RESEARCH ARTICLE

Learning dashboards at scale: early warning and overall first year experience

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ABSTRACT

In this study, we present a case study involving two self-service dashboards providing feedback on learning and study skills and on academic achievement. These dashboards were offered to first-year university students in several study programmes in Flanders, Belgium. Data for this study were collected using usage tracking (N=2875) and a survey taken at the beginning of the second year before (N=484) and after (N=538) the introduction of the dashboards. We found that early dashboard usage is related to academic achievement later in the academic year and that students' review of the feedback received in the first year improved. Although these results are modest in comparison to how high the bar is sometimes set for learning analytics applications, we argue that low-cost deployments of self-service dashboards are an interesting approach to start building experience with similar tools and to start paving the way for future developments.

KEYWORDS

Learning analytics, student dashboards, first-year experience, feedback, learning and study skills, academic achievement, case study, impact

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Introduction

Feedback plays a critical role in the transition from secondary to higher education. First-year students need to adopt to the changing environment, and need to acquire feedback literacy. Learning analytics is a relatively new development in the educational domain, enabling the provision of student-facing dashboards that may provide an answer to resource constraints standing in the way of timely, actionable feedback. However, educators and institutions still need to invest in gaining experience and building learning analytics readiness before they can take full advantage. At the same time

the field of learning analytics itself is still in full development and it is not entirely clear for practitioners what they can expect from it. In this paper, we present findings related to student-facing dashboards designed to provide feedback about learning skills and academic achievement.

The first year, engagement and feedback

The first year in higher education entails the challenging transition from one educational environment into another. At the same time, it brings a significant social displacement, possibly magnified by the students' individual background (Briggs, Clark, and Hall 2012). One of the success factors of the transition is the emphasis on support during the transition into and in the first year of higher education, especially for students with a less favourable background (Yorke and Thomas 2003), for example for first-generation students.

Students' engagement is defined as 'the quality of effort students themselves devote to educationally purposeful activities that contribute directly to desired outcomes' (Hu and Kuh 2002, p. 555) and is considered pivotal for successful learning. In an Australian study focused on the first-year experience, Krause and Coates (2008) underlined the multi-dimensionality of the engagement concept. Seven engagement scales are presented, including the Transition Engagement Scale (TES), defined as 'the extent to which first-year students engage with university life and experiences during the transition process' (Krause and Coates 2008, p. 499) and the Academic Engagement Scale (AES), defined as 'the capacity to manage one's time, study habits and strategies for success as a student' (Krause and Coates 2008, p. 500). The authors also distinguish an Online Engagement Scale (OES), recognising the importance of online tool usage in contemporary education.

One of the most important influences on learning and academic achievement is feedback. It can be conceptualised as information provision from an agent (e.g., instructor, tutor, peer, self) to the learner, following a performance (Hattie and Timperley 2007). Carless and Boud (2018) highlight the centrality of the student as an active sense-making participant in the feedback process. They define student feedback literacy as 'the understandings, capacities, and dispositions needed to make sense of information and use it to enhance work or learning strategies' (Carless and Boud 2018, p. 1316). First-year students need to move away from a more passive attitude towards feedback in secondary education, but educators should be aware of several barriers preventing optimal use of feedback (Winstone et al. 2017). Thoughtful use of learning technologies may help to improve feedback efficiency, for instance using adaptive release of grade information conditional on task completion (Hepplestone et al. 2011).

Recent advancements in learning analytics are paving the way for automated feedback personalising, overcoming some of the resource constraints inhibiting timely and frequent feedback. Pardo (2018) conceptualises a feedback model for data-rich learning experiences. The model is not limited to the single learning experiences and can be applied to several feedback scenarios, including at the level of the study programme.

Learning analytics dashboards

Learning analytics has been defined as a research area that focuses on 'collecting data traces that learners leave behind and using those traces to improve learning' (Duval and Verbert 2012). Two approaches have been elaborated that use these traces: educational

data mining techniques, that identify patterns or compute indicators (Baker and Yacef 2009), and information visualisation techniques, that present the traces in ways that help to steer the learning process (Duval and Verbert 2012). The learning analytics community typically places a key focus on leveraging human judgement (Siemens and Baker 2012). That is, the overall objective is to enable humans to make final decisions by presenting them with relevant data about learners, including potentially information of automated discovery techniques when deemed necessary, but in a visual way that enables end-users to understand data traces and the rationale of predictions.

To support human decision-making, learning analytics dashboards have been elaborated that combine educational data mining techniques with information visualisation techniques (Verbert et al. 2014). The objectives of these dashboards are manifold, and include detecting students at risk (Hu, Lo, and Shih 2014); improving engagement of students during face-to-face lectures (Barr and Gunawardena 2012; Fagen and Kamin 2012); improving balance in group work (Maldonado et al. 2012; Charleer et al. 2017); orchestrating and providing feedback in lab sessions (Rojas, García, and Kloos 2011); supporting awareness of time and resource use in blended or online learning environments (Lafford 2004; Scheu and Zinn 2007; Podgorelec and Kuhar 2011; Ali et al. 2012; Arnold and Pistilli 2012; Dollár and Steif 2012; Govaerts et al. 2012; Leony et al. 2012); supporting the dialogue between advisers and students (Charleer et al. 2018); and providing timely feedback (Corrin and de Barba 2014).

To support these objectives, different visualisation techniques have been put to use to support a variety of stakeholders. Frequently used is the traffic light metaphor proposed in Course Signals (Arnold and Pistilli 2012), where a red light was used to indicate a high likelihood of failure, a yellow light for potential problems, and a green one for a high likelihood of success. Other visualisation techniques such as bar charts, coordinated graphs to enable rich exploration, parallel coordinates, scatter plots and time lines are also commonly used (Klerkx, Verbert, and Duval 2017). In recent years, a key focus has also been placed on designing and evaluating the dashboards with the end-users (e.g. students or academic staff), so as to enable the development of dashboards that address the needs and issues of the user (Bodily et al. 2018). Although first dashboards were mostly targeted towards teachers and advisers (Verbert et al. 2014), student-facing dashboards have gained increased attention (Bodily and Verbert 2017). The objective of these dashboards is to represent data about the learning process to students, and enable them to be an actionable parttaker of the decision making process.

In this article, we present findings related to two such student-facing dashboards designed to provide feedback about learning skills and academic achievement. Early editions of these dashboards were presented by Broos et al. (2017b,c).

Educational context

The study takes place in Flanders, the Dutch-speaking northern part of Belgium. In the academic year 2017–2018, 230.860 students participated in one of the three types of higher education: 6.815 (3%) in arts education, 113.223 (49%) in professional colleges and 110.812 (48%) in universities. Of these university students 58.467 (53%) were female. The Catholic University of Leuven (KU Leuven), where this research was conducted, is the largest institution in the Flemish region, accounting for 42.528 (38%) university students (Vlaamse Overheid 2018).

