OfLA Project
2018-1-UK01-KA203-048090

O9 – Evaluation of the second cycle of studies

Learning Analytics at the Graduate School of Life Sciences

RESPONSIBLE PARTNER:
UMC UTRECHT

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PARTICIPATING PARTNERS:
ARTEVELDE UNIVERSITY OF APPLIED SCIENCES
NOTTINGHAM TRENT UNIVERSITY

Output 9 – Evaluation of the second cycle of studies

These reports will map the process of data-informed advice in the second year of the study.
A1. We will confirm with the new study subjects how we will work alongside them. This time however, we will have selected a new group of courses or degree programs to work with, or will be testing a new approach to using institutional data/ learning analytics in the advising and supporting process. This may include group tutorials, different types of alert or early warning, or advising using a particular pedagogical methodology.
A2. We will monitor and project manage the operation of the learning analytics resources.
A3. We will map how data (on each course and/or centralized) is used to firstly spot students at risk, how students are communicated to and how they are supported. Importantly, this year the reports will also include a summary of how we communicated with staff to set up the new round of interventions and challenges associated with the new cycle of interventions. The reports will also include recommendations for conducting the final cycle or research in 2020-2021.
A4. We will publish the resources to the website. AHS will take the overall responsibility for editing together the reports.

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1. Executive Summary

The overall aim of the 'Onwards from Learning Analytics'-project is to best understand how institutions can use learning analytics and other early warnings to improve the quality of the communication and support provided to students through staff intervention. A first step is to determine when students are actually at risk and what triggers could automatically be generated from the learning management system.

Therefore, we analysed historical data of graduated students. This historical data included student characteristics, grades and study credits for the different components of Masters' education. For a subset of students, those who had obtained their Bachelors' degree at the same institute, additional information was available, such as Bachelors grade point average and grades for bachelor thesis.

Data driven analysis informed by existing knowledge resulted in a description of at-risk students either at the start of the program, or during their Masters' education. Subsequently, a quick literature research was performed to determine if the outcomes of at-risk analysis are confirmed in literature, and to verify if other parameters were being overlooked and thus should be included. In addition, the characteristics of students being at risk were used for hypothesis-driven research. The tested hypotheses included the risk for study delay or lower grades for international students, and students studying abroad during their Masters' education. To a lesser extent, we were also interested in finding subgroups of "excellent" students, whom can be stimulated to achieve more during their studies.

The characteristics of students at risk will be used as triggers to generate automated warnings. One of the future aims is to create a dashboard that is able to generated these warnings and provides an overview of student progress (ideally in comparison to peers or historical cohorts of students). A prototype of this learning analytics dashboard is conceptualised.

2. Introduction

2.0 Institution Background

The Graduate School of Life Sciences (GSLS) in Utrecht, The Netherlands, offers graduate programs in Bio(medical) Sciences. The school offers 17 Masters' programs that share common mandatory elements. These elements consist of a minor and a major research project (6- and 9-months internship, respectively), a writing assignment and program specific theoretical courses. Beyond these common mandatory elements, students also attend elective courses (general courses accessible to all students). The order in which students participate in projects and courses is different for all students. The GSLS aims to provide education tailored to the individual needs of each student, extra support for students that need it, and extra challenges for students who want it.

Each academic year, approximately 1500 students are enrolled in Masters' education at GSLS. 25% of these students have an international background. During Master's education students are located all over the world, which makes identification of students at risk more complicated. Learning analytics will play a vital role in enabling the GSLS to achieve the goal of tailor-made education.

2.1 Needs

In our institution a diverse set of support staff is available to help students when they are struggling during their education. The support staff includes a student counsellor, study coaches and program coordinators. Often students themselves need to reach out for help, because identification of struggling students is not automated. Only when students show sever study delay (having too little credits after a set period of time, often 1 academic year), they are identified using a manual analysis of student progress.

It would be beneficial for students and their progress if they were identified in an earlier stage of study delay or when students are struggling. We expect that data in the Learning Management System (LMS, in our institution Osiris) could be used to help identify students at risk and to predict student success later in Masters' education.

As indicated above, the number of projects and courses per student in Master's education is limited. With a limited number of parameters, it is more difficult to find a solid model to predict study success or if students are at risk. In GSLS we would like to predict 'being at risk' both at the start of the program, and when starting a subsequent project. In order to use learning analytics to identify students at risk, it first needs to be determined when students are 'at risk' and which parameters have predictive value to identify students at risk. Similarly, parameters with predictive value for students with excellent performance were identified.

2.2 Objectives

This year's work focused on data analysis to identify relationships between student analytics variables and progress or grades as potential triggers for a future LA system. To a lesser extent, we were also interested in finding subgroups of "excellent" students, whom can be stimulated to achieve more during their studies.

Objective 1 *Determine the characteristics of a student at risk based on available historical student data*.

Objective 2 *Determine which student analytics variables (best) predict progress and subsequent grades (data-driven research)*

1. *At the start of the program,*
2. *During Masters' education.*

Objective 3 *Perform literature research into existing knowledge about student characteristics that predict "being at risk"*.

Objective 4 Conduct hypothesis-driven research: Research based on prior ideas about characteristics that may put students at risk of underperforming.

1. *The effect on grades*
2. *The effect on time to degree*

Objective 5 Conceptualize a dashboard prototype for the LA system to be implemented.

2.3 'Onwards' from Learning Analytics

The project Onwards from learning analytics is focussed on three stages; triggers, communication and action. Last year, interviews with staff has shown how students at-risk are identified, which is mainly via manual analysis of learning management data and physical observations by staff and peer students. The problem with this procedure is that at-risk students are identified once they are behind their schedule or showing sign of fatigue [see UMCU O6-2.1.2 and 2.1.3]. It would be better, if students at risk were identified in an earlier stage to minimize the gap that these students need to compensate. Support staff, for example student councillors, claim they would benefit when triggers were generated automatically [see UMCU O6-2.4.3].

The first step towards generating automated messages is to have a clear description of variables that indicate when a student is at risk. The variables, such as study progress and grades, are stored in the LMS. The system is currently being expanded with features related to student admission and course registration. Still, analysis of data is only done manually for which data first needs to be extracted using queries. Meaning, the system is not yet used to its potential.

