Transferring learning dashboards to new contexts: experiences from three case studies

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Abstract

This papers focuses on the use of learning dashboards in higher education to foster self-regulated learning and *open education*. Students in higher education have to evolve to independent and lifelong learners. Actionable feedback during learning that evokes critical self-reflection, helps to set learning goals, and strengthens self-regulation will be supportive in the process. Therefore, this paper presents three case studies of learning analytics in higher education and the experiences in transferring them from one higher education institute than the other. The learning dashboard from the three case studies is based on two common underlying principles. First, they focus on the inherent scalability and transferability of the dashboard: both considering the underlying data and the technology involved. Second, the dashboard use as underlying theoretical principles Actionable Feedback and the Social Comparison Theory. The learning dashboards from the case studies are not considered as the contribution of this paper, as they have been presented elsewhere. This paper however describes the three learning dashboards using the general framework of Greller and Drachsler (2012) to enhance understanding and comparability. For each of the case study, the actual experiences of transferability obtained within a European collaboration project (STELA, 2017) are reported. This transferability and scalability is the first-step of creating truly effective Open Educational Resources from the Learning Analtyics Feedback dashboards. The paper discusses how this collaboration impacted and transformed the institutes involved and beyond. The use of open education technology versus proprietary solutions is described, discussed, and translated in recommendations. As such the research work provides insight on how learning analytics resources could be transformed into open educational resources, freely usable in other higher education institutes.

Introduction

Learning Analytics (LA) is a relatively young multidisciplinary field combining theory, design, and data science [1]. It was first mentioned in the Horizon Report in 2012 [2]. The Horizon Report of 2013 placed LA first in the technologies to watch with a one year or less time-to-adaption horizon [3]. In the proceedings of the 1st International Conference on LA and Knowledge, Long et al. defined LA as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” [4].

Based on their literature review [5], Leitner et al. state that despite the boom in research in LA, the area is still in its infancy. On the other hand Gasevic et al, say that LA is entering the phase of maturation where it is impacting research, practice, policy, and decision making. Khalil & Ebner [6] pointed out the dimensions and also stakeholder of the whole process. The reporting part is often fulfilled by learning dashboards. Stephen Few defines a 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” [7]. Learning dashboards can therefore be seen as part of LA concerned with reporting the data, inducing reflection, and evoking understanding in a visual manner to the involved stakeholders.

Ferguson found that LA has the following four significant challenges: integrating experience from the learning sciences, working with a wider range of datasets, engaging with learner perspectives and developing a set of ethical guidelines [8]. Recently, Leitner et al. provide a literature overview of LA in higher education (HE) [5]. They concluded that the limitations in LA most referred to are time needed time to prepare data or getting the results, the size of the available dataset and examined group, and ethical reasons. Furthermore they recommend future studies to focus on stakeholder involvement (Researchers/Administrators, Learners, Teachers).

This papers focuses on the use of learning dashboards in HE. Students in HE have to evolve to independent and lifelong learners. Actionable feedback during learning that evokes critical self-reflection, helps to set learning goals, and strengthens self-regulation will be supportive in the process. Therefore, this paper presents three case studies of LA in HE and the experiences in transferring them from one HE institute than the other. The learning dashboard from the three case studies are based on two common underlying principles. First, they focus on the inherent scalability and transferability of the dashboard: both considering the underlying data, the feedback strategies employed, and the technology involved. Before the learning dashboard (software, feedback models, and actual case studies) can be transferred and released as Open Educational Resources, their scalability and transferability has to be proven. Second, the dashboard use as underlying theoretical principles: Actionable Feedback and the Social Comparison Theory. The Social Comparison Theory states that people evaluate their abilities through comparison to others when they are lacking objective means of comparison [9]. Based on a thorough literature survey Dijkstra et al concluded that students prefer upward comparison (comparing with better-performing students) with similar peers and that this leads to higher self-efficacy and often leads to better performance [10]. Such upward comparison can however decrease the self-concept, the positive effect of self-improvement outweighs the negative effects [10].

The learning dashboards from the case studies are not considered as the contribution of this paper as they have been presented elsewhere. This paper however describes the three learning dashboards using the general framework with the six critical dimensions of Learning Analytics, as proposed by Greller and Drachsler [11] (Figure 1) to enhance understanding and comparability. For each of the case study, the actual experiences of transferability obtained within a European collaboration project [12], considered as the first step toward the development of the feedback dashboards as open educational resources, are reported. The use of open education technology versus proprietary solutions is described, discussed, and translated in recommendations. We believe that the presentation of the three case studies in this paper will help to contribute to the needed “evidence” on how LA can be used in HE and provides based on the obtained experiences, recommendations on how to proceed in order to obtain open education LA Resources, freely usable in any HE institute.