Different from the Anglo-Saxon countries and some other European countries represented regularly in literature, the Belgian higher education system does not impose

a central examination at the end of secondary education, nor an entrance exam when entering higher education (Pinxten et al. 2015). Any student with a secondary school degree is allowed to register for every study programme, with only a few exceptions (medicine, dentistry, and performing arts). This openness is further enhanced by a relatively low registration fee (below 1000 euros). This contributes to a peculiar situation where first-year dropout is a byproduct of the very design of the educational system. For the STEM programmes included in this study a dropout rate of about 40% has been reported at KU Leuven. For some of these programmes, Flemish universities are collectively organising an informative, non-binding positioning test that has been shown to be a valuable diagnostic instrument (Vanderoost et al. 2015). At their own discretion, universities are imposing progress monitoring measures. At KU Leuven, students that do not achieve a 30% ‘study efficiency’ (cfr. *infra*) by the end of the (first) year are not allowed to continue within the study programme. While dropout prevention is a common purpose for learning analytics, it is not *per se* appropriate in this context. Targeted encouragement and advice may contribute to the study success of some students, but for others it may be more beneficial to stimulate the exploration of alternative (study) pathways. It may prevent students from losing an entire year of study when faster reorientation is possible.

The dashboards

During the academic years 2016–2017 and 2017–2018 two types of self-service dashboards were offered to first-year students in nine participating STEM study programmes. One dashboard, undermentioned as *LASSI* (named after the Learning and Study Strategies Inventory data it is based on) contained information and advice about students’ learning and studying skills and was offered to students in the beginning of the first semester. A second dashboard, below called *REX* (‘Results of EXaminations’), provided feedback on academic achievement and was made available after the first exam period (dashboard available from the beginning of February), the second examination period (available from the beginning of July) and a third time for students participating in the re-examinations (available from the beginning of September).

Both dashboards were designed in close cooperation with practitioners (student advisers), study success researchers, and human-computer interaction researchers. While the prevalent inclination of learning analytics in the direction of ‘big data’ may produce all sorts of interesting connections that were previously less accessible, many of those are not immediately transferable to students in a way that allows them to act upon the information. The guiding principle for the *LASSI* and *REX* dashboards was to focus on *actionable* feedback.

LASSI dashboard for learning and study skills

In the current implementation of the semester system, students receive limited feedback during the first months in higher education: typically, the first formal assessment only takes place in the middle of the academic year. This represents a break with earlier

experiences in secondary education where students generally receive more frequent (formal) feedback. First-year students make the transition from being the most ‘senior’ participants in one system to be the ‘juniors’ in the new context, leaving them with limited information to judge their learning skills (Broos et al. 2017a). According to social-comparison theory, individuals with limited information about their position turn to comparing themselves to peers to reduce uncertainty (Festinger 1954). In this study, the LASSI dashboard applied this idea to data that was already being collected within KU Leuven, but not being fed back to students. In order to assess incoming students’ learning and study strategies, several engineering study programmes already administered the Learning and Study Strategies Inventory (LASSI) (Weinstein and Palmer 2002) at the beginning of the academic year. The resulting data was being used for educational research and to guide the organisation of student support services, however students were not directly informed about their results. Also the connection of their individual results with the available support services was never made explicit before.

As a side-effect of this study, seven non-engineering STEM programmes that had not used the test before, introduced it for the first time. The complete LASSI instrument is a 77-item questionnaire that consists of ten scales: attitude, motivation/persistence, time management, anxiety, concentration, information processing, selecting main ideas, study aids, self-testing, and test strategies. However, as shown by Pinxten et al. (2017), only 4 out of 10 scales show a substantial significant relation with student achievement at the end of the first year: time-management (8 items; Cronbach $\alpha = .76$; e.g. ‘I only study when there is pressure of a test’), motivation (8 items, Cronbach $\alpha = .77$, e.g. ‘Even when study materials are dull and interesting, I manage to keep on working until I finish’), concentration (8 items; Cronbach $\alpha = .84$; e.g. ‘I find it hard to pay attention during lectures’) and test strategies (8 items, Cronbach $\alpha = .71$; e.g. ‘I memorise grammatical and technical terms without understanding them’). Therefore, both the test instrument and the resulting dashboard were reduced to these scales to avoid any unnecessary contribution to survey fatigue and to keep the resulting dashboard sufficiently compact. As the focus of the present study is on actionable feedback to students, performance anxiety (8 items, Cronbach $\alpha = .84$, e.g. ‘Even when I’m well-prepared for a test, I feel anxious’) was also included. Correlations between the five LASSI scales are shown in Table 1. All 40 items are rated on a 5-point Likert-type scale (‘Not at all typical of me’ - . . . - ‘Very much typical of me’). For each scale, sum scores were calculated and cut-off values were determined to discriminate five norm groups: ‘very weak’, ‘weak’, ‘average’, ‘good’, and ‘very good’ (Olivier, Lacante, and Briers 2015).

[Table 1 about here.]

The dashboard used a consistent, simple design. Each of the five available scales (time-management, motivation, concentration, test strategies, and failure anxiety) was shown in a different tab. On loading of the dashboard, an additional tab titled ‘introduction’ was shown to explain the intent and structure. Each of the remaining tabs followed the same structure. First the selected scale was defined. Below this, the student was attributed to one of the five norm groups. Using a unit-chart visualisation (one dot is one student) the individual result was contextualised by positioning it against other students following the same study programme (see Fig. 1). In the next pane the results of students of previous years were shown. In the visualisation, each square corresponded to one percent of these students within each of the norm groups. The

colour of the squares represented the academic achievement of these students: green for students with a high study efficiency (80% or above), red for students with a study efficiency below the regulatory 30% norm, and yellow for those in between (see Fig. 2). The purpose of this part was to convince the student of the relevance of the scale to academic achievement later in the year. Lastly, a third pane in each of the five tabs contained a list of tips, recommended actions and concrete support options for students to remediate or improve for the particular scale of the LASSI.

Findings of an earlier edition of the dashboard focused on the human-computer interaction perspective and technical background of the dashboard (Broos et al. 2017b). Based on feedback collected using an inline rating instrument, the previous study reported that students found the dashboard useful (71%, N=167 respondents) and clear (89%), with a less outspoken preference for additional information of the same type (55%). Students that were invited (N=1406) to use the dashboard and effectively did so (80.7%) had higher scores on average for each of the LASSI scales. However, it was also found that for students using the dashboard, the ones also reading the tips for specific scales had lower scores on average for the corresponding scales. The present study differs from the previous one by its focus on STEM programmes; the combination of two different dashboards presented at multiple times throughout the first academic year; the analysis of dashboard usage as an explanatory variable for academic achievement; and the use of a survey to measure the impact on the first-year experience.

[Figure 1 about here.]

[Figure 2 about here.]