With the knowledge that is gained during the second year of the project, we will be able to make a (prototype of) a dashboard that automatically shows, for instance, student progress in credits and average grade during their Masters' education. In the future, the dashboard should be able to compare students own learning progress to peers in the same Masters' program, or peers studying in previous cohorts. This automatically generated overview provides students and student councillors with insight in student progress and could trigger communication when progress is insufficient or grades are declining. On the other hand, could these overviews show which students are progressing really well, and for instance if they meet Cum laude criteria.

Apart from the knowledge and visualization of student progress, we also aim to combine LMS progress data with data retrieved using (well-being) questionnaires and / or data from scoring rubrics that are completed as formative and summative assessment tools in internships. This combination will provide qualitative insights into the quantitative triggers. Support staff could help student with reflecting on feedback, on progress in general and staff could stimulate students to set new goals for future learning experiences.

3. Methodology

The analyses were conducted using a dataset of students that have obtained a degree in one of the 17 programs at the GSLS. Their starting years ranged from 2012 – 2015. Data was available for cohorts starting before 2012 as well, but a major overhaul of the curriculum at that time caused the data to differ substantially. We deliberately choose to only include students who obtained a degree, in order for the dataset to be complete (e.g. grades for all obligatory components, and overall GPA, etc. were available), since the analyses aimed to identify predictive parameters for being at risk during masters' education. Data from students whom had not completed their degree were not included in the analysis, because the number of variables was often very small and the statistical program excludes these cases in analysis.

Extraction of data proved to be a challenge. Some data in Osiris was stored using pdf documents. This way data was available, but not necessarily usable as student analytics data. After extracting the data set from Osiris (thanks to key user Nivard Koning) we noticed that large quantities of data were missing. Cleaning of the dataset (basically completing the extracted file with information stored in PDF files) took a lot of time. We greatly appreciate Anastasia Kurysheva's help to complete this task.

4. Results

4.1 Characteristics of a student at risk based on available student data. (i.e. which variables collected in LMS can best describe the criteria of a student at risk)

Descriptive statistics indicated that the mean grade for major and minor internships is 7.9, with a standard deviation 0.65, on a 10-point scale. Student projects rewarded with a grade 6.6 (i.e. mean grade - 2 times standard deviation) or lower were marked as low achievers and therefore students being at risk. Please note that the number of students having a relatively low grade (6.6 or less) is limited. We argue that the data set only contains successfully graduated students and in order to graduate all projects must be complete with a satisfactory mark (in our case 5.5 or higher).

Theoretically we would expect that students achieve similar or higher grades in subsequent projects, because students learn and get feedback how to further improve their performance. Therefore, a negative deviation in grades (receiving a grade lower compared to the average grade and/ or grade for a previous project), would call for action, since it is assumed that students with declining grades are more likely to get unsatisfactory marks in subsequent projects, and more likely to encounter study delay in general. Data analysis confirmed the hypothesis that a negative deviation of 1.0 on a 10-point scale should be regarded as a second identifier of a student being at risk.

To a lesser extent we were also interested to determine when student could be marked as an excellent student. Excellent students could be stimulated to do additional work or to further expand their skills and knowledge, since the GSLS aims for students 'to make the most of their Master'. We suggest to take into account the criteria for graduating Cum Laude (e.g. all project grades are 8.5 or higher and no re-takes). In addition, analysis of the dataset indicated that mean grades + 2 times standard deviation (9.2 or higher on a ten-point scale) would qualify for being an excellent student.

4.2 Data-driven research: Which student analytics variables (best) predict progress and subsequent grades

4.2.1 At risk prediction at the start of the program

It must be noted that the number of students applying for Masters' education is higher than the number of students enrolling in Masters' programs (due to selection). With this selection bias taken into account, a regression analysis was performed to determine the parameters that contribute to a student being at risk. In this model the prediction to achieve a grade of 6.6 or less for the first project. Regression analysis indicated that being at risk at the start of Masters' education was best predicted using the following parameters (shown in Figure 1):

- previous GPA (usually BSc degree)
- time to previous degree
- age

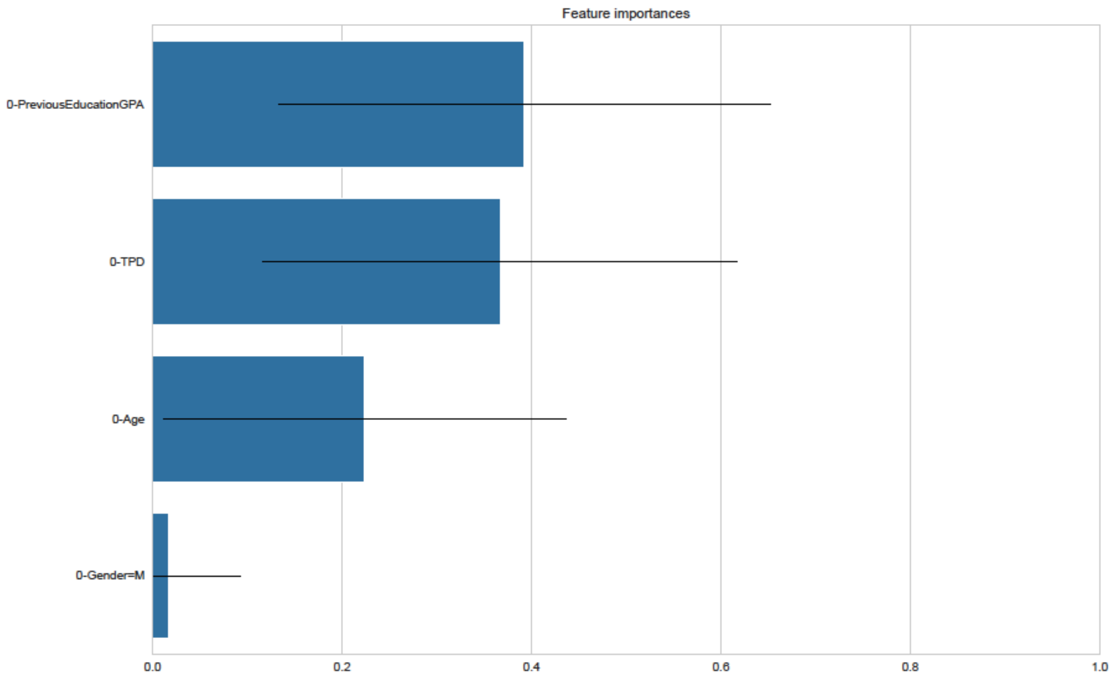


Figure 1. Outcome of risk prediction for the first project in Master's education. *GPA previous education (BSc) and time to previous degree are most predictive for success in the first project.*