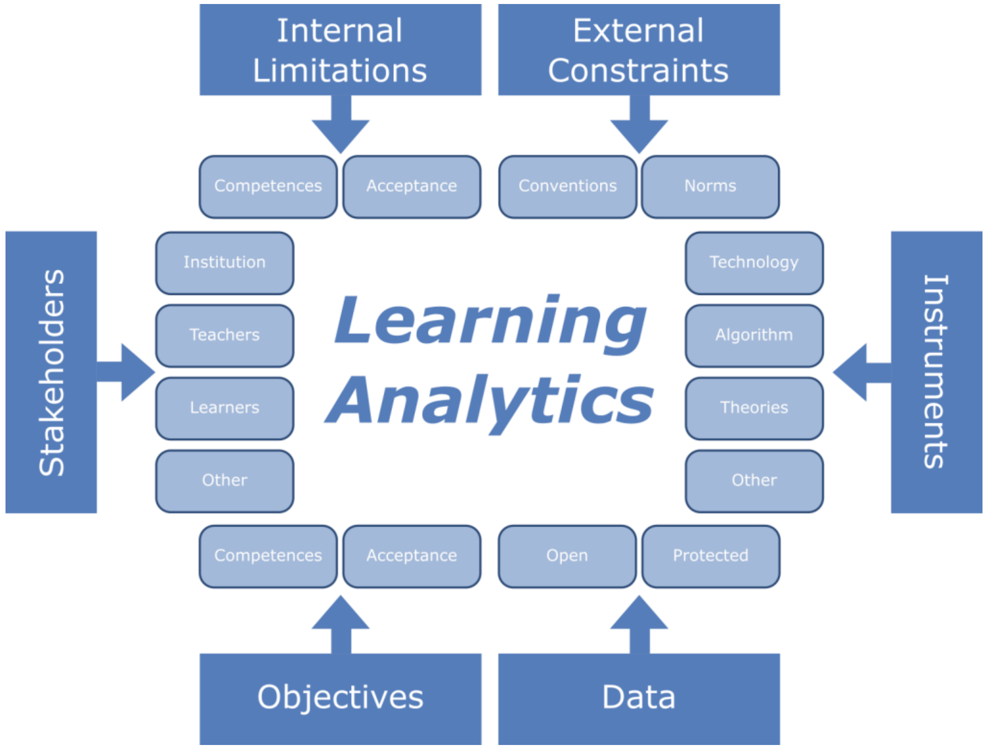

Figure 1: Six critical dimension of Learning Analytics as proposed by Greller and Drachsler [11].

Case studies

The case studies focus on actual and large-scale LA implementations and deployments in HE and range from small data in traditional HE institutes to mid-size data in online MOOCS/SPOCs. Below, each of the case studies is introduced according to the general framework for LA [11]. Next, the main implemented is discussed. Finally, the experiences in transferring the dashboard to other HE institutes is discussed.

Case study 1: Learning and studying skills

Idea of the dashboard + position within general framework

The first case study describes student-facing learning dashboards providing future and freshman students feedback regarding their learning and studying skills, based on a paper-and-pencil questionnaire (the Learning and Study Strategies Inventory [13], [14]). Figure 2 provides some screenshots of the dashboard with some additional explanation. The learning and studying skills dashboard have been described earlier by Broos et al. [15] (freshman students) and by Broos et al. [16] (future students). The shareable description of the freshman student dashboard within the framework of Greller and Drachsler [11] offered by Broos et al. [15] is generalized here, in order to include the intervention for future students is included.

The *stakeholders*, both *data clients* and *data subjects*, are freshman or future students for HE. The intervention uses two populations. Firstly, in order to compare a student to all students in the target audience (freshman in a particular bachelor program or future students interested in a particular bachelor program), the learning skills of all students in the same program are gathered. These students are both the data clients and the data subjects. Secondly, in order to show the importance of the learning and studying skills for being successful in HE, a second cohort is used as data subjects: the academic success in the next phase of similar students in previous academic years is used. For both future and freshman students the academic achievement at the end of the 1st year of earlier cohorts is gathered.

The *objective* of the dashboards is to unveil information on learning skills to future and freshman students. The dashboard combines reflection and prediction [11]. Concerning reflection, students receive feedback on their learning skills and the comparison with peers students [11]. The dashboard uses a "mild" form of prediction. Rather than communicating the "chances of success", the dashboard shows how the first-year academic success of students in previous cohorts is related to the learning and studying skills. No predictive modeling is involved. Thanks to the "small data"-approach the underlying data can be shown "as is", albeit in a summarized and evidently anonymized manner.

