PerActiLA:
Personalized Student Activation through Learning Analytics-based insights about students' learning processes

Combined with

PAELLA:

Personalized student **A**ctivation in **E**ngineering**-**education: **L**everaging **L**earning **A**nalytics for an engaging blended learning course design

Report R5:
The Application of the Interventions

Eindhoven University of Technology

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1. Introduction: The motivational problem in remote online learning

Blended learning, and its online components, play a crucial role in university teaching in the present and the future. The consequences of the Covid-19 transition only underline the vital role of online learning and it is expected that blended learning will remain more prominent in the post-Covid period.

Unfortunately, online learning suffers from several barriers that make life for students more difficult. First, many motivating elements of traditional courses are missing. Students need to develop and maintain a regular schedule, motivate themselves, and persist in their learning activities. Therefore, students' self-regulation of their learning is much more relevant in online courses (Cho & Shen, 2013). Second, the distance between teacher and students is more extensive in online classes than in classes that incorporate regular face-to-face interaction (Rodríguez-Triana et al., 2017). Teachers are less aware of whether students are on track in meeting the course learning goals and of how they experience the teaching. This lack of insight makes it hard to adjust the teaching and quickly intervene when students fall behind in their learning progress. The PerActiLA/PAELLA project aims at helping university teachers to solve this issue.

A promising strategy to empower students consists of interventions that allow for more personalized or differentiated learning. These take into account individual students' deficiencies and difficulties and are expected to be much more effective than general interventions (van Eck et al., 2015). However, since the student-teacher ratio has increased in recent years at Dutch universities, the challenge of how to initiate more personalized learning has become more significant.

The basic idea

As a possible solution to this challenge, **we combine Learning Analytics with personalized instructional (mindset) interventions**. Learning Analytics-based data can be used to provide timely and differentiated feedback on a larger scale (Lim et al., 2021). Both timely feedback and instructional mindset interventions are known to be effective instruments for stimulating students' self-regulation of learning (Burnette et al., 2013; Hattie & Timperley, 2007; Yeager & Dweck, 2012). Moreover, mindset interventions have been successfully scaled up in online settings (Paunesku et al., 2015). Still, they have not yet been applied online in Learning Management Systems (LMSs) in regular blended courses. We plan to apply these personalized mindset interventions via LMSs in four large Bachelor courses, leading to online modules that can be plugged into other courses after their content has been tailored to course-specific student needs.

During the 2010s, many Dutch universities introduced LMSs that automatically collect click-stream data that can potentially be relevant for better understanding the invisible learning processes of students. The recent Covid-19 transition intensified the application of LMSs at Dutch universities to an unprecedented level

- everybody taught and learned (often wholly) online. This creates an enormous source of information that now waits to be exploited to solve the issue of how to activate students' self-regulation of learning through personalized interventions.

In the project, we aim to develop and test a new learning design in four different Bachelor courses. We use click-stream data from the LMS within these courses to push forward *personalized feedback and formative testing* in the Bachelor's program. For selected students with a backlog in their online learning, we aim to offer appropriate *(Mindset) interventions* that stimulate students' self-regulation of learning. For this, we need to address the following challenges:

1. How can we utilize the LMS data to differentiate between students who are on track and those who lag behind in their learning processes? This question is answered in Report 2 and Report 3 of the project.

2. How can we design and apply personalized interventions in LMSs that activate students and stimulate them to better self-regulate their learning? This question is answered in Report 3 and Report 4 of the project.

3. How can we track students in such a way that students' privacy is guaranteed and that they do not feel threatened during online and blended learning? This question is going to be answered in Report 1.

In this report (Report R5), we will discuss the implementation and results of the interventions. First, the data collection will be described. Thereafter, we present the outcomes of the intervention. We focus on two kinds of outcomes:

1. changes in the students' growth mindsets and

2. changes in the students' grades.

For both types of outcomes, we are interested in finding out whether the intervention had an effect (strengthening of growth mindset, higher grade) and, importantly, whether the effect is stronger for at-risk students that were identified via Learning Analytics-based predictive models (see Report R3).