A more extensive list with variables resulted in a model with a better predictive value. However, the additive value of these additional parameters was limited compared to the predictive value of GPA of previous education, time to previous degree and age. It was therefore decided to reduce the number of variables as much as possible to increase the feasibility of identification of students at risk with minimal parameters.

Two notes need to be made. First, the data regarding time to previous degree and grade obtained for BSc thesis was only available for students with bachelor degrees obtained at Utrecht University (which is the majority of student population). Second, age is an important parameter to keep in mind when aiming to identify at risk students and support older students currently enrolled in Masters' education. Of course, age is a parameter that education is not able to influence.

4.1.2 At risk prediction during Masters education

In the analysis for at risk prediction during Master's education, both the negative deviation in grades (1.0 lower compared to previous grade) as well as a low grade (6.6 or less) are used as descriptors of students being at risk. As a consequence, the chance of students being at risk in a subsequent project is bigger compared to the number of students being at risk at the start of the program.

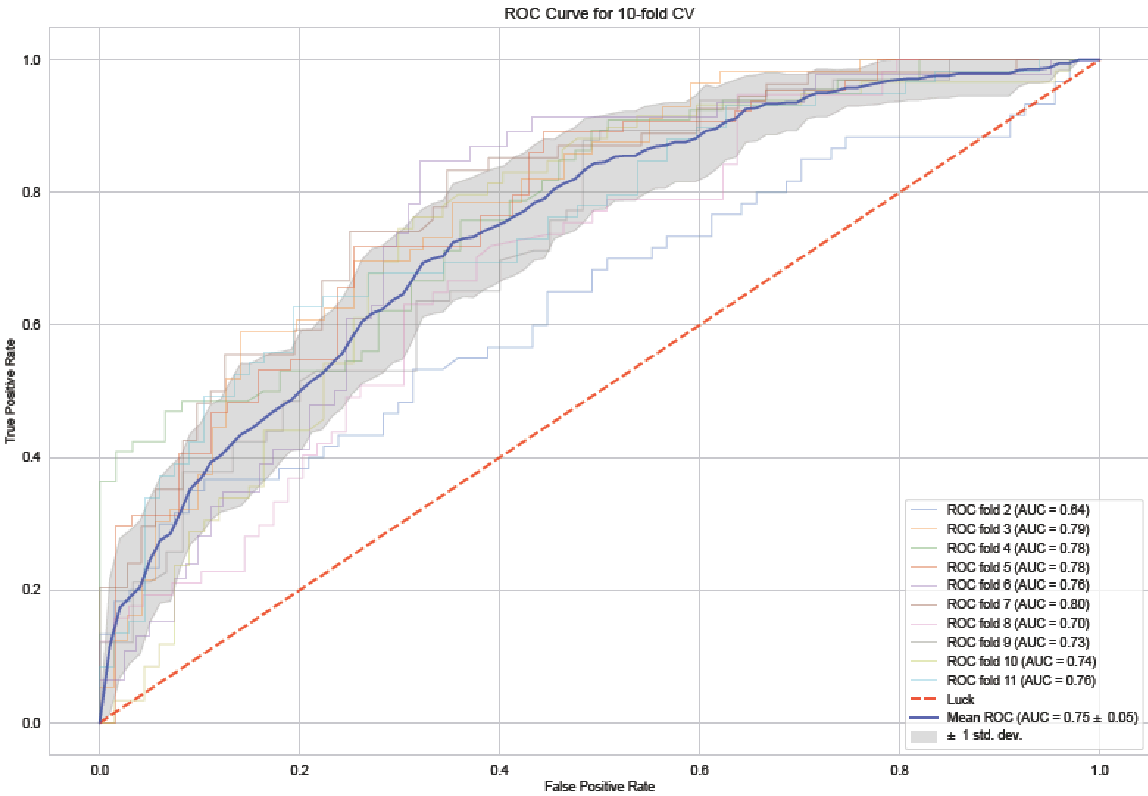


Figure 2a: ROC curve of predictors of at risk in subsequent project. Mean ROC shows an AUC value of 0.75, meaning 75% of the variance is explained with the included variables.