REX dashboard for academic achievement

The REX dashboard provided students with feedback on their academic achievement after each examination period. Similar to the LASSI dashboard, this constituted a repurposing of data that was already available within the institution, but not being fed back to students in an insightful, actionable manner. The default transcripts that students received previously only contained their individual grades and some administrative information. Student advisers noticed that first-year students have difficulties interpreting their grades, especially after the first examination period. Flemish universities grade on a scale of 20, using absolute numbers and without bell curving. For many students grades in higher education are difficult to compare to those in secondary education. For instance, a grade of 7/10 may be considered ‘average’ in many secondary schools, while 14/20 is often seen as a ‘good’ score in university by more experienced students. As shown by the 2017–2018 edition partly depicted by Figure 3, the REX dashboard contextualised the students’ grades by positioning them relative to all other participants in the examination. To unlock this feature, students needed to answer a single question about how they felt about their score first by clicking on an emoticon. The lower part of Figure 3 shows the course level feedback before answering the question. This mechanism of using ‘micro-interactions’ to make the dashboard a bidirectional communication instrument was explained in detail by Broos et al. (2018). Consistent with the LASSI dashboard, each (peer) student was represented by a single dot. These dots were divided in four categories: students who failed the examination with a score below 8/20 (red dots), students failing with a score of 8 or 9 (conditionally tolerable, yellow dots), students succeeding the examination with a score below 14

(darker green dots), and students with a 'high' score of 14 or above (lighter green dots). The category applicable to the student was highlighted and students had the option to position themselves more fine-grained within this category only. On the next tab, students got an overview of their study progress. This tab contained study efficiency data on the programme level for the students and their peers within the same study programme. Study efficiency is defined as the percentage of credits passed relative to the number of credits registered for in a programme. A typical study year has 60 credits and the number of credits attributed to a single course is based on the expected effort required for it. Again dots were used to represent one student and students were divided in groups: below the 30% study efficiency threshold, between 30% and 80%, and 80% or more. Similar to the LASSI dashboard, a pane contained study efficiency data of students in previous years (one square for 1% of students), relating these study efficiencies to the number of years students needed on top of the regular three to complete the Bachelor's programme. Here the goal was to show students that study efficiency in the first year is indeed a relevant indicator for future academic achievement. Other tabs of the REX dashboard contained an introduction, tips to prepare for the next examination period, and information about the university regulations. In this way REX brought all relevant information that is normally spread out in several web pages and brochures together in one place.

[Figure 3 about here.]

Methodology

This section elaborates on the two data collection methods used. The first one is based on usage-tracking of the LASSI dashboard. The second method uses a survey about the first-year experience conducted in the beginning of the second year.

Dashboard usage

Dashboard usage was tracked in detail. This was motivated by the conceptualisation of feedback as an active process and the role of engagement in the first year in higher education. In the beginning of the academic year, students were asked to complete a LASSI test. This test was extended with questions about students' prior achievements in secondary education, the advice of their teachers about their study choice in higher education, and the weekly number of hours of mathematics in their previous programme. The organisation of the test differed between programs. In some cases, a paper-and-pencil edition was used in class and responses were digitised using object mark recognition (OMR) software. Others used an online edition of the test available in PC rooms. For all participating study programmes the test was included in the welcoming activities for first-year students. It was made clear to students that the test results would be used anonymously as part of a research project, but that the data would also be stored with a personal reference in order to facilitate the provision of personal feedback. Only a small number of students did not participate in the test or did participate but did not give their consent for data storage; their data was not stored. Due to fluctuations in student registration numbers in the first weeks of the academic year, the precise number of students not participating could not be determined, but it was estimated below 1%.

Upon availability of the LASSI dashboard, students were invited by e-mail to access

it online using a link in the message. When clicking through, a personalised edition of the dashboard was shown based on the logon credentials of the student. Dashboard usage was logged by the system, including the time of first access. This data was added to the data collected by the survey for further analysis. Later, when examination scores were available, they were also added to enable the analysis of the relationship between dashboard usage early on in the academic year and academic achievement months later. The resulting data set allowed extension of the analysis by Pinxten et al. (2017) that relates LASSI questionnaire outcomes, secondary school and background information with GPA, with new information about dashboard usage. In the academic year 2016–2017 an earlier edition of the LISSA dashboard (Broos et al. 2017b) was used, while an updated edition as shown by Figures 1 and 2 was used in 2017–2018. Changes were mostly cosmetic and with limited impact on the actual content or structure of the dashboard. Because the click-through event precedes the visibility of the dashboard, these changes do not distort the interpretation of dashboard usage across academic years.

Impact on overall first-year experience

To determine the impact of the dashboards offered to first-year students on the overall first-year experience, second-year students were surveyed regarding their first-year experience in the first or second week of the academic year. Data was collected from these second-year students using a paper-and-pencil questionnaire in the first weeks of two subsequent academic years 2016–2017 and 2017–2018 for ten programmes at KU Leuven (Table 2).

[Table 2 about here.]

The survey contained 41 questions (Tables 3 and ??) that asked students to evaluate their first year experience in multiple dimensions: (i) the factors that were important to be successful in the first year; (ii) if they received sufficient information regarding study efforts, academic achievement, and academic well-being, (iii) if the programme stressed the importance of different aspects of the academic life, (iv) their behaviour during the first year, (v) the usefulness and effect of the received information, and (vi) global feelings during the first year. The questions did not contain any reference to the dashboards themselves but only focused on the overall first-year experience. The questions were answered using a five-point Likert scale: not at all typical, not typical, somewhat typical, typical, and very typical.

[Table 3 about here.]

As the dashboards were deployed in the academic year 2016–2017 for the first-year students in nine of the ten programmes, the second-year students surveyed in 2016–2017 did not receive any dashboards in their first year (academic year 2015–2016). The second-year students of the nine intervention programmes surveyed in 2017–2018 did receive the dashboards in their first year (academic year 2016–2017). The differences between the survey responses of the second-year students of 2016–2017 (did not receive dashboards) and 2017–2018 (did receive dashboards) therefore allow to assess the impact of the dashboards on the overall perception of the first-year experience. A randomised controlled trial to account for contextual factors that may have influenced student responses, with some students within the same study programme receiving access to the dashboards and others not, was found to be ethically unacceptable. As the

expected impact of the dashboards was positive based on literature (more feedback), it was decided that all students of the same programme should be able to use the dashboards. The dashboards were not deployed in Engineering Technology, such that this programme serves as a baseline to correct for year-by-year differences that might occur. The difference between the two academic years (pre- and post- intervention) are studied using a Kruskal-Wallis rank sum test. A p-value of 0.01 is used as the threshold for significance.

Results

This section describes the results of two data analysis perspectives. First, the relevance of the usage of the early available LASSI dashboard with regard to explaining academic achievement later in the year is studied. Secondly, the results of the first-year experience survey administered in the second year before and after the introduction of the dashboards will be presented.

Dashboard usage

Data was collected for 3479 students in nine STEM study programmes. For 2693 students data was complete. The missingness of the weighted average score can be explained by students dropping out early without participating in any examination. These students do not have a weighted average grade. As a consequence, these missing values will be replaced with 0. After this adaptation, a non-parametric test (Jamshidian and Jalal 2010) for missing completely at random (MCAR) is conducted. The null hypothesis of MCAR is not rejected by this test ($p=0.293$). Hence, a complete case analysis is valid and will be conducted with $N=2875$ usable observations.