The *data* in the dashboard is "small" and could easily be obtained in any HE institute. Two data sources are used. First, data of learning skills, gathered using paper-and-pencil questionnaires from educational sciences [13], [14]. Second, data from the university's data warehouse regarding the academic achievement of students at the end of the first year. All this data is "non-open".

Regarding *instruments*, the interventions do not use predictive algorithms but focus on visually summarizing the available data to induce self-reflection. The intervention is based on the social comparison theory [9], [17]. The dashboard was (deliberately) implemented using widely accessible technologies, which are either immediately available in most institutions, or replaceable by similar (open-source) products. For instance, the data was brought together in a Microsoft SQL Server 2016 relational database management system (RDBMS) from heterogeneous source systems by an ETL (Extract-Transform-Load) subsystem using Integration Services (SSIS). This implementation is replaceable without loss by other RDMBS's like the open source MariaDB and PostgreSQL or commercial products like IBM DB2 or Oracle Database, depending on the IT architecture and knowledge of the institution. A thin server-side PHP 7 application integrating with the Shibboleth single sign-on environment of the university served as a data API delivering a single JSON data file for each student. Again, a replacement of PHP with other web scripting languages like Python or platforms like Node.js is possible. Most of the user interface adaptability and interactive functions were provided on the client side by a JavaScript web application. The loose coupling of front and back end implementation allowed for quick testing of several alternative representations of the dashboard and provides a hint in the direction of alternative implementations, e.g. in the format of a mobile app.

Let's consider the *internal and external limitations*. As data from two data sources is coupled, students were asked to consent for coupling this data. Moreover, a data-charter was signed with the vice-rector of student affairs. Additionally, students were informed to consent for the use of this data for research, and for providing them feedback through a personalized dashboard. The ethical soundness of the intervention was supported by the inclusion of study counselors and advisors in the development of the dashboard. The interventions were just-in-time: future students received a link to the dashboard prior to entering HE, and freshman students around the middle of the 1st semester, providing them ample time for remediation. Regarding the limitations of the students regarding interpreting LA data, the dashboard uses simple dot matrix charts, complemented with textual explanations.

