Nudging by Predicting: A Case Study

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Abstract: Nudging students to a better learning is a common practice among teachers of small classes which is impossible in large classes. Indeed, no teacher has enough time for giving individual feedback to several tens or hundred students, let alone be sufficiently aware of the progress and difficulties of each of them. This article reports on a case study using computed individual predictions for sustaining the motivation of large class' audiences thus nudging them to a better learning. More precisely, this article reports on a case study in which students are given individual predictions of their withdrawal, or "skipping", and examination performances with the aim of increasing their participation to classes and to homework. A real-life evaluation of the approach in a computer sicence course points to both its effectiveness and its positive reception by students.

1 INTRODUCTION

In classes with up to about 25 students, teachers can be at any time well aware of every student's skills, weaknesses, and difficulties. In such small classes, most teachers constantly nudge their students by drawing their attention to learning-relevant issues or by gently encouraging them. In large classes, that is, classes with several tens to several hundreds of students, which are widespread in higher European STEM education, teachers cannot be aware of the skills, weaknesses, and difficulties of every student. As a consequence, large class teachers can neither provide individual feedback nor individually nudge students to a better learning. This article reports on using learning analytics for automatizing individual feedback and individual nudging in large classes, by using computed individual predictions of the students' future achievements.

The nudging reported about in this article primarily aims at encouraging students not to skip homework assignments. It relies on two kinds of personal predictions: A "skipping prediction" which estimates the likeliness of skipping the next assignment and a "examination fitness prediction" which estimates the likely performance at the course's final examination. The predictors are trained on data (on homework and final examination performances) gathered in former venues of the same course (assuming similar students' behaviours). During the course, students are shown their individual predictions that are constantly updated after their accumulated performances so far.

For the purpose of the case study reported about in this article, the aforementioned individual predictions were integrated as individual feedback to students in an online learning platform which was also used to organize homework submission and correction in a bachelor course on theoretical computer science.

The research presented in this article is focused at the following two research questions:

1. Can the learning behavior of students be positively impacted with such a nudging?
2. What are the students' attitudes towards such a nudging?

To answer these questions, student homework performances in a course venue with prediction-based nudging were compared to homework performances of students in previous course venues, where no such nudging took place. The results point to positive changes in the students' behaviour: Students subjected to the described nudging skipped slightly less assignments and students who skipped one assignment submitted the next assignment slightly more often than students who were not nudged.

Furthermore, survey results show that students found the predictions they were nudged with neither discouraging nor particularly encouraging but nonetheless interesting. The observation of a general interest among students for the proposed nudging is backed with an analysis of the students' behaviour during the course: The students consulted their own

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individual predictions throughout the semester with a raise in consultation towards the end of the semester.

This article extends former research that introduced predictors of examination performance and skipping, and reported on their quality (Heller and Bry, 2018). The novel contributions of this article is a report on an experimental evaluation of the influence of reports generated by these predictors on student behaviour.

This article is organized as follows. Section 1 is this introduction. Section 2 surveys the related literature. Section 3 describes the methods of the experiment. Section 4 reports on the results of the evaluation. Section 5 discusses the results and limitations of the evaluation. Section 6 concludes this article with perspectives for future work.

2 RELATED WORK

This article refers to learning analytics, homework error classification, dropout and examination performance prediction, and automated feedback to learners. Former research on these issues is reviewed in the following.

Cooper defines homework as "tasks assigned to students by school teachers that are meant to be carried out during non school hours" (Cooper, 1989, p. 86). While the impact of homework on learning outcomes is still a debated issue (Cooper, 1989; Trautwein and Köller, 2003), homework is mostly considered beneficial because it can mediate self-efficacy (Zimmerman and Kitsantas, 2005). In the educational setting evaluated in this article, homework is always reviewed by teachers and results in individual feedback to learners which is known to be among the most effective enablers of learning (Hattie and Timperley, 2007; Hattie, 2015).

The predictors used in the evaluation reported about in this article rely on sequences of categorized homework submissions. The categorization scheme used for these predictors which is presented in Section 3 is inspired from Radatz' investigations of procedural errors (Radatz, 1979) and Newman's error analysis (Clements, 1980). Radatz' procedural error category "errors due to insufficient quality of conceptual understanding" is closely related to the category "Insufficient Knowledge" used in building the predictors used in the evaluation reported about in this article. Newman's error analysis (Clements, 1980) is based on a hierarchy of steps (which may result in errors) in problem solving tasks. Both Radatz' and Newman's categorization schemes have been designed for mathematics education. They are therefore appropriate influences for the work reported about in this article, the application area of which is computer science.