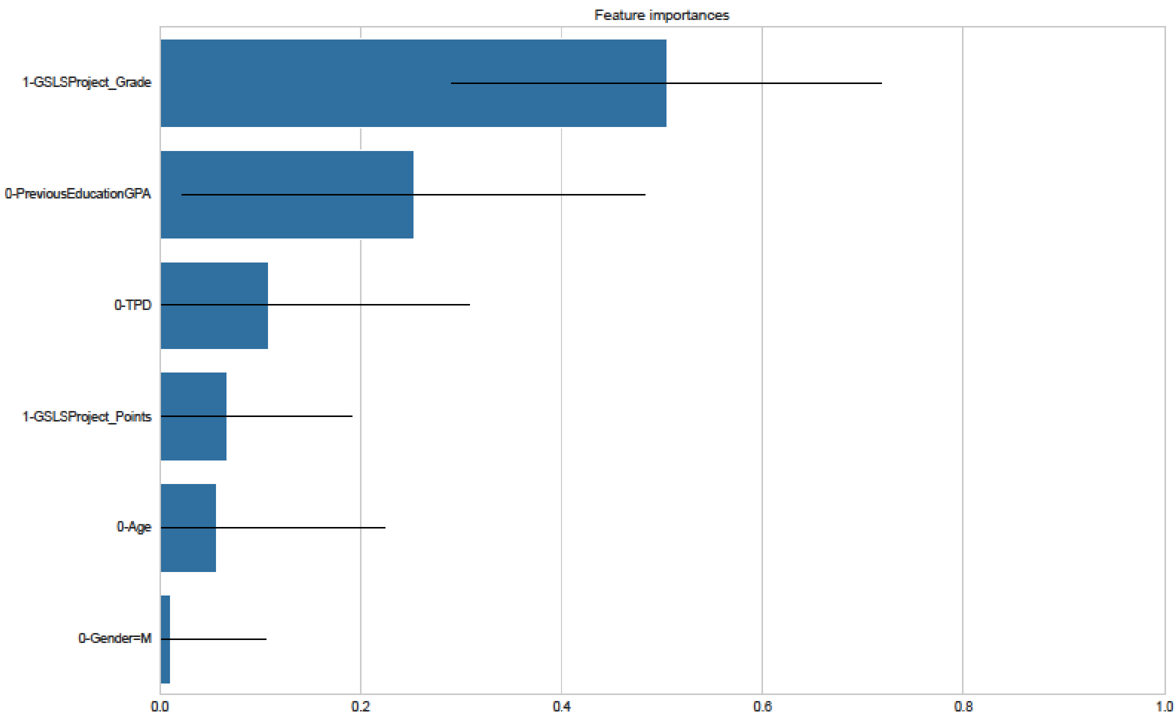


Figure 2b: Predictors of at risk in subsequent project

As shown in Figure 2b, the grade achieved in previous Master's project has the largest predictive value followed by the previous education GPA. Time to previous degree, project points (i.e. credits of the first projects) and age also predict the chance of success in a new project, albeit to a lesser extent.

Similar results were obtained when we aimed to predict the grades in a third Master's project. In this case previous education GPA and Grades for previous projects were again most predictive.

In conclusion, GPA of previous education, time to previous degree and grades obtained in previous projects are most predictive. The data also suggest that older students are more likely to encounter study delay or being at risk for lower grades.

4.3 LA parameters to predict study success described in literature

We performed a quick literature research into existing body of knowledge about student characteristics that predict "being at risk". The aim of this search was to determine if the outcomes of the data-driven analyses (previous section) are confirmed in literature, and to determine if other parameters were overlooked and should be included in the analysis.

The most common measure in LA studies are previously obtained grades (Hamm et all, 2018; Mathiasen, 1984; Choi et all., 2018; Banihashem et al., 2018). In most cases learning analytics was based on trace data, i.e. all activities of learners in an online learning environment. This trace data is clustered to identify frequently occurring sequences of activities, sometimes referred to as profiles of student behaviour (Aldowah et al. 2019; Jovanović et al., 2017; Maldonado-Mahauad et al., 2018). In addition to clustering to identifying (new) groups of activities or groups of students, trace data is also frequently analysed to better understand observable learning behaviour. In these cases, trace data is used to predict or explain differences in learner achievement. An example of trace data in relation to learning outcomes is the use of formative assessments related to performance on summative exams (Bouwmeester, 2013). Other studies aimed to gain insight in (lack of) student engagement in course activities (Choi et al. 2018; Macfadyen and Dawson, 2010), procrastination versus course persistence, and handling of failed quizzes (Saqr et al., 2017).

(Review) studies that focused on students being at risk describe low estimated grades and or disengagement as outcomes for being at risk (e.g. Russell et al., 2020). Other outcomes are the non-success rates in courses, knowledge retention rates or time to degree (Russell et al., 2020; Campbell et al. 2007; Hu et al., 2014). To identify underlying causes for these outcomes, authors have looked into the use of performance feedback, estimated grades, passing or failing a course (Stewart et al., 2011; Choi et al., 2018), resilience or successful adaptation, for instance passing retakes (Sarra et al. 2019; Russell et al., 2020).

This brief summary of literature indicates that learning analytics research often includes similar variables as were included in the at-risk analysis in section 4.2. Although, learning analytics showing student engagement with learning materials at individual course level is also frequently used.

4.4 Hypothesis-driven research: Research based on prior ideas about characteristics that may put students at risk of underperforming.

The hypothesis-driven research questions were answered using a combination of visual exploratory analysis, and statistics. At UMCU, 25% of student population has an international background, meaning that these students obtained their Bachelor degree at a university other than Utrecht University (this includes other Dutch universities). For (some of) these students it can be more difficult to blend in, and therefore students might struggle a bit more, especially in the start of their Masters' education. These struggles may reflect as a study delay (see 4.4.2.2) or in lower grades for projects (see 4.4.1.1). Therefore, we anticipated that students with an international background would have more difficulty to complete the program.

A second thing to keep in mind, is that some students perform a project abroad. Doing a project abroad requires a lot of paper work (for instance, arranging a place to stay and insurance) that needs to be taken care of before a project. Students doing a project abroad involve international students doing a project in their home country, and/or students (often top of the class) that are referred to international colleagues by a supervisor from their first project.

We hypothesized that studying abroad or being an international student may affect students' grades in different projects and the total time to degree (see 4.4.2.3). Data shows both box plots and jittered plots for a more fine-grained view of the results.

In addition to the comparative analyses, correlation analysis was performed to visualize patterns in grades and duration of study components. We observed correlations between bachelor GPA versus masters' GPA (4.4.1.2), bachelor thesis grade versus writing assignment in masters' education, grades for major and minor research internships and the total duration of bachelor and masters education (4.4.2.1).

4.4.1 Studying the effect on grades

4.4.1.1. Are grades for international students different compared to grades achieved by students with a bachelor degree from UU?

As shown below, the average grade in Masters education and the distribution of the average grade are similar for students with a national and international background.