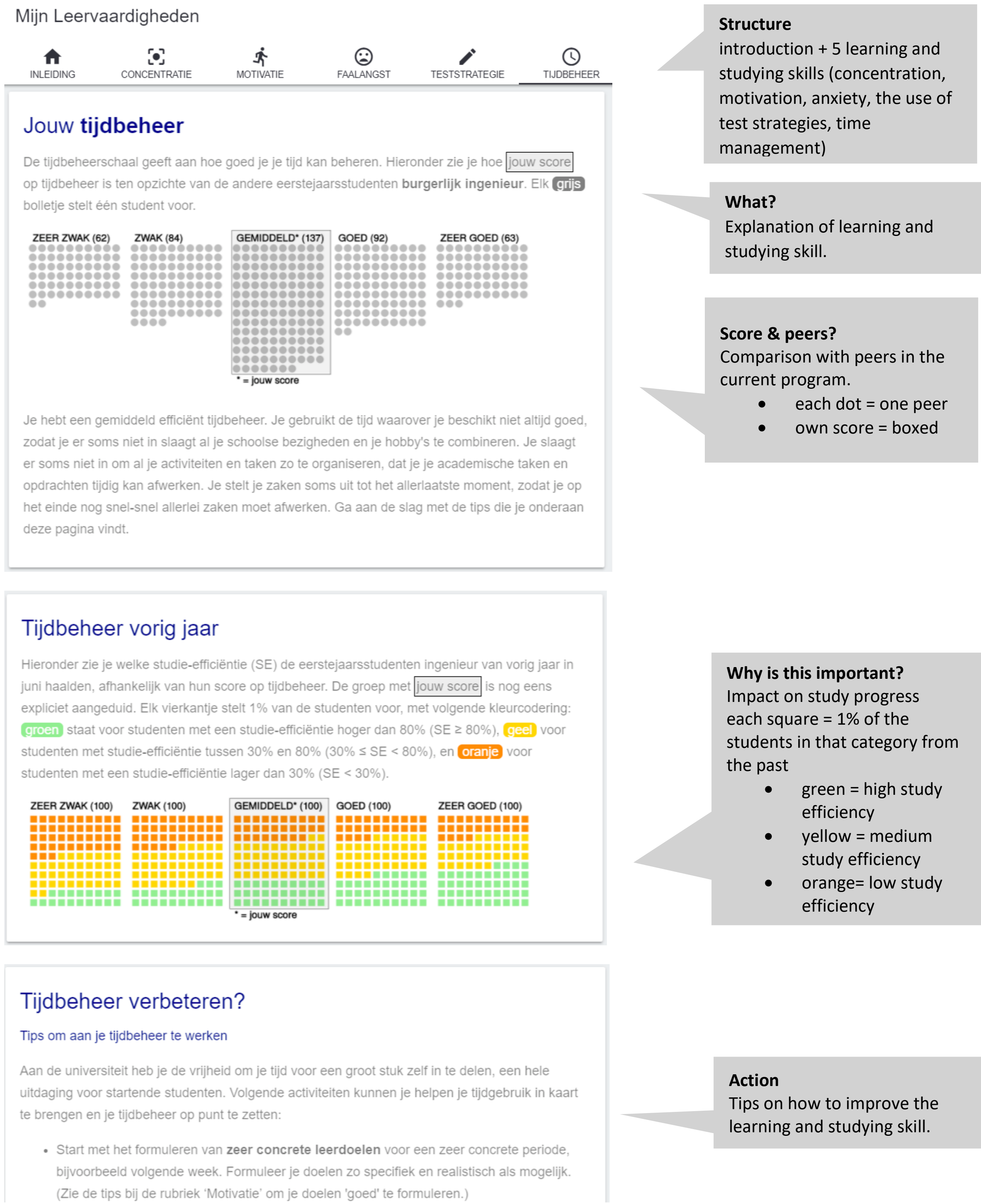

Figure 2: Screenshot of dashboard for feedback on learning and studying skills as deployed at KU Leuven (in Dutch)

Main implementation

The dashboard for *freshman students* was developed, implemented, and deployed at the University of Leuven, Belgium (KU Leuven). Broos et al. reported on the scalability and usefulness of the dashboard

[15] and the impact of the learning profile of the dashboard use [18]. Both papers were based on a deployment within 11 different STEM (Science, Technology, Engineering, Mathematics), offering the dashboard to 1406 first-year students. Meanwhile, the dashboard has been deployed to 27 programs within this university, offering feedback to 4397 first-year and bridging (students that obtained a professional bachelor that enter an academic master) program.

The dashboard for *future students* was part of the feedback dashboard after the positioning test for future engineering students [19], [20]. Broos et al. reported on the development, implementation, and evaluation using the Evaluation Framework for LA (version 4, [21]) and first-use of the dashboard in [16] for 421 students. In the meanwhile the dashboard has been used for an additional 635 students.

During the development, a lot of stakeholders were involved: practitioners (study advisors of the programs), data management of the university, researchers on first-year study success, and data visualization experts. When scaling the intervention from a pilot within 11 STEM programs to 27 programs scattered around KU Leuven, the acceptance of both students and staff showed to be very high. Student unions and program advisory committees to whom the dashboard was presented, embraced the extra opportunities for feedback. No concerns to use this data for learning dashboards have been noted. Thanks to the involvement of practitioners in the design process the ethics of the intervention was strongly guarded. As an example, the dashboard never talks about "changes of success" as study advisors stress that it creates the perception that studying is similar to a random game, while students can actually change their behavior to improve their learning. While the involvement of practitioners in the development has contributed to the acceptance and ethics of the dashboard, it also resulted in larger amount of text. Study advisors stress the importance of nuance and the textual explanation of the graphs to avoid misinterpretation. Therefore, the final student-facing dashboards somehow lose the "dashboard"[7]-feeling, which by definition, should allow an immediate overview.

Transferring to other contexts

The scaling from a pilot in 11 STEM programs to 27 university-wide programs required different adaptations. While the dashboard was already "parameterized" to automatically fill in the program-name or the contact info of the study advisor, the study advisors stressed the importance to customize the text to the specifics of their program. Therefore, a technological solution that allowed this customization, while still coupling different similar programs was offered. After this adaptation, all programs were willing to join. It was noted later however, that the study advisors merely made changes to the dashboard (only two programs from a different campus removed referral to the central services of the university, as this service was not available for students of this two campuses). Therefore, we conclude that customization is important to increase acceptance, even while the actual use is limited.

The dashboard for future students was deployed for all future students of the three Flemish universities offering the Bachelor of Engineering Science. This introduced particular challenges in data protection and sharing and the ethics. Furthermore, as these participants are not subscribed to the HE institutes and are therefore not subject to the HE's regulations. Broos et al. elaborate on particular solutions in [16].