Learning Analytics have been defined 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" (Siemens, 2010). One application of Learning Analtics is predicting dropout, which is often mentioned in the literature on distance education and MOOCs (Massive Open Online Courses) (Cambruzzi et al., 2015; Onah et al., 2014; Ye and Biswas, 2014; Kizilcec et al., 2013) where dropout is usually defined as discontinued participation (Lykourentzou et al., 2009) or in terms of periods of inactivity (Halawa et al., 2014; Tan and Shao, 2015). The predictor discussed in this article predicts "skipping" defined as "missing a learning activity", more precisely, missing a homework assignment, which is related to dropout. Various types of data have been used for predicting dropout: Among others measures of engagement or satisfaction (Dejaeger et al., 2012; Giesbers et al., 2013), demographic data, and performances (such as quiz performances) (Lykourentzou et al., 2009). A large variety of statistical methods have been used for predicting dropout: Among others Support Vector Machines (Lykourentzou et al., 2009), Neural Networks (Lykourentzou et al., 2009; Guo, 2010; Cambruzzi et al., 2015), Decision Trees and Bayesian Classifiers (Dekker et al., 2009).

One predictor related to those used for the evaluation reported about in this article is presented by Kizilcec et al.: For predicting the dropout of a MOOC's audience, the participants' assessments were automatically labelled as "Auditing", "Behind", "On Track", or "Out". "Behind" for example refers to learning actions performed behind schedule. The predictor was based on an analysis of these labels' trajectories (Kizilcec et al., 2013).

A large variety of data have been used for predicting examination performances, among others emotional affects (Pardos et al., 2013), grades in previously attended courses and demographic data (Guruler et al., 2010; Cripps, 1996), and engagement measures (Abdous et al., 2012; Cripps, 1996). The methods used for predicting examination performances reach from Neural Networks (Oladokun et al., 2008), to Decision Trees, (Guruler et al., 2010) to Regression Analysis (Abdous et al., 2012). By comparing various data sources, Tempelaar et al. found that computer-assisted assessments such as quiz performances are the most effective in predicting examination performances. (Tempelaar et al., 2015) Merceron and Yacef found that the use of supplementary learning materials impacts on final grades (Merceron and Yacef, 2008). Recently, Jovanović et al. used cluster analysis to identify patterns of platform use related to self-regulation and examination performance (Jovanović et al., 2017).

Some learning management systems provide feedback through "learning analytics dashboards". Such dashboards are typically only provided to teachers and display descriptive statistics (Verbert et al., 2013). Students can benefit from such dashboards too: Showing learners their own learner model has been shown to improve self-assessments (Kerly et al., 2008) and motivation (Corrin and de Barba, 2014). Park et al. found that such dashboards have no significant impact on examination performances but that students reported that the dashboard positively impacted on their learning behavior (Park and Jo, 2015). Cambruzzi et al. let teachers contact (typically via email) students matching a "dropout profile" which resulted in significant decreases of the dropout rate (Cambruzzi et al., 2015). This result is comparable to that reported about in (Onah et al., 2014): Students learning with an experimental MOOC who had more teacher contacts exhibited a higher retention than students with fewer teacher contacts. Another interesting observation is reported in (Arnold and Pistilli, 2012): A significantly higher retention and a higher percentage in good grades was achieved through emails informing students of their current performance prediction. These email reports were often perceived as personal communication from the instructor which again stresses the importance of personal contact.

3 EVALUATION METHOD

Course, Participants, and Course Organization. The course in which the experiment was conducted, an introduction to theoretical computer science, is part of the computer science bachelor curriculum. The course is offered every year. It lasted 14 weeks from April to July 2018 and was attended by 433 students of whom 113 were female and 315 male. The teaching staff consisted of one professor who held weekly presence lectures, and one research associate and five student tutors who held weekly tutoring lessons where homework assignments were discussed. The final examination took place immediately after the course had ended. 11 voluntary homework assignments were given at each of the weeks 2 to 12. Each homework consisted of 3 to 4 exercises which had to be delivered one week after their assignment. During the course, written feedback was provided for all submitted homework assignments by the research assistant and the student tutors. Submissions of a sufficient quality (especially including no plagiarisms) were rewarded with a bonus for the final examination amounting to up to 10% of the examination mark.