2. Description of the data collection

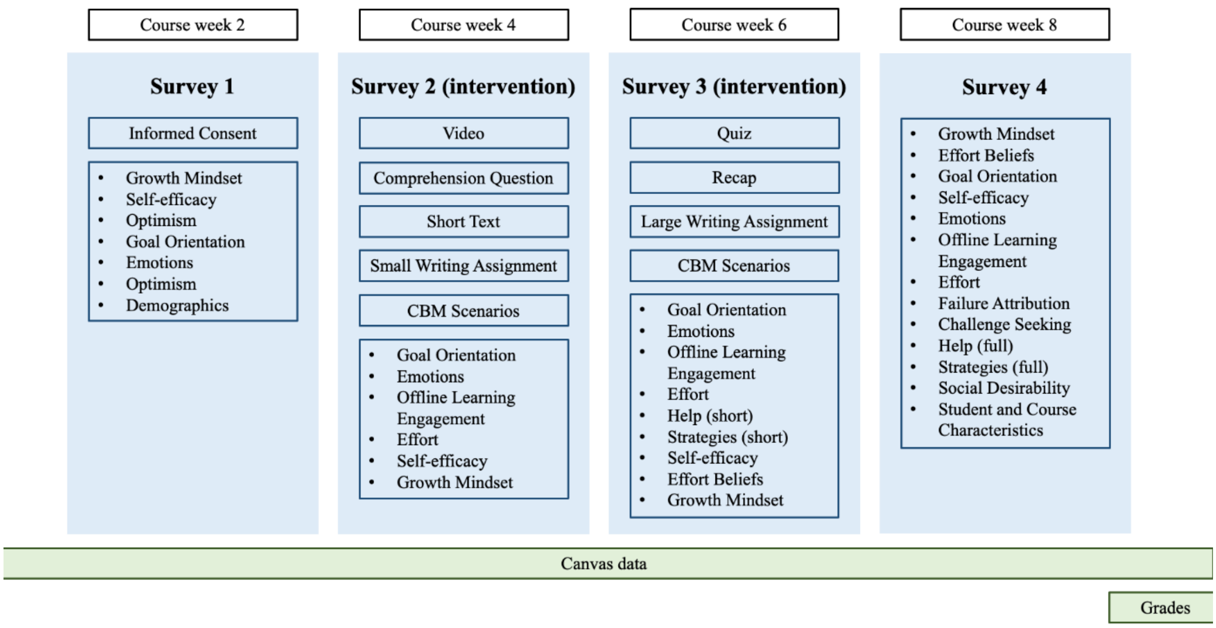
Below, we will discuss how we collected the data for each course. In general, every alternating course week (starting in week 2) the invitation to the survey was sent out at the beginning of the week. A reminder was sent to the students about a week after the invitations were sent out. For each survey, 1 reminder email was sent. These reminders were only sent to students who had not completed the survey. If there were any students who had completed only parts of the survey, they were reminded of their incomplete participation and encouraged to complete it (instead of a general reminder).

2.1 Data collection in course 1

Figure 1 shows a visual overview of the data collection during the first course. In course 1, we used four different survey measurement waves. The middle two surveys (2 and 3) included the intervention elements (for details see Report R4). The overview shows which measurements were included in which wave. Interesting to note is that a selection of indicators was measured in (almost) every wave to be able to investigate the progress of these variables throughout the course. These repeatedly measured variables included students' growth mindset.

In addition to self-reported data, online learning data from Canvas was continuously collected from the week before the start of the course until the end. Grades, including the final exam grade, were collected after the final exam of the course.