The decision was made to set up a pilot with the dashboard at one faculty of TU Delft for the first quartile of the academic year 2017-2018, with the consideration being that a successful pilot at one faculty could lead to the dashboard then being piloted campus-wide. The chosen faculty was selected due to its previous work with LA and the intrinsic interest that was present. About 700-800 freshman students would use the dashboard in the pilot. An internal project was set up for this purpose, with ample time dedicated to get support from all required organizational levels, i.e. faculty, educational directors, IT department, board of ethics, etcetera. Organizational permissions were relatively straightforward to achieve. However, integration of the dashboard with existing university infrastructure proved more time-consuming and challenging than anticipated, leading to delays in launch of the pilot. Still, the intention is to launch the pilot in the academic year 2017-2018.

Case study 2: Academic achievement

Idea of the dashboard + position within general framework

The second case study describes student-facing learning dashboards providing future and freshman students on feedback regarding their academic performance, based on results on tests or exams. Figure 3 provides some screenshots of the dashboard with some additional explanation. The academic achievement dashboard has been described earlier by Broos et al. [22]. This previous work also offered a shareable description of the intervention but used the categories of Bodily and Verbert [23] to this end.

The *stakeholders*, both *data clients* and *data subjects*, are similar to the previous case study. The intervention uses two populations. Firstly, in order to compare a student all students in the target audience (freshman in a particular bachelor program or future students interested in a particular bachelor program), the first population consists of all students within the same program or that have been doing the same test. Secondly, in order to show the impact of the academic performance on later academic achievement, a second cohort is used for the data subjects: the academic performance in HE (for future students: study success at the end of the first year; for the freshman: number of years needed to finish the bachelor) of similar students in previous academic years is used.

The *objective* of the dashboards is to show the impact of early academic achievement to future and freshman students and to hereby induce self-reflection. As in the previous case study reflection is used rather than prediction.

The *data* in the dashboard is "small" and could easily be obtained in any HE institute. For the freshman students merely one data source is used: academic performance and throughput data from the university's data warehouse. For future students, the test results from the positioning test [19], [20] have been gathered. All this data is "non-open".

This case study uses the same *instruments and has similar internal and external limitations* as the previous case study.