Predictions and their Presentation. An online learning platform was used through which students could access the course learning material and homework assignments, deliver their homework, receive feedback on their homework, form learning groups, and ask questions on the lectures and on the homework assignments which were answered by the teaching staff and/or by fellow students.

This platform also provides a course schedule and each student with personal analytics (accessed from an "analytics" tab next to an "homework assignment tab" on a "course navigation bar"). A student's personal analytics consisted of three numerical indicators: "Project Assessment", a summary of the homework performances in this course so far; "Skipping Prediction" a prediction presented in Figure 1, and "Examination Fitness Prediction" presented in Figure 2. Personal predictions were updated every week.

Data Collection and Datasets. The basis for the predictions were sequences of categorized homework submissions after the following categorization scheme introduced in (Heller and Bry, 2018):

- **SKIP**, for skipped, when a homework assignment is not delivered.
- **IK**, for insufficient knowledge, reflected by an incorrect use of symbols, statements like "I don't know how to solve this", or an answer not fitting the question, requiring the student to re-learn parts of the course.
- **OE**, for other errors, that is, errors not due to insufficient knowledge.
- **NE**, for no errors, otherwise.

Four datasets were evaluated for this article. Each dataset consisted of a sequence of homework submissions categorized after the aforementioned scheme for each student. The datasets were gathered from venues of the same course on theoretical computer science in the years 2015, 2016, 2017 and 2018.

The datasets gathered in 2015, 2016, and 2017 are referred to as *reference datasets*. They were gathered from course venues run as described above (with presence lectures and presence tutorials, and the same system of bonus points), yet without prediction-based nudging for the students. Homework delivery and correction took place for these course venues on an online learning platform that did not support

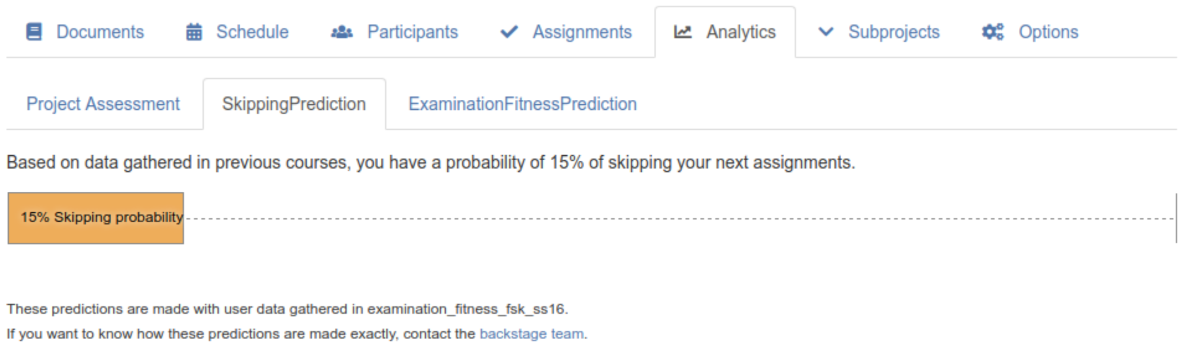

Figure 1: Student view of a personal skipping prediction.

