to focus on their perspective. A closely related work to this paper was published by Bodily & Verbert [4]. They provided a systematic review that focused exclusively on student-facing LA systems, including dashboards, educational recommender systems, EDM systems, ITS and automated feedback systems. The systems were analysed based on functionality, data sources, design analysis, perceived effects on learners and actual effects.

Although other works looked into the learning theory foundations of game-based learning [46], one major limitation of previous dashboard reviews is that none investigate the connection to learning sciences. Moreover, [35] and [4] provide recommendations for the design of learner dashboards, but none suggest the use of educational concepts as a basis for the design or evaluation of the dashboards. Through this systematic literature review we aim to bridge this gap by investigating the relation between educational concepts and the design of learning dashboards. Dashboard design was previously examined by looking at the type of data displayed on the dashboard and the type of charts or visualisation that were used. However, in this study, we will specifically focus on how the data presented on the dashboard is contextualised and framed to ease the sense-making for the learners.

Throughout this literature review, we explore how educational concepts are integrated into the design of learning dashboards. Our study is guided by the following research question: *According to which educational concepts are learning analytics dashboards designed?*

2 Methodology

Prior to the systematic review, we conducted an informative literature search in order to get an overall picture of the field. We ran the systematic literature review following the PRISMA statement [31] and we selected the following databases which contain research in the field of Technology Enhanced Learning: ACM Digital Library, IEEEXplore, SpringerLink, Science Direct, Wiley Online Library, Web of Science and EBSCOhost. Additionally, we included Google Scholar to cover any other sources, limiting the number of retrieved results to 200. We searched the selected databases using the following search query: *"learning analytics" AND (visualization OR visualisation OR dashboard OR widget)*. The first term narrows down the search field to *learning analytics*, while the second part of the query is meant to cover different terminologies used for this type of intervention, addressing one of the limitations identified in [35]. Although the scope of this review is limited to visualisations that have learners as end-users, it was not possible to articulate this criterion in relevant search terms. Therefore, the approach that we took was to built a query that retrieves all dashboards, regardless of their target end-users, and remove the ones that fall out of our scope in a later phase.

The queries were run on February 20$^{\text{th}}$, 2017, collecting 1439 hits. Each result was further screened for relevance, i.e. whether it described a learning dashboard aimed at learners, by examining the title and the abstract, thus reducing the list of potential candidate papers to 212. Eleven papers that we came across during the informal check and fit the scope of our survey were also added to the set of papers to be further examined. Next, we accessed the full text of each of these

223 studies in order to assess whether they are eligible for our study considering the following criteria:

1. the paper's full text is available in English;
2. the paper describes a fully developed dashboard, widget or visualisation, i.e. we excluded theoretical papers, essays or literature reviews;
3. the target user group of the dashboard is learners;
4. the authors explicitly mention theoretical concepts for the design;
5. the paper includes an evaluation of the dashboard.

We identified 95 papers that satisfied the first three criteria. Only half of these papers have theoretical grounding in educational concepts, suggesting a large gap between learning sciences and this type of learning analytics interventions. The focus of this study is set on *26 papers* that describe dashboards that both rely on educational concepts (criterion 4) and were empirically evaluated (criterion 5). The list of papers included in this review is available at *bit.ly/LADashboards*.

3 Results

We started this investigation by collecting the theoretical concepts and models used in the dashboards and analysing the relationships between the purpose of the dashboards and the concepts that were employed in the development of the dashboard. Next, we looked at how the design of these dashboards integrate different concepts from learning sciences.

3.1 Learning theories and models

By analysing the introduction, background and dashboard design sections of each of the papers included in this study, we identified 17 theories, models and concepts that we bundled into six clusters (see Table 1).