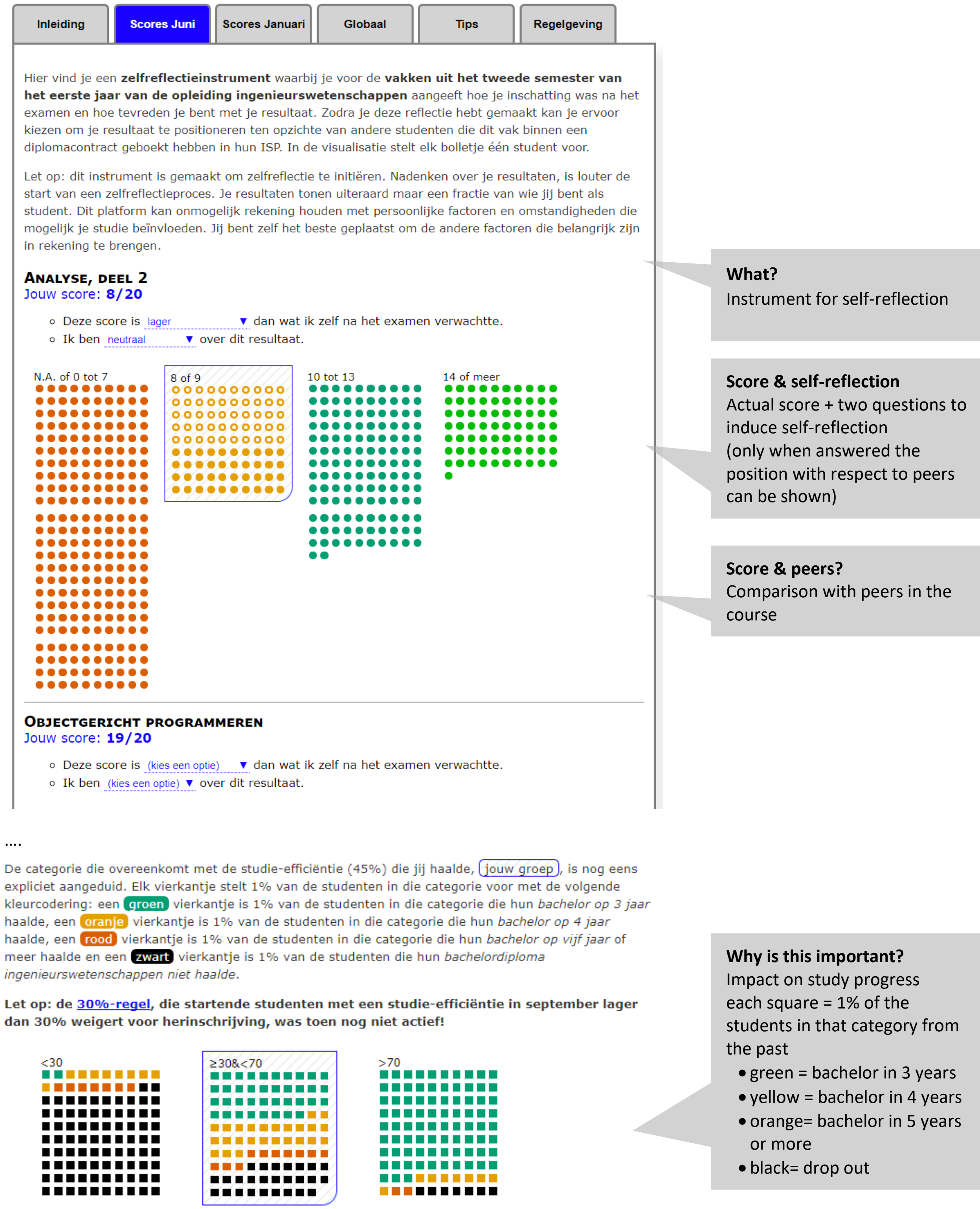

Figure 3: Screenshots of dashboard for feedback on academic achievement as deployed at KU Leuven (in Dutch)

Main implementation

The dashboard for *freshman students* was developed, implemented, and deployed at the University of Leuven, Belgium (KU Leuven). Broos et al. reported on the scalability, perceived usefulness, and adoption of the dashboard [22] based on a deployment within 11 different STEM (Science, Technology, Engineering, Mathematics), offering the dashboard to 1905 first-year students. The dashboard will be deployed to 27 programs within this university, offering feedback to more than 4500 first-year and bridging (students that obtained a professional bachelor that enter an academic master) program. The dashboard for *future students* was part of the feedback dashboard after the positioning test for future engineering students [19], [20] (see previous case study). Similar to the previous dashboard, different stakeholders were involved during development and deployment, which has resulting in high acceptance rate, but rather text-rich "dashboards".

Transferring to other contexts

Similar to the first case study, the scaling from a pilot in 11 STEM programs to 27 university-wide programs requires different adaptations, of which most prominent the ability for customization of the textual parts to accommodate for program-specific information.

Plans for piloting the second dashboard at TU Delft, were made in parallel with the first dashboard. The academic achievement dashboard would be run at the same faculty of TU Delft, with again 700-800 first year students using the dashboard in the third quartile of the academic year 2017-2018. Organizational aspects for the academic achievement dashboard were arranged and managed as part of the project for the first dashboard. Unfortunately the delays for the launch of the first dashboard impacted the launch of the second dashboard as well. Still, the intention is to launch the second dashboard in the academic year 2017-2018.

Further, a combination of the academic achievement dashboard and the LISSA dashboard [24], developed within the ABLE project [25] as open educational technology, is currently developed at TU Graz. The dashboard is placed on top of the campus management system of TU Graz, CAMPUSonline. Thereby getting rid of the major challenges concerning data privacy and data security as well as preparing for a bigger scope, so it may be distributed to all 35 universities currently working with CAMPUSonline in middle Europe.

Case study 3: MOOC/SPOC learning tracker

Idea of the dashboard + position within general framework

The third case study describes a student-facing learning dashboard providing students in online courses with feedback on their activities: the "learning tracker". Figure 4 provides a screenshot of the learning tracker with some additional explanation. The goal of the learning tracker is to "promote learners awareness of both their own SRL behavior and that of successful peers through social comparison" [26].

The learning tracker has been described earlier by Davis et al. [26], [27]. The learning trackers was deployed within different MOOCs and the impact on the student engagement and MOOC completion rate was studied. Davis et al. [26] reported that the learning tracker improves the achievement (final grade) of learners who are already highly education, but not for less educated learners. Additionally, they found that the learning tracker causes desirable changes in the learner engagement. Application of the learning tracker to a self-paced pre-university calculus MOOC, with very low overall completion rate (1.7%, [26]), did not result in a significant increase in completion rate nor engagement [26].