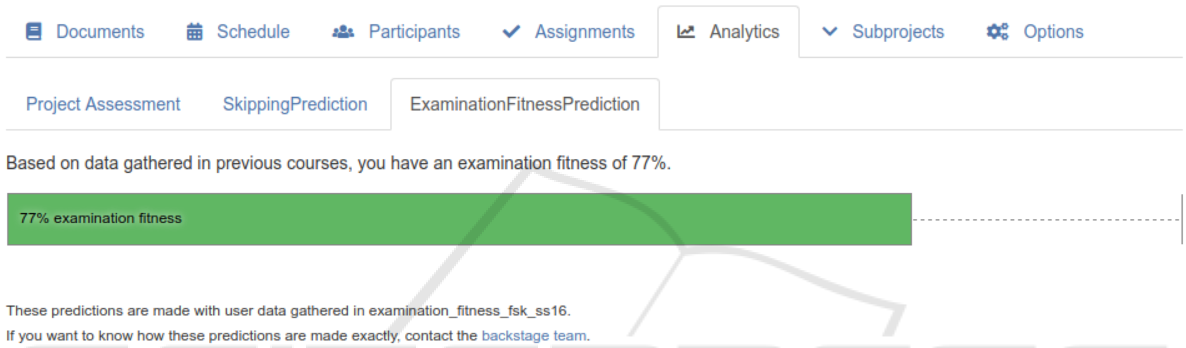

Figure 2: Student view of a personal examination fitness prediction.

discussion of material. The categorization of homework submissions for these reference datasets was performed by the research team after the end of the course.

The dataset obtained in 2018 is referred to as *nudged-students dataset*. For this course venue, the above-mentioned learning platform provided every student with individual predictions on skipping behaviour and examination performances introduced in (Heller and Bry, 2018). The homework submissions were categorized by the research assistant and the student tutors during the course using the online learning platform which had been tuned to the task: Using it, the teachers could categorize the homework submissions in a process similar to the grading of an examination. The categorization aimed not only at providing the data needed for building the predictors but also to provide the students with feedback: When categorizing a submission as “IK” (for insufficient knowledge), for instance, a document was attached to the submissions which listed course material to re-learn. A submission neither categorized as “IK” or “NE” (for no errors) was categorized by default as “OE” (for other errors).

During the course, usage data (such as login times) were recorded.

For the evaluation reported about in this article, only the data from students that delivered at least one assignment was considered. The reference datasets describe the behaviour of 272 students in 2015, 344 students in 2016 and 383 students in 2017. The nudged-students dataset describes the behaviour of 338 students. After the course’s end, a survey was conducted to assess the students’ attitude towards receiving personalized skipping and examination performance predictions.

Predictors. Skipping and examination performance predictions as described in (Heller and Bry, 2018) were used to nudge students to further attend classes and to further deliver homework, that is, not to skip. If the nudging had a positive influence on the students’ skipping behaviour then the predictors would perform worse on the nudged-students dataset than on the reference datasets. Indeed, the purpose of nudging students with predictions of their skipping and examination performances is to incite them to disprove the predictions.

The predictors were trained with the reference datasets and applied to the nudged-students dataset. Specificity and sensitivity were retained as estimates of the predictors’ performances. The predictors’ performance on the reference datasets was assessed with a 10-fold cross validation (Heller and Bry, 2018).

Resuming participation after a student had skipped assignments was of special interest. This behaviour was analysed for each student by considering pairs of homework submissions according to the following scheme:

- S-S: number of times a skipped assignment followed a skipped assignment
- S-D: number of times an assignment was delivered when the previous assignment was skipped
- D-S: number of times an assignment was skipped when the previous assignment was delivered
- D-D number of times an delivered assignment followed an delivered assignment

The averages of these four values were computed for all datasets.

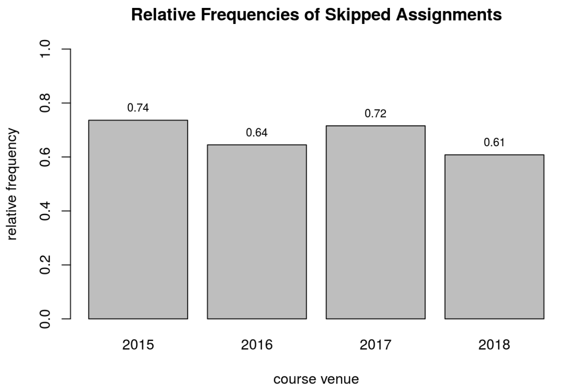

Figure 3: Relative frequencies of skipped homeworks in the reference datasets (2015, 2016 and 2017) and in the nudged-students dataset (2018).