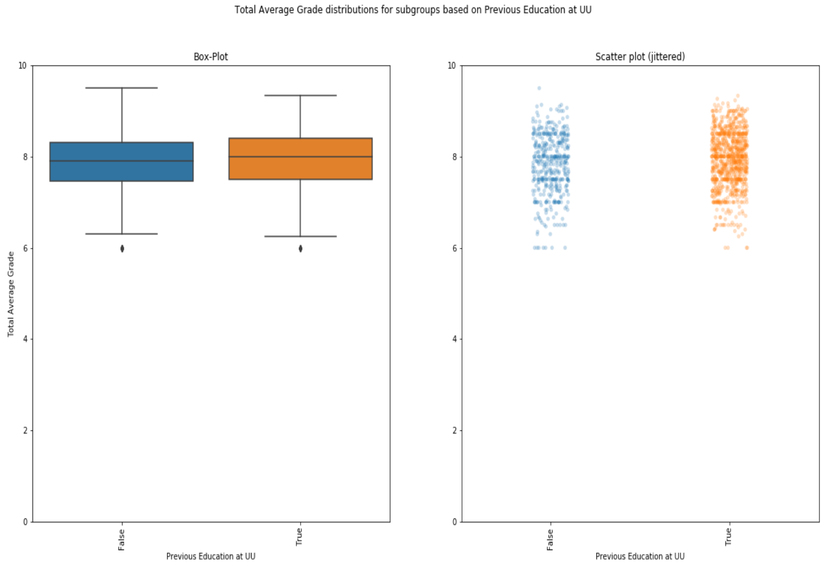


Figure 3: Mean grade and distribution of average grades for master students. Subgroup are student with a bachelor degree obtained at Utrecht University or outside UU (i.e. international students).

A more detailed look into the grades obtained for the projects of Masters' education show that international students obtain grades similar to student with a bachelor degree from Utrecht University. This is the case for (4a) the major research internship, (4b) the minor internship, and (4c) the writing assignment.

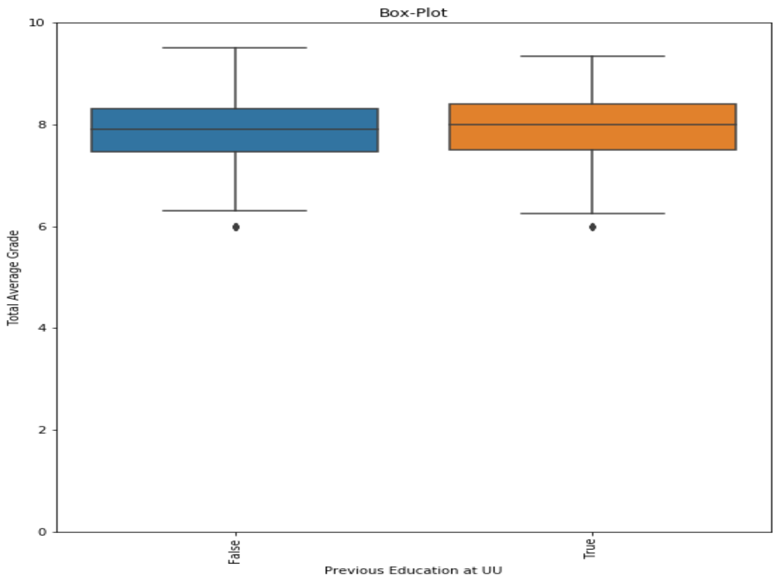


Figure 4a: Mean grade and distribution of major research internship. Subgroup are student with a bachelor degree obtained at Utrecht university or outside UU (i.e. international students).

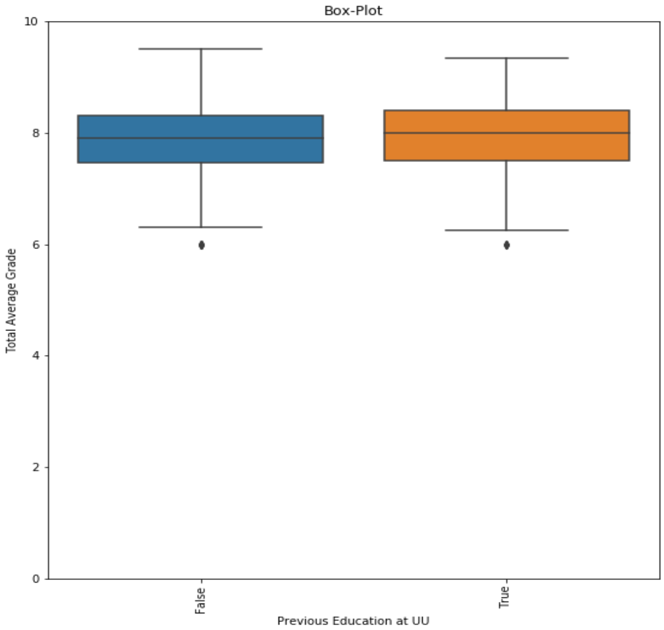


Figure 4b: Mean grade and distribution of minor research internship. Subgroup are student with a bachelor degree obtained at Utrecht university or outside UU (i.e. international students).