The *stakeholders*, both *data clients* and *data subjects*, are learners subscribed to a MOOC. The intervention uses two populations. Firstly, it tracks the behavior of all current learners. Secondly, the learning tracker uses the aggregated activity of past learners that successfully completed the MOOC.

The *objective* of the learning tracker is to unveil information on MOOC learning activity to MOOC learners. The learning tracker combines reflection and prediction [11]. Concerning reflection, students receive feedback on their own MOOC activity and the comparison to past successful peers [11]. Concerning prediction, the dashboard uses a “mild” form: the learning trackers shows the learning profile of past successful students in order to induce similar behavior for the current MOOC learners.

The *data* in the learning tracker is based on interaction of current and past learners on the MOOC platform, available from the standard edX tracking log system [26].

Regarding *instruments*, the interventions do not use predictive algorithms but focus on visually summarizing the available data to induce self-reflection. The intervention is based on the social comparison theory [9], [17]. The learning tracker is available as open source [28].

Now, we discuss *internal and external limitations*. Data gathered from edX is subject to the privacy statement [29]. Previous research has shown that the leaning tracker is mostly effective for experienced learners and that cultural context of learners impact both engagement and completion [26].

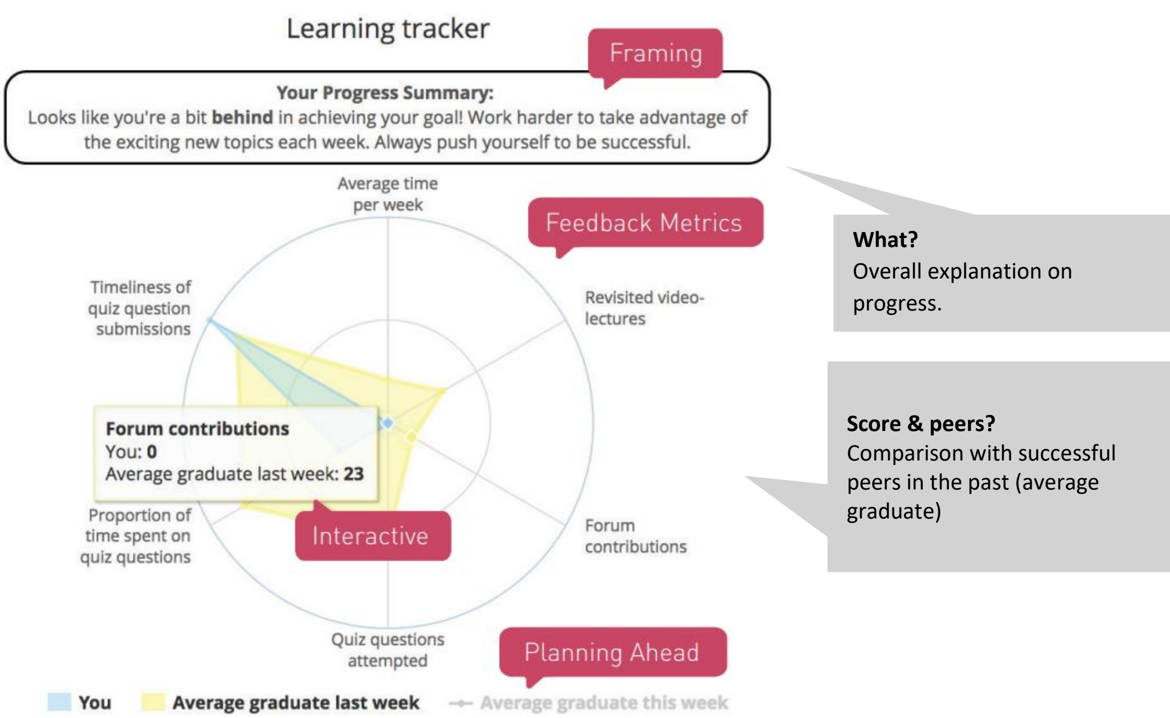

Figure 4: Annotated screenshot of the learning tracker from [26].

Main implementation, scaling, and experiences

As discussed above the learning tracker has been tested in four different MOOCs using a control and treatment group with in total 3304 active (spend more than 5 minutes on the platform) learners in the treatment group [26]. While the learning tracker has been shown to be easily transferable to other MOOCs on the same platform, the particular context of the MOOC (self-paced or not, highly education learners or not, cultural background of participants) has been shown to affect the impact of the learning tracker [26].