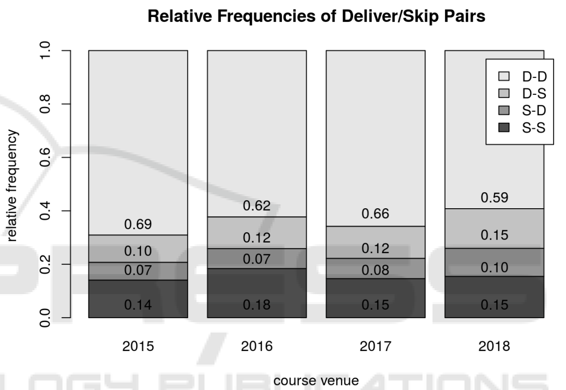

Figure 4: Relative frequencies of Pairs deliver/skip behavior for reference datasets (2015, 2016 and 2017) and the nudged-students dataset (2018).

4 EVALUATION RESULTS

This sections reports on the results of the evaluation. Indications for behavioural changes are first examined by comparing the behavioural data from the nudged-students dataset to the reference datasets. The students' attitudes towards the nudging are then examined using survey data.

Indications of Changes of Behaviour. Figure 3 shows the relative frequencies of all skipped homeworks for the three reference datasets (2015, 2016 and 2017) and the nudged-students dataset (2018). The frequency of skipped assignments is the lowest in the nudged-students dataset.

Fisher's Exact Test was applied to test the significance of the differences in skip rates in the nudged-students dataset on the one hand, an in the reference datasets on the other hand. Significant differences ($p < 0.01$) were found when comparing the nudged-students dataset with the reference datasets of 2015 and 2017, but not when comparing it with the reference dataset of 2016. While only two of the three reference datasets showed significant differences to the nudged-students dataset, this suggests that the nudging investigated in this article contributes to reduce the skipping behaviour of students. Indeed, the nudged-students dataset exhibits the lowest skipping rates of all four examined datasets.

Figure 4 shows the relative frequencies of pairs of behaviours S-S, S-D, D-S and D-D. The pairs reflecting behaviour changes, that is D-S and S-D, are slightly more frequent in the nudged-students dataset than in the reference datasets. This rise in behaviour changes seems to come at the expense of a stable delivering behaviour, that is, D-D but not at the expense of a stable skipping behaviour, that is, S-S which is comparable in all datasets.

One indication that the students' nudging achieves its goal is that the skipping predictor performs worse on the nudged-students dataset than on the reference datasets. While there may be other factors reducing the predictors' quality (which are discussed in the next section), the nudging works well if students change their behaviours, thus making the predictions false. The skipping predictor exhibits a slightly worse sensitivity on the nudged-students dataset than on the reference datasets. The specificity is comparable in both cases, as seen in Table 1.

System Usage. Throughout the course, the students looked at their personal predictions as Figure 5 shows.

Table 1: Comparison of the skipping predictor for the reference datasets and the nudged-students dataset.

	reference	nudged-students
sensitivity	72.9%	67.2%
specificity	84.7%	85.2%

There is a notable peak at the start of the course, possibly caused by the novelty of the system, and a slow rise towards the end of the course, possibly caused by the students being concerned of their expected examination performances. In average, the students retrieved their personal predictions about once a week (median interval in days: 6.9, first quartile 2.7, third quartile 12.4) which corresponds to the frequency with which the predictions did change.

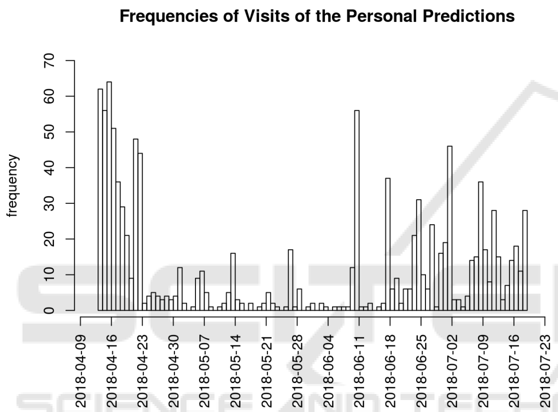

Figure 5: Number of visits of the personal analytics page per day.

Student Attitude. 65 students participated in the final survey. The students were asked to answer the following 5 questions for each of skipping prediction and examination performance prediction on a 6 point Likert scale ranging from “not at all” (1) to “absolutely” (6):

The displayed predictions ...

- ... motivated me to learn more.
- ... was interesting for me.
- ... discouraged me.
- ... was helpful.
- ... motivated me to hand in the next assignments.