EC1: Cognitivism cluster relies upon the cognitivism paradigm which posits that learning is an internal process, involving the use of memory, thinking, metacognition and reflection [1]. This is the most represented category through self-regulated learning (SRL), 16 papers citing the works of Zimmerman [48], Pintrich [33] or Winne [44]. Deep vs surface learning theory explains different approaches to learning, where deep learners seek to understand the meaning behind the material and surface learners concentrate on reproducing the main facts [21]. *EC2: Constructivism cluster* is rooted in the assumption that learners are information constructors and learning is the product of social interaction [1]. Social constructivist learning theory [24] and Paul-Elder's critical thinking model [11] have been used mostly in dashboards aimed to offer learner support in collaborative settings, while Engeström's activity theory [12] was used as a pedagogical base for supporting university students overcome dyslexia. *EC3: Humanism cluster* puts the learner at the centre of the learning process, seeking to engage the person as a whole and focusing on the study of the self, motivation

Table 1. Six clusters presentation of educational concepts identified and the papers in which they appear. The list of papers included in this review is available at *bit.ly/LADashboards*

Cluster	Educational concept	Freq.	Papers
EC1: Cognitivism	Self-regulated learning	16	D1; D4; D5; D7; D9; D11; D12; D14; D15; D18; D20; D21; D22; D23; D25; D26
	Deep vs surface learning	2	D16; D19
EC2: Constructivism	Collaborative learning	6	D12; D13; D14; D16; D24; D26
	Social constructivist learning theory	4	D7; D13; D19; D22
	Engeström activity theory	1	D12
	Paul-Elder's critical thinking model	1	D19
EC3: Humanism	Experiential learning	2	D4; D13
	Learning dispositions	1	D2
	21st century skills	4	D2; D11; D13; D19
	Achievement goal orientation	3	D15; D19; D24
EC4: Descriptive models	Engagement model	1	D10
EC5: Instructional design	Universal Design for Learning instructional framework	1	D19
	Formative assessment	3	D3; D6; D19
	Bloom's taxonomy	3	D3; D4; D22
EC6: Psychology	Ekman's model for emotion classification	1	D23
	Social comparison	3	D8; D15; D25
	Culture	1	D25

and goals [8]. More recent works focus on developing 21st century skills [40] and learning dispositions [36]. Achievement goal orientation theory is concerned with learners' motivation for goal achievement [32]. *EC4: Descriptive models* cluster includes the engagement model [16] which differentiates between behavioural, emotional and cognitive engagement. Several papers also cover the pedagogical use of dashboards, aligning the *EC5: Instructional design* in which the dashboard is embedded with Bloom's taxonomy [3], formative assessment [34] or Universal Design for Learning framework [6]. While the majority of these clusters contain concepts belonging to the learning sciences field, we also identified three concepts that originate in the broader field of *EC6: Psychology*: Ekman's model of emotions and facial expressions [10], social comparison [14] and culture [18, 22].

3.2 Dashboard goals and educational concepts

In order to understand the reasons behind using these educational concepts, we analysed the goals of the dashboards and looked at how their use was explained in the papers. We extracted the goals of each dashboard and categorised them based on the competence they aimed to affect in learners: metacognitive, cognitive,

Table 2. Competencies, the goals that are intended to affect each competence and the papers in which they appear. The list of papers included in this review is available at *bit.ly/LADashboards*

Competence	Goal	Freq.	Papers
C1: Metacognitive	Improve metacognitive skills	4	D6; D7; D20; D23
	Support awareness and reflection	20	D1; D2; D3; D4; D6; D7; D9; D10; D11; D12; D13; D14; D17; D18; D20; D21; D22; D23; D25; D26
	Monitor progress	8	D7; D8; D11; D15; D19; D20; D22; D23
	Support planning	2	D20; D22
C2: Cognitive	Support goal achievement	3	D9; D18; D25
	Improve performance	3	D16; D23; D24
C3: Behavioural	Improve retention or engagement	2	D10; D25
	Improve online social behaviour	7	D7; D13; D14; D16; D19; D24; D26
	Improve help-seeking behaviour	1	D17
	Offer navigational support	2	D8; D15
C4: Emotional	Deactivate negative emotions	1	D9
	Increase motivation	4	D2; D8; D15; D19
C5: Self-regulation	Support self-regulation	13	D1; D4; D7; D9; D11; D12; D15; D19; D20; D21; D22; D23; D25

behavioural or emotional (see Table 2). Most of the dashboards do not serve only one goal, but rather aim to catalyse changes in multiple competencies. A fifth category *C5: Self-regulation* was also added to account for papers that explicitly described their goal as supporting self-regulation, a concept that involves all four competencies [48].