Figure 1 Data collection overview course 1



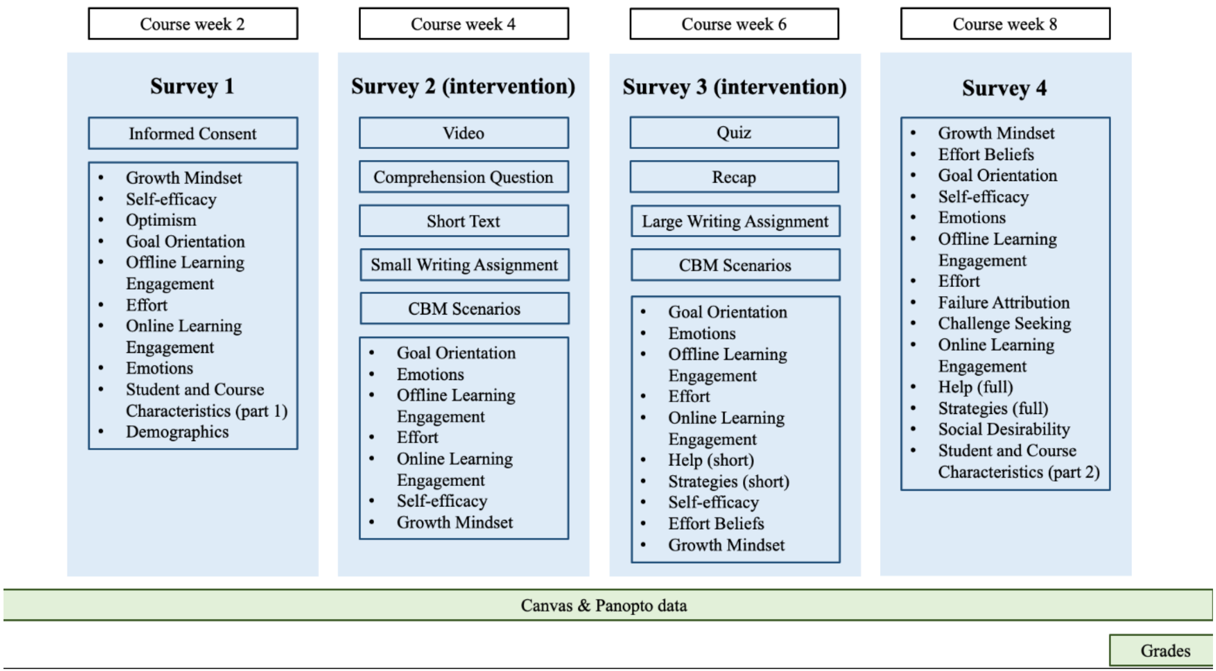
2.2 Data collection in course 2

Figure 2 shows a visual overview of the data collection during the second course. Similar to the first course, in this second course we also used four different survey measurement waves. Again, the middle two surveys contained the intervention elements.

The same repeated measurements as in the first course were also collected for this course. These include students' growth mindset.

Furthermore, in addition to Canvas LMS data, Panopto video-related online learning data was also continuously collected for this course. The video-related data from Canvas as collected in the first course showed some limitations in what we could learn from it. Therefore, we decided to use another source. Grades, including the final exam grade, were collected after the final course exam.