A multivariate regression model is fitted to predict the weighted average score (*wavg*) of students. First, the full model is investigated. Next, backward variable selection is applied to reduce the number of variables. The full model is the following:

$$wavg = \beta_0 + \beta_1 * dbuser + \beta_2 * schooltype + \beta_3 * math.hrs + \beta_4 * math.score + \beta_5 * physics + \beta_6 * chemistry + \beta_7 * pioneer + \beta_8 * mot + \beta_9 * tmt + \beta_{10} * anx + \beta_{11} * tst + \beta_{12} * con + \beta_{13} * advice.$$

In this model *wavg* is the final weighted average grade on 20 of the students in September; *dbuser* is a binary variable indicating if a student used the LASSI dashboard or not; *math.hrs* is a categorical variable that represents the weekly number of hours of mathematics courses the student had in the last two years of secondary education (8 hours, 6-7 hours, or less). *math.score*, *physics* and *chemistry* denote the final scores in secondary education for the corresponding courses (over 90%, 80-90%, 70-80%, 60-79%, or less); *pioneer* represents if students are the first in their family to enroll in higher education (yes, no, unknown); *mot*, *tmt*, *anx*, *tst*, *con* are the raw LASSI test scores (labeled as in table 1); *advice* is categorical and represents the advice of the teacher board in secondary education about the study choice of the student in higher education (fully positive, partly positive, negative, unknown/other).

The F-statistic indicates that there exists a relationship between the predictors and the response; the null hypothesis that all coefficients are jointly equal to 0 is rejected ($p < 0.0001$). In addition, dashboard usage has a significant impact on *wavg* in the full model ($p < 0.0001$). The interpretation of the coefficient is that using the dashboard

results in an increase of the expected wavg of 1.292, given that the other covariates stay fixed. The model has an R^2 of 0.296, which means that the model can explain 30% of the variation of wavg.

To test if the model with the dashboard variable has a higher likelihood than the model without the dashboard variable, a likelihood ratio test is applied. The test statistic is the following:

$$-2(\ell^{(0)}(\beta|\mathbf{X}) - \ell^{(1)}(\beta|\mathbf{X})) \sim \chi^2(1).$$

The χ^2 statistic has a value of 44.140 and corresponds to a p-value of < 0.001 . Hence, the null hypothesis of no difference between likelihoods of both models is rejected; the inclusion of dashboard use results in a significant increase in likelihood in the full model.

Next, stepwise variable selection is applied to reduce the number of variables in order to have a more parsimonious model. Backward variable selection based on the F-test is made with $\alpha=0.10$ as threshold. The final reduced model is the following:

$$\text{wavg} = \beta_0 + \beta_1 * \text{dbuser} + \beta_2 * \text{schooltype} + \beta_3 * \text{math.hrs} + \beta_4 * \text{math.score} + \beta_5 * \text{physics} + \beta_6 * \text{chemistry} + \beta_7 * \text{pioneer} + \beta_8 * \text{mot} + \beta_9 * \text{tmt} + \beta_{10} * \text{anx} + \beta_{11} * \text{con} + \beta_{12} * \text{advice}.$$

The R^2 of the final model is equal to 0.296. The coefficients, standard errors and p-values of the model are shown in Table 4. As shown in Table 4, dashboard use has a significant impact on wavg in this model. Given that all the other variables stay fixed, using the dashboard results in 1.329 units increase in the expected value of wavg. In addition, a likelihood ratio test is applied to compare the final model with and without dashboard use as a predictor. The test statistic has a value of 47.091 ($p < 0.0001$). Hence, dashboard use significantly increases the likelihood of the final model.

[Table 4 about here.]

With the same data, predictions can be made about whether the student is at risk. A student at risk is defined as a student with a weighted average score in September lower than 8.5. In order to have an unbiased estimate of the predictive accuracy for new cases, a hold-out test set is randomly selected. More specifically, 60% of cases ($n=1953$) are used for training and 40% of the cases ($n=1306$) are solely used for evaluating the model.

A logistic regression model is fitted to predict whether the student is at risk. First the full model will be fitted and afterwards backward variable selection is conducted. The full model is the following:

$$\text{logit}(p) = \beta_0 + \beta_1 * \text{dbuser} + \beta_2 * \text{schooltype} + \beta_3 * \text{math.hrs} + \beta_4 * \text{math.score} + \beta_5 * \text{physics} + \beta_6 * \text{chemistry} + \beta_7 * \text{pioneer} + \beta_8 * \text{mot} + \beta_9 * \text{tmt} + \beta_{10} * \text{anx} + \beta_{11} * \text{tst} + \beta_{12} * \text{con} + \beta_{13} * \text{advice}.$$

Next, backward variable selection is applied in order to reduce the number of covariates. Backward selection is applied with the χ^2 statistic and an α equal to 0.10. The reduced model is the following:

$$\text{logit}(p) = \beta_0 + \beta_1 * \text{dbuser} + \beta_2 * \text{schooltype} + \beta_3 * \text{math.hrs} + \beta_4 * \text{math.score} + \beta_5 * \text{chemistry} + \beta_6 * \text{pioneer} + \beta_7 * \text{tmt} + \beta_8 * \text{advice}.$$

The model has a Nagelkerke pseudo R^2 of 0.245. In addition, the Hosmer-Lemeshow statistic indicates the model fits the data well ($g=50$, $p=0.286$). The coefficients, standard errors, and p-values are shown in Table 5. The table indicates that dashboard use significantly reduces the odds of being at risk. The odds of being at risk for a student that used the dashboard is multiplied with $e^{-0.621}$. Hence, given that all other covariates stay fixed, using a dashboard results in a decrease in odds with a factor of 0.537. To assess the impact of dashboard use on the likelihood, a likelihoodratio test is applied to the reduced model with and without dashboard use. The test indicates dashboard use results in a significant increase in likelihood ($\chi^2 = 15.984, p < 0.001$)

[Table 5 about here.]

Next, the predictive accuracy is assessed on the hold-out test set. A confusion matrix is created for both the reduced model with and without dashboard use. The confusion matrix of the model with dashboard use is shown in Table 6, the confusion matrix of the model without dashboard use in Table 7.

[Table 6 about here.]

[Table 7 about here.]

The model without dashboard use contains 16 more false negatives. Whether the difference is also statistically significant is assessed with the McNemar's X^2 test. The null hypothesis of marginal homogeneity means that both models have the same accuracy. The test statistic is the following:

$$\chi^2 = \frac{(b - c)^2}{b + c} \sim \chi^2_{df=1},$$

where b equals the number of times where model 1 was right and model 2 wrong and c the number of observations where model 2 is wrong and model 1 right. Let model 1 denote the model with dashboard use, and model 2 the model without dashboard use. In this case b is equal to 39 and c is equal to 23. The difference in accuracy is statistically significant ($\chi^2 = 4.129, p=0.042$). Hence, the null hypothesis of equal predictive accuracy of both models is rejected.