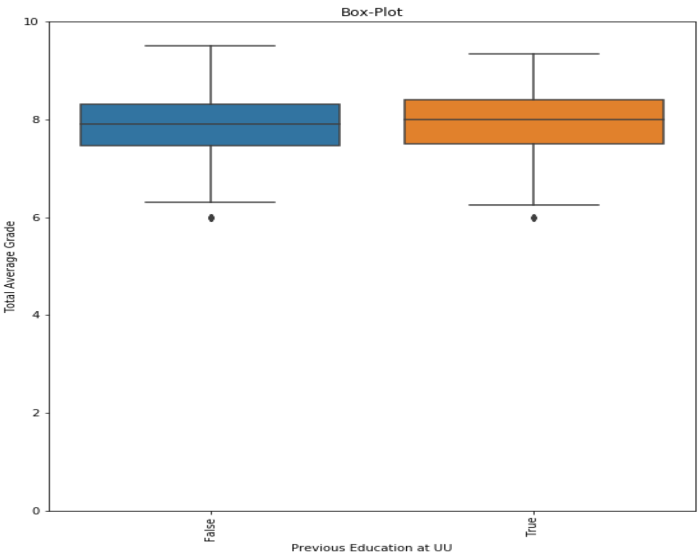
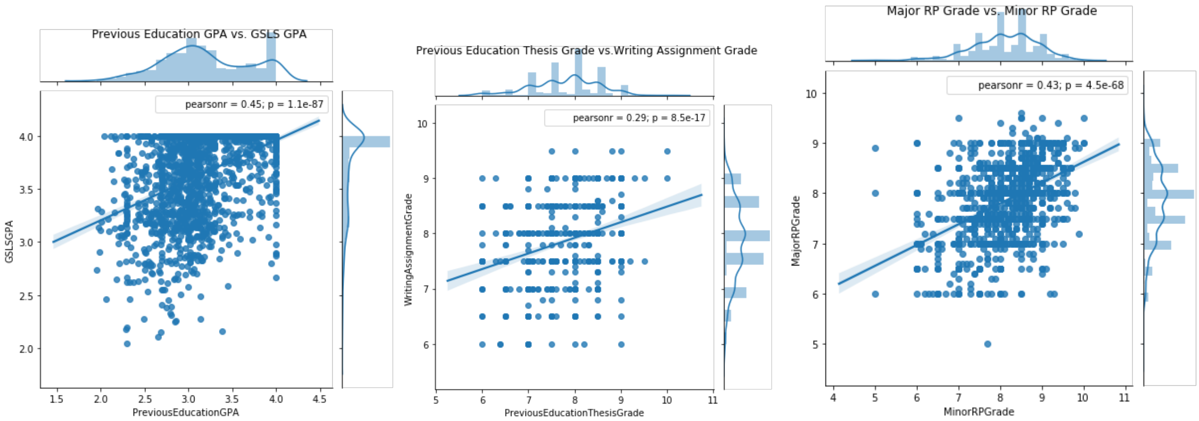


Figure 4c: Mean grade and distribution of writing assignments. Subgroup are student with a bachelor degree obtained at Utrecht university or outside UU (i.e. international students).

It can be concluded that students with an international background are not more likely to be at risk for lower grades compared to students with a bachelor degree obtained at UU.

4.4.1.2 *Are previously obtained grades predictive for grades obtained in Masters education?*
As shown in Figure 5, the average GPA obtained in previous education is significantly correlated with the GPA obtained in Masters education (Figure 5a, r= 0.45).

Similarly, the bachelors' thesis grade significantly correlates to the writing assignment grade in Masters education (Figure 5b, r = 0.29). And thirdly, the grade obtained for a major research project correlates significantly with the grade obtained for the minor internship (5c, r=0.43). Indicating that students with a relatively low grade, either average grade for previous education, or Bachelor thesis grade, or a first internship, is predictive for relatively low grade in follow up projects.



Figures 5a, b, c: Regression analysis for a) BSc versus MSc GPA, b) thesis grade BSc versus Writing assignment MSc, and c) major versus minor research project.

It can be concluded that different components of education correlate significantly. Meaning that students with a relatively high GPA in bachelor also obtain a relatively high GPA in masters' education. Similarly, thesis grade in bachelor correlates with the grade for writing assignments in masters' education, and grades for major and minor internship as well.

4.4.2 Studying the effect on time to degree

It is important to realize that the average time to degree in Masters education at UU is 2 years and 4 months (i.e. 28 months). In this time students earn 120 credits.

4.4.2.1. Is there a correlation between time to degree in bachelor's and master's education?
As shown in Figure 6 there is no correlation between time-to-degree in BSc and MSc education. One of the explanations is that for some students an extremely long time-to-degree was indicated, while it is not clear if students actually spent all this time to obtain the degree, or whether they, for instance, paused their studies. This holds true for both BSc as well as MSc data.

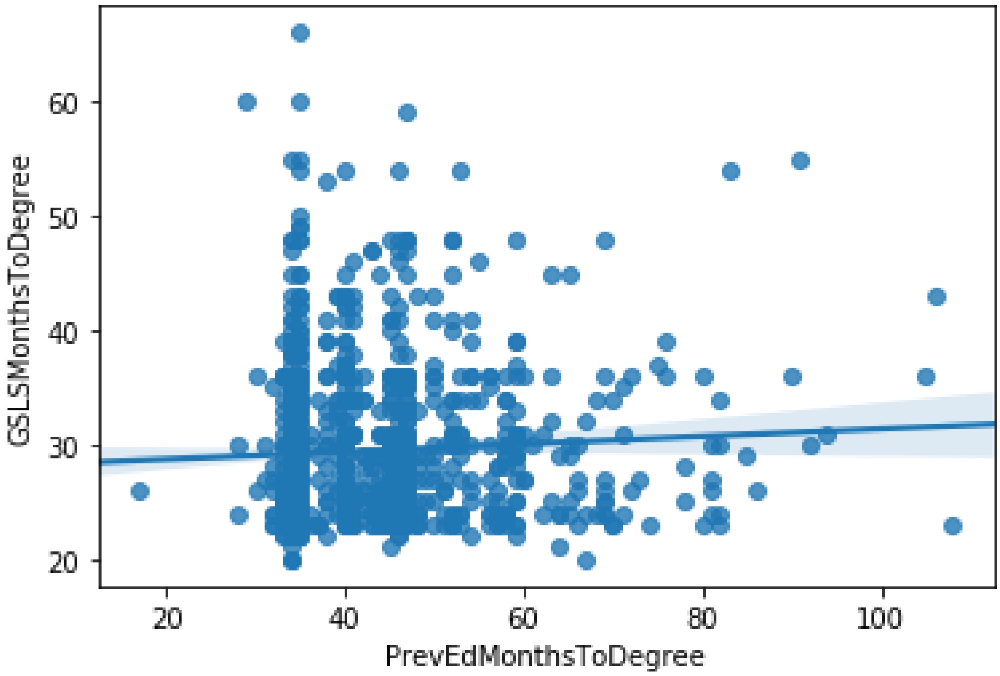


Figure 6: Regression plot for MSc time-to-degree and BSc time-to-degree. The regression coefficient is 0.056.

In summary, there is no correlation in time to degree in bachelor and masters' education.

4.4.2.2 Do international students need more time to complete masters' education?
In line with the analysis regarding grades, we also wondered if international students would have different time-to-degree compared to students with UU- BSc degree. As shown in Figure 7, the average and range in time-to-degree for international student is similar to students with a BSc degree obtained at UU. The jittered plot on the right-hand side may suggest that internal students need less to time to complete the program, but this was not significant.