Table 2 summarizes the results of the survey. The students did not find any of the predictions discouraging, nor did they report to have been motivated to a higher participation to do homework. The examination fitness prediction was perceived as more interesting than the skipping prediction, which is consistent with findings by Schumacher and Ifenthaler who found that self-assessments are among the most liked features of learning analytics systems by students(Schumacher and Ifenthaler, 2018).

5 DISCUSSION

The results indicate certain behaviour changes. In the case study, students skipped less assignments than in the previous course venues during which no nudging took place. Also, the students varied more frequently between skipping and delivering homework than in the previous course venues without nudging: There were more students that resumed work after having skipped one assignment and less students that stuck to work after having submitted an assignment. This might indicate that the students felt empowered to “take their learning in their own hands”; “should I do my homework” seemed to be a question to be answered on a weekly basis instead of once and for all. This suggests a form of learners’ empowerment or better learners’ self-regulation which should be seen as a positive result.

The students expressed a relatively neutral attitude towards the predictions they were shown, calling them neither motivating nor discouraging, of limited helpfulness and more interesting than helpful. Yet the results show a positive impact on the learning behaviour and the students also consulted their personal predictions regularly what indicates interest, with a clear peak in consultation towards the end of the course. This might be explained by the approaching final examination.

The results reported about in this article suffer from some limitations. First, the survey was completed by only 64 students which might not be representative of the 344 students of the nudged-students dataset. The limited coverage of survey might especially affect the results on motivation and discouragement: If some students felt discouraged by their predictions (or other aspects of the online learning platform or of the course itself), they might also have been discouraged to participate in the survey. Also, the survey did not include questions on the possible reasons of skipping assignments, which could have brought further insight on the students’ motivations.

Second, the experiment was conducted in an “everyday” educational setting by comparing data that was gathered in different course venues, yielding different conditions under which the datasets were gathered: Some of the teaching staff (especially the student tutors) changed over the years which might have resulted in different kinds of homework reviews, and while the topics and the amount of exercises remained

Table 2: Student' responses for the examination fitness and skipping predictor.

	examination fitness			skipping		
	1st Quartile	Median	3rd Quartile	1st Quartile	Median	3rd Quartile
motivation	1	1.5	2	1	1.5	2
interest	3	4	5	2.5	3	3.5
discourage	1	1.5	2	1	2	2.5
helpful	2	3	4	2.5	3	4
more	1	1.5	2	1.5	2	2.5

fairly similar, the exercises were reworked, improved, and in some cases even changed from course venue to course venue. Furthermore this study design does not allow to compare examination results between nudged and not nudged students, which would allow to draw further conclusions on the effectiveness of the intervention, because examinations differ from year to year and are not standardized.

Note that while the study design presented in this article which consists of evaluating and comparing different course venues has its flaws, alternatives are often simply incompatible with real-life teaching: Students randomly assigned to control and treatment groups, which would be necessary for an A/B test for instance, could not be expected to stay isolated from each other for the duration of a whole course, which would be necessary to reasonably conduct such a study.

6 CONCLUSION AND PERSPECTIVES FOR FUTURE WORK

The evaluation reported about in this article has shown that the perceived usefulness, and the impact on the learners' behaviour of confronting them with personal predictions on their homework skipping and on their examination performances could be improved. Four improvements of the approach appear possible and desirable:

1. While every student could see her current predictions, *changes* in these predictions were not displayed. Two successive predictions often varied in only a few percentage points, possibly too few to be easily noticed.
2. The current predictions were provided on demand: The students had to actively visit their analytics page. The system regularly sends reports on recent user actions (such as new assignments or posted questions), but the learning analytics were not included in these reports. Regular reports on newly published or newly updated learning analytics could be send.
3. The learning analytics delivered to one student could include aggregated learning analytics referring to the student's peers like prediction averages. Though, such informations could be either encouraging or discouraging, depending on the students (Onji, 2009).

This article has reported on an experiment relying on individual predictions of homework skipping and examination performances for nudging students to a better learning. The evaluation results point to the effectiveness of the approach: Nudged students skipped assignments slightly less than non-nudged students. Further work on the origin of homework skipping and how to combat it in large lectures is therefore needed. The evaluation revealed the students' interest in the nudging with individual predictions of homework skipping and examination performances, and indications of an increased learner empowerment were found. Limitations of the approach have been discussed.

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