Figure 1 illustrates the relation between the goals of the dashboards and the educational concept clusters listed in Table 1. We can draw some interesting observations from these connections. Firstly, the largest part of the visualisations aim to influence learners' *metacognitive* competence, with the purpose of supporting awareness and reflection. This aim is often motivated by SRL theory, a learning concept that heavily relies on the assumption that actions are consequences of thinking as SRL is achieved in cycles consisting of forethought, performance and self-reflection [49]. SRL also motivates the goal of monitoring progress and supporting planning, but to a lesser extent. Social constructivist learning theory and collaborative learning also appear quite frequently in relation to metacognition, due to the collaborative setting in which the dashboards were used. Dashboard developers argue that for effective collaboration, learners need to be aware of their teammates' learning behaviour, activities and outcomes. Other concepts used for affecting the metacognitive level are formative assessment as it implies evaluation of one's performance, 21st century skills with the focus on *learning how to learn* and social comparison as a means for framing the evaluation of one's performance.

Secondly, there is a strong emphasis on supporting the *self-regulation* competence by using cognitivist concepts. The design of these dashboards is usually informed by SRL theory. Constructivist concepts are also commonly used for the development of these dashboards because the context in which these dashboards were deployed is the online collaborative learning setting. Less used are instructional design concepts, more notable being the use of formative assessment as a means for reflection and self-evaluation.

Thirdly, in order to affect the *behavioural* level, SRL is again one of the most commonly used concepts, alongside social constructivism and collaborative learning. Social comparison has a stronger presence on this level as it is used to reveal the behaviour of peers as a source of suggestions on how learners could improve. Surprisingly, very few dashboards aim to support learners on the *cognitive* level, i.e. acquiring knowledge and improving performance, and the few that do, rely mostly on SRL and social comparison. Finally, in order to animate changes on the *emotional* level, dashboards build mostly on social comparison and the modelling of learning dispositions and 21st century skills.

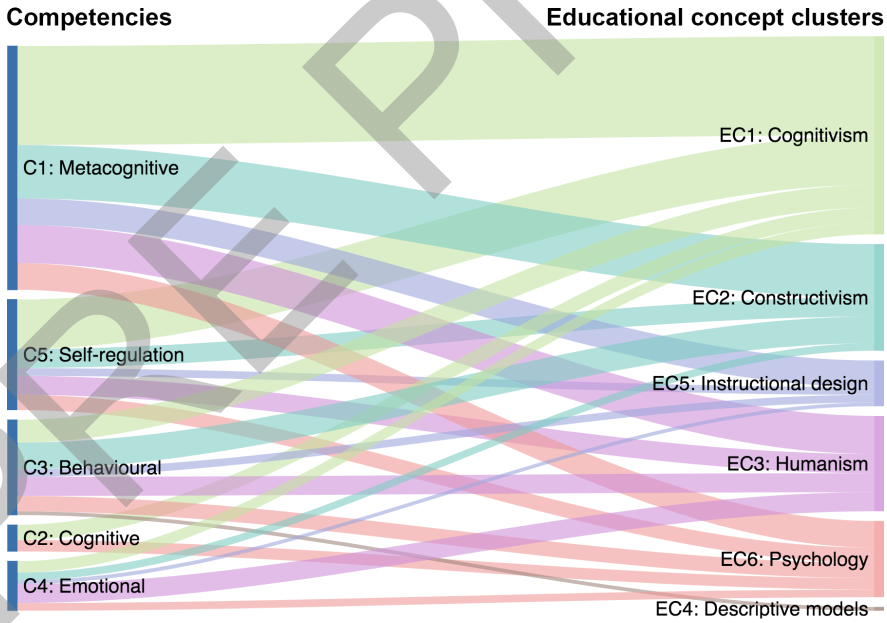

Fig. 1. The competence level targeted by the dashboards included in the review in relation to the educational concept clusters that were used as a theoretical basis for their development.