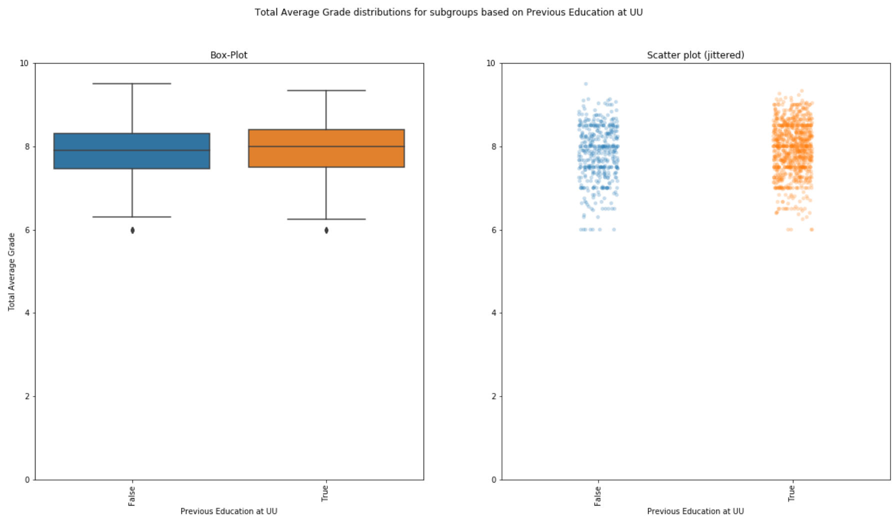


Figure 7: Distributions for time-to-degree, for (inter)national students.

In summary, time to degree for international students is similar to time to degree for students with a bachelor obtained at UU.

4.4.2.3. Do students need more time to complete masters' education when they choose do a minor research internship abroad?

As stated in the beginning of section 4.4, doing an internship abroad requires additional effort e.g. paper work for the application procedure, arranging a place to live, insurance, etc. It was therefore assumed that students doing a project abroad are more likely to encounter study delay. The projects abroad most often involve a minor research internship, major research internships and writing assignments are almost always arranged within our own institute.

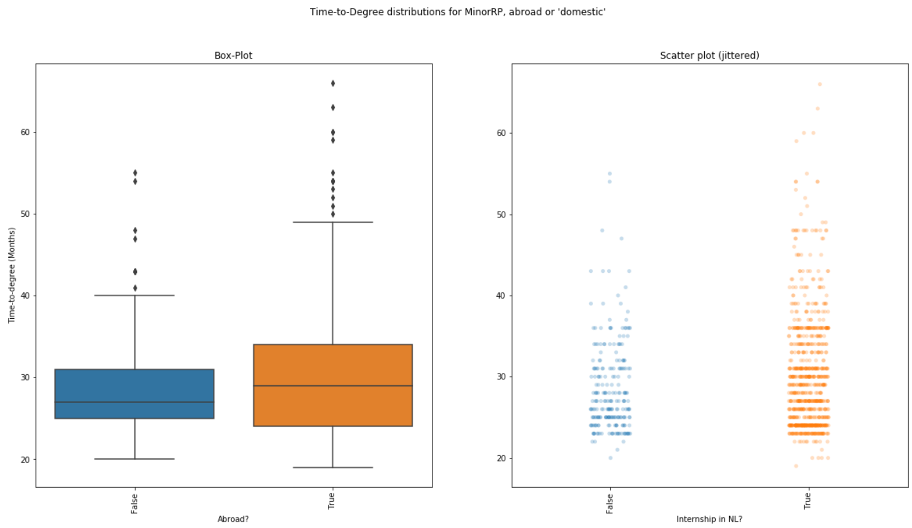


Figure 8: Distributions for time-to-degree for minor research project, for students (not) going abroad.

As shown in Figure 8, the average time-to-degree is comparable for both groups. Meaning that students going abroad for a project are not necessarily at risk for study delay. An explanation for this might be that these students are better aware of all the paperwork and for instance restrictions in time to visit a country (Visa requirements). We hypothesise that this awareness may result in better planning of the components of Masters' education. A second explanation, might be that students doing an internship abroad often are top of the class and are better able to regulate and organize their learning.

In conclusion, doing an internship abroad is not a cause for study delay.

4.5 Conceptualize a dashboard prototype for the LA system to be implemented.

As there is currently no working LA system, we conceptualized a study progress dashboard using data that is commonly available in our student learning management system (Osiris, https://www.caci.nl/en/osiris). The purpose of this dashboard is to provide a tool for study councillors or tutors to support students during their studies. We constructed a dashboard view that tracks student progress over time, and allows for annotation (of results for the three major projects) using additional data resources (qualitative data from rubrics) in the near future.

For generating alerts, we advise to include the following triggers.

- *End date projects*
  In the application procedure, students also indicate an expected end date, in which extension due to theoretical courses are taken into account. This expected end date could be included in the dashboard, and once students pass the predicted deadline, an alert could be raised to the student, and after an additional 3 months an alert could also be raised to student councillors and the program coordinator and supervisor involved.
- *Mile stone mark*
  Data driven analysis indicated that students spend on average 28 months to get their degree. In principle, it should be feasible to earn 60 credits within 14 months. Especially when students start with their major research internship, worth 51 credits, which is usually the case. If student do not manage to have 60 credits at this stage, an alert should be raised to both the student and support staff. (related to the blue line in Figure 9).
- *GPA, thesis grade bachelor or average grade*
  Data driven analysis indicated that previously obtained grades and GPA of previous education correlate with grades for subsequent projects. In the dashboard, a line could be visualised that shows students previous GPA or representative grades. When student's grades for projects or courses are lower compared to their previous achievements, an alert could be raised. (related to the green line in Figure 9)
- *At risk alert*
  Data driven analysis also showed that at risk students score grades below 6.6 for their first project. These relatively low scores should also result in an immediate alert to students to discuss their study approach and the feedback they have received in order to make plans for improvement.