Transferring to other contexts

The learning trackers was proposed as an add-on for feedback for the SPOCs developed at KU Leuven by the Faculty of Science and Medicine as a preparation for the entrance exam of Medicine in Flanders, Belgium. The involved teachers and study advisors welcomed this new addition, but expressed concern on how to measure "successful completion" as "passing the entrance exam" would be the only real impact. Secondly, they doubted whether higher engagement in the SPOC would lead to higher score or pass rate in the entrance exam, as a lot of other factors impact student success. Finally, they discussed the "causality" of SPOC engagement and passing the entrance exam, as higher SPOC engagement could just indicate that the learner is more motivated and therefore inherently more likely to pass the entrance exam. Therefore, recommending the learnings to be more active in the SPOC might not be the "right" action. To couple SPOC activity to entrance exam score, students were asked to self-report their score and asked for permission to link it to their SPOC activity.

Based on the open-source technology stack developed by TU Graz [30] within the STELA project [12], the learning tracker is currently being deployed to a SPOC of KU Leuven. Obtaining the data from the MOOC provider has however shown to be challenging. It proves to be non-trivial to transfer data of a university-built course after a request from the institute. This is connected to the general LA data ownership issue [31].

Discussion and conclusion

This papers proposed three large-scale learning dashboards in HE that foster self-regulated learning and open education. The experiences of transferring each of the three dashboards to another context was presented. To conclude and provide recommendations we take a step back to the three limitations that Leitner et al. [5] defined for LA in HE: time needed time to prepare data or getting the results, the size of the available dataset and examined group, and ethical reasons.

Regarding **ethics** none of the main implementations of the three dashboards, nor their transfer to other contexts have been hindered based on ethical reasons. We believe this is due to the involvement of practitioners like study advisors, study counselors, and teachers from the initial development of the dashboards. This approach has not only proven successful for increasing acceptance but also to strengthen the ethical dimension of the interventions.

Learning dashboards using "**small data**" have proven to be a conversation starter for LA in HE [22]. The focus on easily available data such as learning dispositions and academic performance, not only fosters scalability to other institutes but also allows to offer these initial learning dashboards students and staff already in an early stage of LA development within an institute. From these dashboards students and staff can get a first experience on what LA has to offer. It allows to have a "down to earth" discussion on the position of LA at institutional level rather than adhering to a vague and often refusing mindset on what LA could be. Moreover, it allows IT staff to get acquainted with new technology and starting to build a LA technology stack at institutional level: possibly combining open educational resources or open source implementations with existing university systems.

Thanks to the above focus on “ethics” and “small data” the case studies have been reaching more than 1400 students each. We therefore recommend this approach to circumvent the typical problem with “available data and limited size of examined groups”.

The case studies have indeed confirmed that “time needed to prepare data or getting results” might limit LA deployment. On the one hand, the “small” data approach have been shown to alleviate part of this problem. On the other hand the use of data from external providers (case study 3: learning tracker in MOOCs) have been shown to be non-trivial, hereby slowing down the transfer of the learning dashboards to other context.

Each of the dashboard systems proposed in this paper was implemented deliberately using widely accessible **technologies**, which are either immediately available in most institutions, or replaceable by similar products. This complies with the goal of the STELA project architecture: the proposed architecture does not prescribe a definite stack of technologies, but rather provides a blueprint of required components, in order to optimally demonstrate the compatibility thereof with existing IT architectures. In the end, the goal is to offer IT managers a modular framework that can be used to integrate open-source modules with existing, and possibly proprietary, university systems. We believe this approach facilitates the acceptance of the LA solution by IT managers, which we identify as important but often overlooked stakeholders in any implementation of technology enhanced learning (TEL) at scale. In addition, we want to make specific parts of the solution available as modules, which should be relatively easy to integrate within other applications. For instance, the dot chart generator was implemented in different forms: as server and client side code generating DOM elements, and as a standalone on-the-fly image generator.

Finally, even within the European context the different national and institutional regulations have been shown to hinder transferability. Modular technology stacks have been proven useful in this context, as they allow, depending on the particular context, to look for a technological solutions that complies with privacy regulations. In the second case study for instance, the academic achievement dashboard was implemented on top of the campus management system, hereby avoiding data transportation outside the campus management system, which would be hard to obtain. The upcoming evolution on **privacy** (GDPR) might hinder, definitely on a short term, the deployment of LA in practice. On the other hand GDPR might, definitely on the long term, prove to be an advantage for LA at European scale as it provides a common framework and context to all member states and as learning dashboard allows to build a *useful* view on the gathered student data.

To conclude, we believe that the presentation of the three case studies in this paper will help to contribute to the needed “evidence” on how LA can be used in HE and provides based on the obtained experiences, recommendations on how to proceed in order to obtain open education LA Resources, freely usable in any HE institute.

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