Impact on overall first year experience: survey

Tables 8 and 9 present the results of the questionnaires for the nine intervention programmes. For the non-intervention programme, no significant differences were found between the two subsequent years, which indicates that other global factors, beside the deployment of the dashboards, did not cause differences in the perception of the first-year experience (Tables 10 and 11).

In the intervention group, significant differences ($p < 0.01$) are observed for the following six of the 41 questions :

- (1) During the first year I received sufficient information to compare my study efforts with the study efforts of my peers.
- (2) During the first year I received sufficient information to compare my academic achievement with the academic achievement of my peers.

- (3) During the first year I received sufficient information to compare my academic achievement with the expectations of the programme regarding my academic achievement.
- (4) During the first year I received sufficient information regarding my academic achievement (results on tests, examinations, etc.)
- (5) The information I received during the first year helped me to position myself with respect to peer students.
- (6) In general I was satisfied with the information I received during the first year.

[Table 8 about here.]

[Table 9 about here.]

From the list above, questions, three and four concern the information received regarding academic achievement. This academic achievement is the subject of the REX dashboard. The fifth question addresses social comparison, which is underlying both the LASSI and the REX dashboard.

The significant difference observed on the first question from the list above is somehow surprising as neither the LASSI and the REX dashboard are directly targeting study efforts. However, the learning and studying skills of the LASSI dashboard and the academic achievement of the REX dashboard are related to study efforts, which provides a possible explanation for the observed difference. Finally, the sixth question of the list above shows that students were, after the deployment of the LASSI and REX dashboards, more satisfied with the information they received during the first year. So, from the observed significant differences above, we can conclude that the deployment of dashboards, although limited in scope, still impacts the perception of the overall first-year experience. This impact is however mainly limited to the dimensions directly targeted by the dashboards. Students report they were more satisfied with the information received, but no significant difference in beliefs in what is important to be successful, deeper reflection, or self-reported behavioural change are observed.

[Table 10 about here.]

[Table 11 about here.]

Discussion and conclusion

Previous studies have shown the critical role of feedback in education (Hattie and Timperley 2007), and support in the first year (Yorke and Thomas 2003; Briggs, Clark, and Hall 2012), but also introduced the concept of feedback literacy (Carless and Boud 2018). Learning analytics provides opportunities for a new feedback model (Pardo 2018), and student-facing dashboards have recently gained attention (Bodily and Verbert 2017). However few studies have analysed dashboard usage by first-year students in higher education at scale.

In this study two student-facing dashboards were offered in the first year of nine STEM programs. The LASSI dashboard provided feedback on the learning and study skills of students and the REX dashboard on academic achievement. Student dashboard usage early in the academic year was recorded and it was found to contribute significantly as an explanatory variable for academic achievement later on in the year. On average, dashboard usage resulted in a non-negligible 6.4 percentage points increase in end scores. But it would be imprudent to conclude that the increased achievement is caused by the impact of dashboard usage. Rather we expect that dashboard usage signals a disposition of students linked to their engagement, feedback literacy, and/or conscientiousness. Additional research is required to further explore how dashboard usage relates to these concepts, for instance by investigating the relationship with the engagement scales presented by Krause and Coates (2008). A practical implication of the result of our analysis is that dashboard usage may qualify as an early warning signal by itself. This would be especially interesting given the limited resources required to collect this type of data and the scarcity of available indicators early on in the first academic year. Student advisers could use this information to flag students they should reach out to. Although the present study did not present a predictive model, student-facing dashboard usage may be explored as a means to complement early warning systems with data that is available early in the first year.

A survey for second-year students looking back on the first-year experience was conducted before and after introduction of the dashboard. Significantly improved perceptions were found for items related to information about academic achievement, study efforts, and enabling social comparison. The availability of the self-service dashboards improved the satisfaction of students with the information received in the first year. However, changed beliefs of what constitutes successful study, deeper reflection, or behavioural change could not be demonstrated as a result of introducing the self-service dashboards LASSI and REX. A natural progression of this work is to analyse the effect of a more continuous deployment of self-service dashboards throughout the academic year, instead of the three or four moments explored here.

One could question the added value or *impact* of the self-service dashboards presented in this study: early dashboard usage is related to academic achievement, but an accurate predictive model could not be constructed, and second-year students are more satisfied looking back on first-year feedback, but did not change their behaviour or beliefs. We would argue that this ignores the relatively limited cost of these interventions. Data that was already available in the institution, or required only limited effort to collect, was used as an opportunity to provide targeted feedback to students, bringing relevant but otherwise fragmented information together. In our opinion, the bar for learning analytics should not be set too high and inflated expectations for applications with a relatively low cost in comparison to other interventions in education should be avoided. It has been argued that feedback literacy needs to be acquired over time and we expect self-service dashboards like the ones presented here to contribute to

this learning process. This may apply equally to data literacy of educators or learning analytics maturity at the institutional level. Notwithstanding the growing concern for impact in learning analytics or recent calls to strengthen its theoretical foundation (e.g. Jivet et al. 2018), we would encourage institutions to launch simple, scalable interventions similar to the ones in this study, to gain experience and learn from the data they produce. It would be a false assumption that feedback is a fully explored terrain already and that the existing body of work applies unaltered to technology-enhanced feedback methods. As such, new questions need to emerge and will contribute to a better understanding of how students deal with automated feedback and how such feedback can be improved. Rapid low-cost, low-risk pilot tests are an increasingly important instrument for contemporary research. Based on the data collected from them further iterations can be adjusted and expectations can be refined. ‘Starting small soon’ creates the necessary stakeholder buy-in and support for larger developments later on (Shneiderman 2016, Chapter 9).

From the practice perspective, carrying out this study in our own institution has resulted in several unanticipated by-products. It has fueled conversations between study advising services of the different faculties involved, and provided a platform for the exchange of good practices. The study has tightened the collaboration between researchers and several central services of the university, as well as encouraged dialogue between scientific disciplines. An implication of this is the possibility that the impact of modest approaches to learning analytics should not immediately be expected in terms of changing student behaviour or improving achievement, but rather in their contribution as a smaller piece in a more complex educational system.

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	tmt	mot	con	tst
(tmt) time management	—			
(mot) motivation	.63**	—		
(con) concentration	.55**	.51**		
(tst) test strategies	.30**	.28**	.48**	—
(anx) performance anxiety	-.01	-.08**	.26**	.46**

Table 1. Bivariate correlations between the five retrieved LASSI scales (N=1509).

	Programme	Pre (2016-2017)	Post (2017-2018)
Intervention	Biochemistry and Biotechnology	33	33
	Biology	37	45
	Chemistry	29	25
	Physics	23	48
	Geography	18	20
	Geology	11	13
	Informatics	43	56
	Engineering Science	267	274
	Mathematics	23	24
	Total	484	538
No inter- vention	Engineering Technology	102	103
	Total	102	103

Table 2. Programmes with pre- and post-intervention surveys and responses per programmes. In the first nine programmes dashboard were deployed in the academic year 2016-2017. In the engineering technology programme, no dashboards were deployed such that it acts as a “baseline” measurement.