3.3 Reference frames

According to the framework for designing pedagogical interventions to support student use of learning analytics proposed by Wise [45], learners need a "*representative reference frame*" for interpreting their data. We analysed this aspect by looking at how the information was contextualised on the dashboard based on the dashboard goals. We identified three types of reference frames: i) social, i.e. comparison with other peers, ii) achievement, i.e. in terms of goal achievement, and iii) progress, i.e. comparison with an earlier self (see Table 3).

Apart from the origin of the reference frame, the three types are also characterised by where in time the anchor for comparison is set. The social reference frame focuses on the present, allowing learners to compare their current state to the performance levels of their peers at the same point in time. The achievement reference frame directs learner' attention to the future, outlining goals and a future state that learners aim for. Finally, the progress reference frame is anchored in the past, as the learners use as an anchor point a past state to evaluate what they achieved so far. In the following paragraphs we discuss in detail each type.

Social The most common frame was showing learners their data in comparison to the whole class. We also identified cases where learners had access to the data of individual members of their working groups in collaborative learning settings. In other cases, learners compared themselves to previous graduates of the same course. In order to avoid the pitfalls of averages in heterogeneous groups, D22 allowed learners a more specific reference: peers with similar goals and knowledge. A few dashboards compared learners to the "top" students, while on some dashboards learners had the option to choose against which group they compare themselves. On one dashboard, learners compared their self-assessment of group work performance with the assessment made by their peers. We also looked at how the data of the reference groups is aggregated. Most of the dashboards displayed averages (16 dashboards), while only six showed data of individuals and three presented a learner's ranking within the reference group.

Table 3. The reference frames for comparison and their frequency. The list of papers included in this review is available at *bit.ly/LADashboards*

Type	Reference frame	Freq.	Papers
Social	Class	15	D1; D3; D4; D5; D7; D8; D11; D15; D16; D18; D19; D21; D22; D23; D24
	Teammates	2	D14; D26
	Previous graduates	2	D21; D25
	Top peers	4	D8; D15; D16; D24
	Peers with similar goals	1	D22
Achievement	Learning outcomes	15	D2; D3; D4; D5; D6; D8; D9; D11; D12; D15; D16; D20; D21; D22; D24
	Learner goals	1	D22
Progress	Self	10	D1; D2; D3; D4; D5; D10; D18; D23; D25; D26