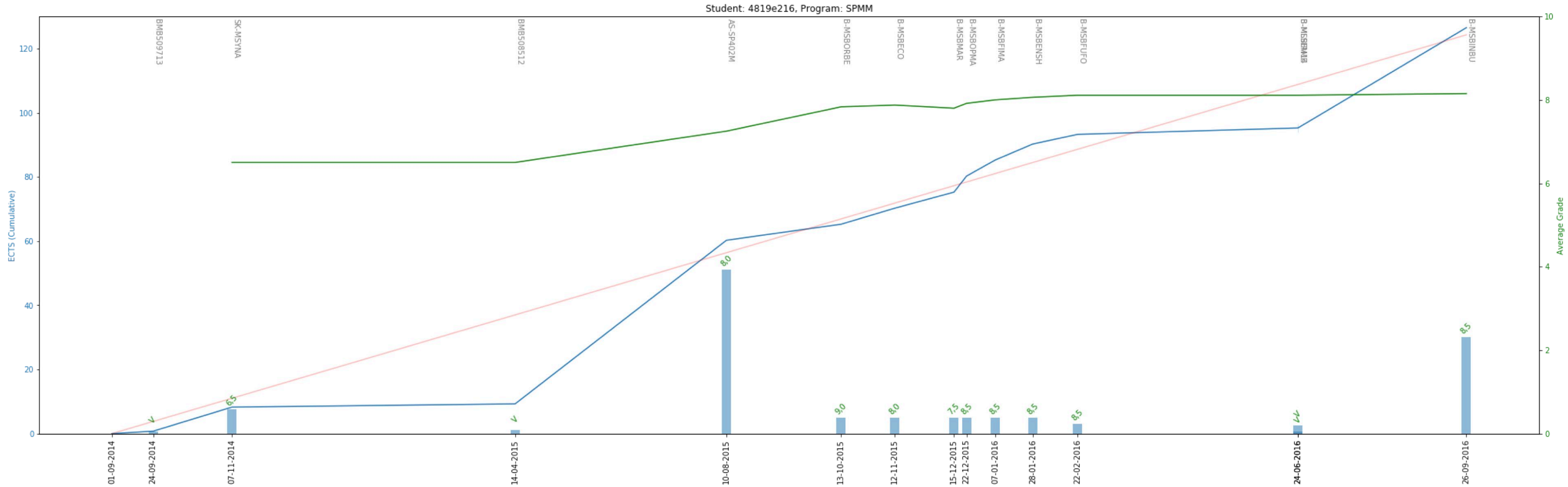


Figure 9: This is an example for a student's timeline within our dashboard concept. It is currently just based on data from the student information system (Osiris). On the x-axis, we find each course the student has taken (with date below, and course code above). The blue bars indicate the amount of study credits (EC) and in green the grade acquired for this course. The blue line is the accumulating amount of EC. The red line indicates the "nominal" study rate (60 EC/year). The green line tracks the student's total average grade.

5. Summarizing conclusion

Ad1 and 2. In masters' education in the Graduate School of Life Sciences, students do a major and a minor research internship, they do a writing assignment and attend theoretical courses. The characteristics of a student being at risk were identified using data driven analysis in combination with the rules and regulations that need to be met in the graduate school. For future risk prediction at the start of a Masters' program (most often students start with a research project), we define a student being at risk when (s)he is likely to obtain a grade of maximum 6.6 on 10-point scale. For these predictions the following overarching parameters must be taken into account

- Grade Point Average of previous degree (BSc)
- Time to previous degree
- Age
- Gender

In subsequent projects, it is relevant to include grade of previous project at Masters' level. For this prediction a second criteria for being at risk is included, knowing a negative grade deviation of 1.0 points compared to average grade previous education of previous project.

Ad 3. A search in literature confirmed that historical achievements are most predictive for success in current and future projects. In addition to the information collected in the LMS, other sources of data for at-risk prediction could include the number of retakes (either successful or not). In the student learning system (Blackboard), institutes could also track student's activity, for instance number and success rate of quizzes, time spent, resources use. These additional parameters are not included in the prototype of our dashboard, but definitively be beneficial to include.

A4. In the hypothesis driven analyses, we aimed to understand why students might be more likely to achieve lower grades or encounter study delay. It turns out that students with an international background obtain similar grades for projects and need comparable time to complete the degree. Also doing part of the program abroad, is not a cause for study delay.

We can confirm that previous performance is predictive for future success. The Grade Point Average of previous education (BSc) is predictive for GPA in Masters' education, and grades for projects within Masters' education are predictive for grades in subsequent projects.

A5. In the prototype of the dashboard the progress of one student is visualized. In the dashboard both the average grade during Masters education, the number credits earned, and the grades and credits per successfully completed project are displayed. In the future, we aim to visualize the progress of one specific student compared to the progress of peers in the same cohort, and otherwise in comparison to historical data that was used in the analyses described in this report. Suggestions for raising alerts are indicated.

6. Discussion/ future plans

The learning management system (LMS) is mainly used as a storage facility and therefore not used to its full potential. For instance, the information that is stored in uploaded PDF files is not directly readable and this information is not extracted from the LMS when doing analysis. We largely recommend that variables such as grades, study credits, start and end date of projects is also stored as written data in LMS.

After severe cleaning of the dataset, we were able to make description of students being at risk at the start of their program, and being at risk for relatively low grades in subsequent projects. The triggers will be even more meaningful when the currently included variables are accompanied with qualitative data. One frequently used data source is a rubric for research skills. Other rubrics provide feedback on writing assignments or presentation skills. The scoring of these rubrics helps students to identify weaknesses in their performance and it would be helpful if supervisors support the student in making concise learning goals for subsequent projects. Efforts are being made to digitize this system of collecting rubric-based feedback, allowing for this data to be integrated in a future learning analytics (LA) system.

An alternative idea, is to combine the progress data obtained via the LMS, with data retrieved via motivation or engagement questionnaires. The aim is to adapt the content of existing workshops to workshops in which students also discuss their study progress and struggles. To stimulate reflection on study progress and performance, we would like students to complete motivation and / or engagement questionnaires before these meetings. In the adapted workshops, a new assignment will be introduced to discuss the outcomes of the questionnaire in relation to study progress and obtained grades.

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