Table 3. Questions of the questionnaire offered to second-year students to reflect on their first-year experience.

Question	Abbreviation
To be successful in the first year, it was important to	reasonSuccess
... use good study techniques.	_1
... study hard.	_2
... attend classes.	_3
... prepare classes.	_4
... meticulously follow student email.	_5
... regularly check the virtual learning environment for new messages and content.	_6
... feel well in the programme (academic well-being).	_7
During the first year I received sufficient information to compare	compare_
... my study efforts with the study efforts of my peers.	_Effort1
... my study efforts with the expectations of the programme regarding my study efforts.	_Effort2
... my academic achievement with the academic achievement of my peers.	_Achieve1
... my academic achievement with the expectations of the programme regarding my academic achievement"	_Achieve2
... my academic well-being with the academic well-being of my peers.	_Wellbe1
... my academic well-being with the expectations of the programme regarding my academic well-being.	_Wellbe2
During the first year, the study programme stressed the importance of	emphasis_
... using good study techniques.	_1
... studying hard.	_2
... attending classes.	_3
... meticulously following student email.	_4
... regularly checking the virtual learning environment for new messages and content.	_5
... feeling well in my studies (academic well-being).	_6
During the first year, I	actionY1_
... optimized my study techniques.	_1
... studied hard.	_2
... attended almost all classes.	_3
... prepared classes well.	_4
... meticulously followed my student email.	_5
... regularly checked the virtual learning environment for new messages and content.	_6
During the first year I received sufficient information regarding my	sufficientInfo_
... study efforts (time studied, study material, study techniques, etc.)	_1
... academic achievement (results on tests, examinations, etc.)	_2
... academic well-being (how I feel in the programme)	_3
The information I received during the first year	receivedInfo_
... was useful	_1
... made me reflect on my studies	_2
... made me adapt my study behaviour (study effort, study techniques, etc.)	_3
... helped me to position myself with respect to peer students	_4
... made clear what was expected from me	_5
... showed the possible impact of my activities and achievements on my future study pathway	_6
... helped me to make study-related decisions	_7
In general I was satisfied with the	satisfaction_
... information I received during the first year	_1
... support I received during the first year	_2
During the first year I felt	experienceY1_
... lost	_1
... unsure about my study efforts	_2
... unsure about my academic achievements	_3
During the first year I used the supporting services	_4

	Dependent variable:
	wavg
dbuser	1.329*** (0.194)
schooltypeBSO	-4.833 (3.425)
schooltypeKSO	-4.461** (1.959)
schooltypeOther	-1.206*** (0.327)
schooltypeTSO	-0.925*** (0.178)
math.hrs6-7u	2.231*** (0.216)
math.hrs8u	2.720*** (0.231)
math.score>90%	1.966*** (0.390)
math.score60-70%	0.691*** (0.214)
math.score70-80%	1.543*** (0.225)
math.score80-90%	2.092*** (0.262)
fys>90%	1.435*** (0.370)
fys60-70%	0.437* (0.232)
fys70-80%	0.890*** (0.240)
fys80-90%	0.928*** (0.273)
chem>90%	2.088*** (0.374)
chem60-70%	0.587*** (0.218)
chem70-80%	0.680*** (0.228)
chem80-90%	1.204*** (0.264)
mot	0.038* (0.020)
tmt	0.085*** (0.017)
anx	0.025* (0.013)
tst	-0.035* (0.020)
adviceNeg	-0.923*** (0.213)
adviceFullpos	0.519*** (0.162)
adviceOther	-0.500** (0.204)
Pionieer	-1.353*** (0.202)
PionieerUnknown	-1.183*** (0.408)
Constant	1.260* (0.684)
Observations	3,150
R ²	0.296
Adjusted R ²	0.290
Residual Std. Error	3.378 (df = 3121)
F Statistic	46.825*** (df = 28; 3121)

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 4. Estimates, standard errors and p-values of the parameters of the linear regression model.

	<i>Dependent variable:</i>
	atrisk
dbuser	−0.621*** (0.155)
schooltypeBSO	12.304 (535.411)
schooltypeKSO	15.323 (349.190)
schooltypeOther	0.722** (0.280)
schooltypeTSO	0.445*** (0.152)
math.hrs6-7u	−0.918*** (0.174)
math.hrs8u	−1.440*** (0.194)
math.score>90%	−1.114*** (0.408)
math.score60-70%	−0.559*** (0.177)
math.score70-80%	−0.956*** (0.188)
math.score80-90%	−1.402*** (0.238)
chem>90%	−1.004** (0.410)
chem60-70%	0.115 (0.180)
chem70-80%	−0.010 (0.182)
chem80-90%	−0.457** (0.226)
tmt	−0.062*** (0.013)
adviceNeg	0.682*** (0.177)
adviceFullpos	−0.444*** (0.144)
adviceOther	0.447*** (0.169)
Pionieer	0.429** (0.182)
PioneerUnknown	0.647* (0.333)
Constant	2.897*** (0.408)
Observations	1,953
Log Likelihood	−991.519
Akaike Inf. Crit.	2,027.039

Note:

*p<0.1; **p<0.05; ***p<0.01

Table 5. Estimates, standard errors and p-values of the parameters of the logistic regression model.

	Predicted 0	Predicted 1	Total
Actual 0	800	111	911
Actual 1	236	159	395
Total	1,036	270	1,306

Table 6. *Confusion matrix of the model with dashboard use*

	Predicted 0	Predicted 1	Total
Actual 0	784	127	911
Actual 1	236	159	395
Total	1,020	286	1,306