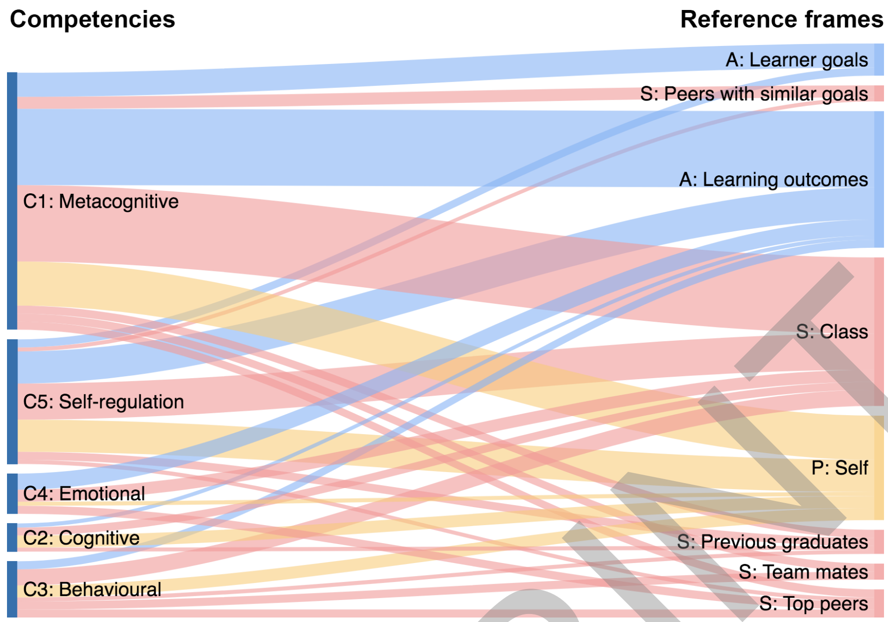

Fig. 2. The competence level targeted by the dashboards in relation to the three reference frames identified: social (S: red), achievement (A: blue) and progress (P: yellow).

Achievement The second way of framing the information displayed on the dashboard is in terms of the achievement of the learning activity. Here, we distinguish between two types of goals: i) learning outcomes set by the teachers and ii) learner goals set by the learners themselves. One purpose of presenting learners' performance in relation to *learning outcomes* was to illustrate mastery and skillfulness achievement. Content mastery was expressed through the use of key concepts in forum discussion (D16, D24), performance in quizzes covering topics (D5, D8, D9, D15) or different difficulty levels (D3). The acquisition of skills was quantified through the number of courses covering those skills in the curriculum objectives (D21), while learning dispositions were calculated from self-reported data collected through questionnaires (D2). A second purpose for using teacher defined goals is to support learners in planning their learning by offering them a point of reference as to how much effort is required for the completion of a learning activity (D11). Concerning the *learner goals*, our results were surprising. Only one dashboard allowed learners enough freedom to set their own goals: on D22, learners could establish their aimed level of knowledge and time investment and follow their progress in comparison to their set targets.

Progress The third frame of reference refers to whether dashboards allow learners to visualise their progress over time, by having access to their historical data. This functionality directly supports the "execution and monitoring" phase of the SRL cycle [48]. Our results show that only 10 dashboards offered this feature, while the rest displayed only the current status of the learners.

4 Discussion

Through this literature review, we seek to investigate the relation between learning sciences and learning analytics by looking into which educational concepts inform the design of learning analytics dashboards aimed at learners. Our investigation revealed that only 26 out of the 95 dashboard designs identified by our search have grounding in learning sciences and have been evaluated. This might indicate that the development of these tools is still driven by the need to leverage the learning data available, rather than a clear pedagogical focus of improving learning. The most common foundation for LA dashboard design is *self-regulated learning* theory, used frequently to motivate dashboard goals that aim to support awareness and trigger reflection. Two findings related to the use of SRL are striking.

Firstly, very few papers have a secondary goal besides fostering awareness and reflection. However, being aware does not imply that remedial actions are being taken and learning outcomes are improved. Moreover, awareness and reflection are not concepts that can be measured objectively, making the evaluation of such dashboards questionable. According to McAlpine & Weston, reflection should be considered a mechanism through which learning and teaching can be improved rather than an end in itself [30]. Thus, we argue that LA dashboards should be designed and evaluated as pedagogical tools which catalyse changes also in the cognitive, behavioural or emotional competencies, and not only on the metacognitive level.

Secondly, since more than half of the analysed dashboards rely on SRL, we took a closer look at how the different phases of the self-regulation cycle are supported, i.e. fore-thought and planning, monitoring and self-evaluation [49]. The investigation of the reference frames used on the dashboards revealed that there is little support for goal setting and planning as almost no dashboard allowed learners to manage self-set goals. Moreover, tracking one's own progress over time was also not a very common feature. These two shortcomings suggest that current dashboards are built mostly to support the "reflection and self-evaluation" phase of SRL and neglect the others. This implies that apart from a learning dashboard, online learning environments need to provide additional tools that facilitate learners to carry out all the phases of the SRL cycle, supporting learners in subsequent steps once awareness has been realised. These findings emphasise the need of designing LA dashboards as a tool embedded into the instructional design, potentially solving problems related to low uptake of LA dashboards [28].