Table 7. *Confusion matrix of the model without dashboard use*

	2016-2017		2017-2018		comparison		
	answers	mean	answers	mean	Δ mean	p	kruskal significance
reasonSuccess1	{0,8,82,243,148}	3.77	{1,11,77,270,176}	3.78	0,01	0.3624	
reasonSuccess2	{1,18,144,236,84}	3.60	{3,27,156,259,92}	3.57	-0,03	0.6673	
reasonSuccess3	{16,61,155,177,74}	3.43	{15,60,195,187,79}	3.49	0,06	0.7817	
reasonSuccess4	{39,137,202,85,20}	3.06	{45,160,228,81,24}	3.05	-0,01	0.4612	
reasonSuccess5	{40,153,184,88,17}	2.97	{42,144,218,114,19}	3.05	0,08	0.101	
reasonSuccess6	{8,61,188,185,42}	3.4	{12,72,195,212,47}	3.36	-0,04	0.9525	
reasonSuccess7	{3,7,76,245,153}	3.76	{1,9,75,282,171}	3.75	-0,01	0.6503	
compareEffort1	{17,147,188,120,12}	3.06	{15,103,239,160,18}	3.27	0,21	0.0002616	**
compareEffort2	{7,60,208,198,11}	3.32	{10,65,236,213,14}	3.33	0,01	0.8111	
compareAchieve1	{22,120,176,145,21}	3.11	{4,35,156,265,78}	3.50	0,39	<2e-16	***
compareAchieve2	{7,74,223,167,13}	3.33	{3,56,236,221,22}	3.41	0,08	0.001453	*
compareWellbe1	{25,141,201,106,7}	3.05	{26,156,232,117,6}	3.07	0,02	0.9692	
compareWellbe2	{30,123,225,95,5}	3.11	{23,150,262,98,4}	3.14	0,03	0.7975	
emphasis1	{10,55,174,200,44}	3.39	{5,62,173,241,55}	3.39	0	0.1544	
emphasis2	{2,20,136,252,74}	3.54	{5,24,163,280,65}	3.48	-0,06	0.1346	
emphasis3	{6,51,150,217,59}	3.42	{5,54,200,225,53}	3.45	0,03	0.1365	
emphasis4	{17,124,183,128,31}	3.18	{24,113,215,151,33}	3.22	0,04	0.4088	
emphasis5	{6,62,176,191,47}	3.41	{11,64,201,224,36}	3.35	-0,06	0.5141	
emphasis6	{49,156,187,78,12}	2.91	{44,177,200,99,16}	2.94	0,03	0.3269	
actionY1_1	{10,54,145,212,62}	3.4	{11,56,171,226,72}	3.44	0,04	0.9564	
actionY1_2	{9,61,158,179,77}	3.48	{9,73,155,227,72}	3.39	-0,09	0.9187	
actionY1_3	{24,62,76,139,183}	3.69	{35,72,75,160,195}	3.6	-0,09	0.5498	
actionY1_4	{65,195,163,53,8}	2.70	{87,205,169,64,10}	2.64	-0,06	0.6453	
actionY1_5	{22,81,134,168,79}	3.35	{19,78,134,216,90}	3.37	0,02	0.1082	
actionY1_6	{10,56,126,195,97}	3.5	{12,57,127,232,109}	3.49	-0,01	0.4618	

Table 8. Survey responses (part 1) for the intervention group. The answers to the questions are shown using a notation with curly brackets that contain in this order the number of students that indicated the answer 'not at all typical', 'not typical', 'somewhat typical', 'typical', and 'very typical'. The mean is calculated by converting 'not at all typical' to '1', 'not typical' to '2', 'somewhat typical' to '3', 'typical' to '4', and 'very typical' to '5'. The indicated p-value is the result of a Kruskal-Wallis rank sum test between the answers on the two subsequent years. The last column indicates the level of significance uses the following coding: * $p < 0.01$; ** $p < 0.001$; *** $p < 0.0001$.

	2016-2017		2017-2018		Comparison		
	Answers	Mean	Answers	Mean	Δ Mean	p Kruskal	Significance
sufficientInfo1	{7,80,217,162,14}	3.31	{5,83,264,170,13}	3.37	0,06	0.7682	
sufficientInfo2	{3,38,157,247,37}	3.39	{2,18,137,308,70}	3.48	0,09	4.652e-06	***
sufficientInfo3	{35,152,192,91,12}	2.99	{26,165,241,90,13}	3.09	0,1	0.581	
receivedInfo1	{0,21,193,238,32}	3.49	{1,22,167,307,38}	3.41	-0,08	0.01335	
receivedInfo2	{13,100,184,165,22}	3.21	{6,106,234,166,24}	3.31	0,1	0.8787	
receivedInfo3	{13,118,198,126,27}	3.22	{23,136,201,149,27}	3.14	-0,08	0.662	
receivedInfo4	{21,163,207,81,12}	3.05	{14,108,206,182,26}	3.23	0,18	1.082e-12	***
receivedInfo5	{6,40,196,218,22}	3.39	{4,41,226,244,21}	3.41	0,02	0.9965	
receivedInfo6	{10,55,187,187,44}	3.41	{8,66,206,214,40}	3.38	-0,03	0.7464	
receivedInfo7	{3,75,210,180,15}	3.33	{9,82,210,209,25}	3.30	-0,03	0.4296	
satisfaction1	{2,34,175,239,34}	3.42	{3,18,168,303,41}	3.42	0	0.006789	*
satisfaction2	{5,22,138,253,64}	3.49	{4,24,150,283,70}	3.49	0	0.8467	
experienceY1_1	{117,235,88,31,12}	2.26	{132,245,99,42,16}	2.29	0,03	0.618	
experienceY1_2	{30,140,152,135,27}	3.01	{32,155,196,117,34}	3.08	0,07	0.4409	
experienceY1_3	{27,124,163,138,32}	3.10	{40,151,176,127,39}	3.04	-0,06	0.1098	
experienceY1_4	{62,72,151,144,54}	3.13	{52,93,160,158,70}	3.19	0,06	0.3943	

Table 9. Survey responses (part 2) for the intervention group. The answers to the questions are shown using a notation with curly brackets that contain in this order the number of students that indicated the answer 'not at all typical', 'not typical', 'somewhat typical', 'typical', and 'very typical'. The mean is calculated by converting 'not at all typical' to '1', 'not typical' to '2', 'somewhat typical' to '3', 'typical' to '4', and 'very typical' to '5'. The indicated p-value is the result of a Kruskal-Wallis rank sum test between the answers on the two subsequent years. The last column indicates the level of significance uses the following coding: * $p < 0.01$; ** $p < 0.001$; *** $p < 0.0001$.