Furthermore, our analysis revealed that social framing is more common than achievement framing. Comparison with peers is usually used in order to motivate students to work harder and increase their engagement, sometimes by "inducing a feeling of being connected with and supported by their peers" [41]. When looking at the theoretical concepts that inform the design of the studied dashboards, only two theories would justify the use of comparison with peers: social comparison theory and achievement goal orientation theory.

Social comparison [14] states that we establish our self-worth by comparing ourselves to others when there are no objective means of comparison. However, empirical research in the face-to-face classroom has shown that comparison to self-selected peers who perform slightly better has a beneficial effect on middle school students' grades, whereas no effects were found when there was a bigger gap in performance [23]. Despite the availability of such research, social comparison theory is rarely used to inform the design of dashboards. Only 3 works rationalise the use of comparison by grounding it on social comparison theory and validations of this theory in educational sciences [7, 20, 27]. Moreover, learners usually got to see their data in comparison to the average of their peers. Averages are often misleading because they are skewed by data of inactive learners and the diversity of learning goals among learners, offering a misguided reference frame.

A second theory that might support the use of social comparison is *achievement goal orientation theory*. This theory distinguishes between mastery and performance orientations as the motivation behind why one engages in an achievement task [32]. In contrast to learners who set mastery goals and focus on learning the material and mastering the tasks, learners who have performance goals are more focused on demonstrating their ability by measuring skill in comparison to others. We found few dashboards that contextualised the data in terms of goals achieved, while the majority used different groups of peers as a frame of reference. This finding suggests that the design of current dashboards is more appealing to performance oriented learners, neglecting learners who have a tendency towards mastery. Indeed, as Beheshitha et al. [2] observed, learners that considered the subject matter of the course more motivating than competition between students were more inclined to rate negatively the visualisation based on social comparison. We found only one dashboard proposal that catered to the needs of learners with different achievement goal orientations. Mastery Grids [20] provides an open learner model for mastery oriented learners on which they can monitor their progress, as well as social comparison features for performance oriented learners.

The lack of support for goal achievement and the prevalence of comparison fosters competition in learners. On the long-term, there is the threat that by constantly being exposed to motivational triggers that rely on social comparison, comparison to peers and "being better than others" becomes the norm in terms of what defines a successful learner. We argue that learning and education should be about mastering knowledge, acquiring skills and developing competencies. For this purpose, comparison should be used carefully in the design of learning dashboards, and research needs to investigate the effects of social comparison and competition in LA dashboards. More attention should be given to the different needs of learners and dashboards should be used as pedagogical tools to motivate learners with different performance levels that respond differently to motivating factors. As Tan [39] envisioned, "differentiated instruction can become an experienced reality for students, with purposefully-designed LA serving to compress, rather than exacerbate, the learning and achievement gap between thriving and struggling students".

5 Conclusion

This paper presents the results of a systematic survey looking into the use of educational concepts in learning analytics dashboards for learners. Our main findings show that, firstly, *self-regulated learning* is the core theory that informs the design of LA dashboards that aim to make learners aware of their learning process by visualising their data. However, just making learners aware is not enough. Dashboards should have a broader purpose, using awareness and reflection as means to improve cognitive, behavioural or emotional competencies. Secondly, effective support for online learners that do not have well developed SRL skills should also facilitate goal setting and planning, and monitoring and self-evaluation. As dashboards mostly aim to increase awareness and trigger self-reflection, different tools should complement dashboards and be seamlessly integrated in the learning environment and the instructional design. Thirdly, there is a strong emphasis on comparison with peers as opposed to using goal achievement as reference frame. However, there is evidence in educational sciences that disproves the benefits of fostering competition in learning. Our findings suggest that the design of LA dashboards needs better grounding in learning sciences.

Finally, we see the need to investigate the effectiveness of using educational concepts in the design of LA dashboards by looking at how these tools were evaluated, what are the effects perceived by learners and how learning was improved. Our study was limited by a narrow focus set within the LA field, a relatively recent research area. Valuable proposals could also be found in related fields, e.g. educational data mining. We plan to answer these research questions in the future by extending this work.

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