	2016-2017		2017-2018		Comparison		
	Answers	Mean	Answers	Mean	Δ Mean	p	Kruskal
reasonSuccess1	{1,4,20,56,21}	3.55	{0,4,14,62,31}	3.65	0.1		0.09127
reasonSuccess2	{0,8,25,56,12}	3.41	{0,7,33,57,16}	3.51	0.1		0.9903
reasonSuccess3	{1,4,22,45,30}	3.75	{2,6,29,60,16}	3.45	-0.3		0.02979
reasonSuccess4	{20,42,30,9,1}	2.51	{22,41,39,8,2}	2.63	0.12		0.6972
reasonSuccess5	{21,34,33,12,2}	2.62	{13,37,43,17,3}	2.88	0.26		0.08286
reasonSuccess6	{7,14,33,36,11}	3.27	{2,11,35,50,15}	3.44	0.17		0.06231
reasonSuccess7	{0,2,22,51,27}	3.73	{2,2,24,69,16}	3.44	-0.29		0.1316
compareEffort1	{4,17,52,29,0}	3.26	{7,25,54,27,0}	3.13	-0.13		0.2031
compareEffort2	{1,15,47,37,2}	3.33	{2,12,60,35,4}	3.46	0.13		0.9359
compareAchieve1	{2,26,48,24,2}	3.22	{10,33,49,20,1}	2.98	-0.24		0.04677
compareAchieve2	{2,12,54,34,0}	3.37	{3,20,58,30,2}	3.32	-0.05		0.2591
compareWellbe1	{4,17,57,22,1}	3.34	{10,22,56,25,0}	3.12	-0.22		0.3161
compareWellbe2	{3,19,61,18,0}	3.36	{8,16,63,24,1}	3.29	-0.07		0.6658
emphasis1	{0,18,38,40,5}	3.30	{1,19,32,53,6}	3.21	-0.09		0.3769
emphasis2	{0,3,30,58,10}	3.47	{1,4,21,69,16}	3.42	-0.05		0.1299
emphasis3	{0,14,25,49,12}	3.35	{3,15,42,48,3}	3.24	-0.11		0.01515
emphasis4	{11,32,32,20,6}	2.90	{6,31,39,29,6}	3.07	0.17		0.149
emphasis5	{6,9,30,46,10}	3.29	{3,12,35,47,11}	3.36	0.07		0.9669
emphasis6	{7,35,42,17,0}	2.93	{10,39,41,21,0}	2.84	-0.09		0.8317
actionY1_1	{4,14,28,45,10}	3.26	{2,19,30,42,20}	3.42	0.16		0.5405
actionY1_2	{3,12,40,41,5}	3.32	{1,19,35,40,18}	3.44	0.12		0.2588
actionY1_3	{6,8,13,33,41}	3.74	{2,11,16,40,44}	3.79	0.05		0.9636
actionY1_4	{19,46,31,3,2}	2.51	{27,43,35,7,1}	2.47	-0.04		0.9178
actionY1_5	{10,28,33,24,6}	2.97	{3,25,35,40,10}	3.21	0.24		0.0103
actionY1_6	{6,10,30,36,19}	3.46	{0,10,28,55,20}	3.51	0.05		0.1466

Table 10. Survey responses (part 1) for the non-intervention group. The answers to the questions are shown using a notation with curly brackets that contain in this order the number of students that indicated the answer ‘not at all typical’, ‘not typical’, ‘somewhat typical’, ‘typical’, and ‘very typical’. The mean is calculated by converting ‘not at all typical’ to ‘1’, ‘not typical’ to ‘2’, ‘somewhat typical’ to ‘3’, ‘typical’ to ‘4’, and ‘very typical’ to ‘5’. The indicated p-value is the result of a Kruskal-Wallis rank sum test between the answers on the two subsequent years. No significant differences were observed (threshold 0.01).

	2016-2017		2017-2018		Comparison	
	Answers	Mean	Answers	Mean	Δ Mean	p Kruskal
reasonSuccess1	{1,4,20,56,21}	3.55	{0,4,14,62,31}	3.65	0.1	
sufficientInfo1	{1,13,44,37,5}	3.39	{4,21,49,38,1}	3.19	-0.20	0.08447
sufficientInfo2	{0,3,46,45,6}	3.55	{1,11,45,50,6}	3.39	-0.16	0.4544
sufficientInfo3	{6,23,52,17,1}	3.19	{9,32,46,26,0}	2.96	-0.23	0.7199
receivedInfo1	{1,4,41,47,8}	3.50	{1,4,42,62,4}	3.39	-0.11	0.8557
receivedInfo2	{2,15,36,42,5}	3.27	{2,20,38,46,6}	3.23	-0.04	0.8316
receivedInfo3	{5,21,30,37,7}	3.13	{3,23,40,42,5}	3.19	0.06	0.9356
receivedInfo4	{5,38,46,12,0}	2.98	{8,45,43,17,0}	2.84	-0.14	0.7154
receivedInfo5	{1,8,44,42,6}	3.46	{3,9,32,66,2}	3.19	-0.27	0.2565
receivedInfo6	{1,15,47,33,5}	3.40	{4,19,38,46,6}	3.20	-0.2	0.6278
receivedInfo7	{1,11,47,36,6}	3.46	{1,19,39,50,4}	3.23	-0.23	0.9168
satisfaction1	{0,7,34,56,4}	3.35	{1,15,39,55,2}	3.23	-0.12	0.09665
satisfaction2	{0,6,26,49,20}	3.59	{1,8,37,57,8}	3.39	-0.2	0.02343
experienceY1_1	{30,42,21,8,0}	2.20	{33,59,15,5,1}	2.04	-0.16	0.3673
experienceY1_2	{7,27,31,32,4}	2.98	{9,37,40,21,6}	2.97	-0.01	0.1394
experienceY1_3	{9,22,30,36,4}	2.98	{9,33,38,27,6}	2.99	0.01	0.2220
experienceY1_4	{19,21,30,23,8}	2.87	{26,30,28,24,5}	2.61	-0.26	0.1773

Table 11. Survey responses (part 2) for the non-intervention group. The answers to the questions are shown using a notation with curly brackets that contain in this order the number of students that indicated the answer ‘not at all typical’, ‘not typical’, ‘somewhat typical’, ‘typical’, and ‘very typical’. The mean is calculated by converting ‘not at all typical’ to ‘1’, ‘not typical’ to ‘2’, ‘somewhat typical’ to ‘3’, ‘typical’ to ‘4’, and ‘very typical’ to ‘5’. The indicated p-value is the result of a Kruskal-Wallis rank sum test between the answers on the two subsequent years. No significant differences were observed (threshold 0.01).

Figure 1. Screenshot of the LASSI dashboard (translated from the original in Dutch). Shown are the tabbed interface containing tabs for the Introduction and each of the five learning skills covered by the test. The current view is for a student with average time management skills. The top pane contains a description of the time management scale and shows what norm group the student is in. In the visualisation each peer student is represented by a single dot. The text below the visualisation provides guidance for interpretation of the norm group the student is in.

Previous year

Below you can see which study efficiency (SE) first year students in the @nameStudyProgram@ achieved last year in June, in relation to their time management score. The **jouw score** group has been explicitly labeled. Every dot represents one student with the following color code: a **groen** dot is a student with a study efficiency higher than 80% ($SE \geq 80\%$), an **geel** dot is a student with a study efficiency between 30% and 80% ($30\% \leq SE < 80\%$), and a **oranje** dot is a student with a study efficiency lower than 30% ($SE < 30\%$).

How to improve?

Tips to work on your time management skills

- It is important to realize that you are responsible for your own time management, you can control your time usage. The following activities can help you improve your time management.
- Start by formulating specific learning goals for a very specific period, for example next week. Formulate your goals as specific and realistic as possible. (Also see the tips on motivation to help you formulate your

Figure 2. Screenshot of the bottom part of the time management tab of the LASSI dashboard for a student in the average norm group. The 'Previous year' pane contains a visualisation of the academic achievement of students in previous years for each of the five norm groups. Each square represents 1% of students. A third pane titled 'How to improve?' contains tips, remediation recommendations, and links to support services.

Figure 3. Screenshot of the REX dashboard (translated). Of the five tabs, 'Scores' is currently selected. The screenshot shows the unlocked visualisation for the course 'Analyse, Part 1' after the student responded to the question 'How do you feel about this score'. For the course 'Fundamentals for Communication and Information Theory' the initial position is shown, with a blurred and greyed-out visualisation.