Figure 2 Data collection overview course 2

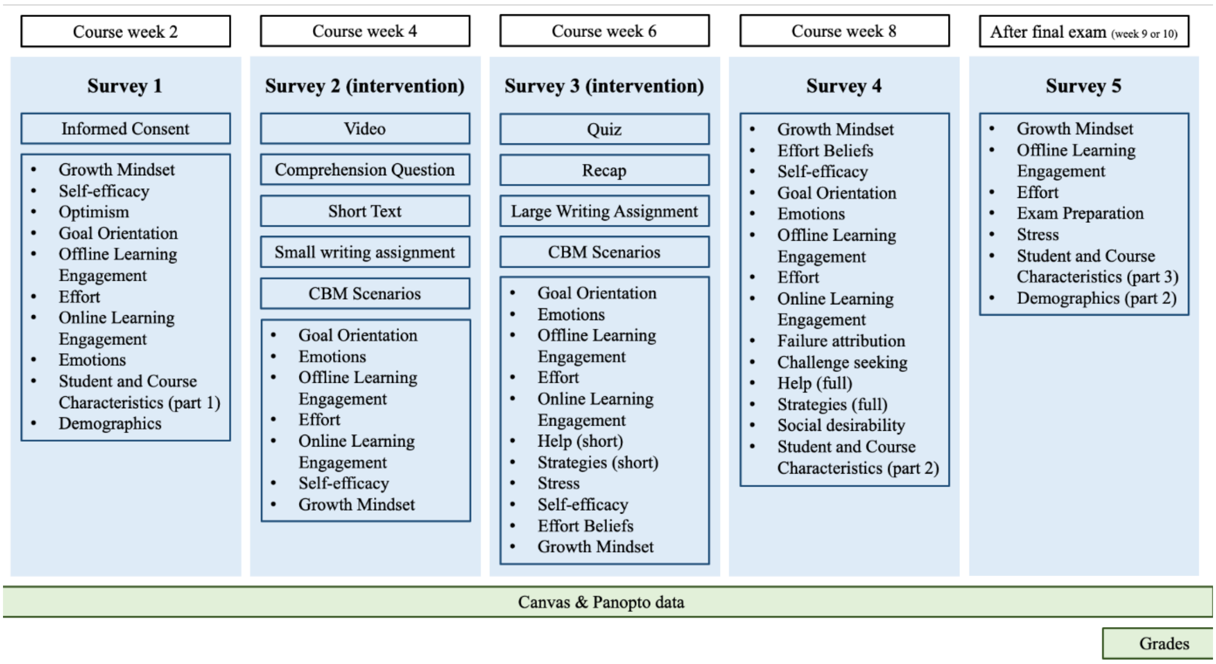


2.3 Data collection in courses 3 and 4

Figure 3 shows a visual overview of the data collection during the third and fourth courses. A major change for the third and fourth courses was that instead of four survey measurement waves, five survey measurement waves were used to collect data for these two final courses. This fifth measurement wave was added to be able to examine changes in mindset after the completion of the course. This final measurement was very short and was sent out just after the final exam. Survey 1-4 remained very similar to the first two courses (with surveys 2 and 3 containing intervention elements).

Similar to the second course, both continuous data from Canvas and Panopto (video-related) were collected. Grades, including final exam grades, were collected after the final course exam.

Figure 3 Data collection overview courses 3 and 4



3. Descriptive results of the data collection

This section will shortly discuss the initial results of the data collection for each course. We present the response rates and sample sizes. Thereafter, we discuss measurements and some other descriptive findings.

3.1 Response rates and sample size

Course 1

For the first course, a total of 111 students participated in the study. This means that 52.6 percent of the course students joined the study (in total 211 course students). Of these 111 participants, 76 completed all four surveys for this course. Other participants either dropped out, joined in later, or completed a selection of surveys. Nevertheless, we can use the answers of these "drop-outs" or "incompletes" as we apply mixed (or multilevel) models in our analyses. These allow us to include the answers of those respondents who did not fill in all four surveys.

Table 1 shows the number of responses per survey. What is interesting is that the later surveys had more participants, indicating that our continued invitations to all students (with a message saying that you could join the study at a later survey) were beneficial to the number of responses received.

Table 1: Number of responses per survey for course 1

	Survey 1	Survey 2	Survey 3	Survey 4
Number of responses	90	95	93	96

total n=111

Table 2 shows the number of participants per condition. Not all students completed an intervention session and were thus not assigned to a condition. Therefore, the numbers do not add up to 111. The final division was close to our intended division of 40-60 (in percentiles), with somewhat fewer students in the placebo condition.

Table 2: Number of responses per condition in the survey for course 1

	Control condition	Growth mindset condition
Number of participants	40	60

total n=100

Course 2

During the second course, a total of 77 students participated in the study. This means that 79.4 percent of the course students joined the study (in total 97 course students). Of these 77 participants, 63 completed all four surveys for this course. Other participants either dropped out, joined in later, or completed a selection of surveys. Table 3 shows the number of responses per survey. We see only a slight drop in numbers from the first survey going to the fourth survey. This second course showed a high percentage of course students participating and a low number of drop-outs.

Table 3: Number of responses per survey for course 2

	Survey 1	Survey 2	Survey 3	Survey 4
Number of responses	71	69	68	66

total n=77

Table 4 shows the number of participants per condition. Not all students completed an intervention session and were thus not assigned to a condition. Therefore, the numbers do not add up to 77. The final division was close to our intended division as described for course 1.

Table 4: Number of responses per condition in the survey for course 2

	Control condition	Growth mindset condition
Number of participants	31	40

total n=71

Course 3

For the third course, a total of 134 students participated in the study. This means that 65.0 percent of the course students joined the study (in total 206 course students). Of these 134 participants, 79 completed all five surveys for this course. (See Report R4 for more details on the number of measurement waves.) Other participants either dropped out, joined in later, or completed a selection of surveys. Table 5 shows the number of responses per survey. There is a large difference between the total number of participants and the total number of complete responses, especially when you compare it to the second course. It seems that there was an especially large drop-off after the first survey. It could be that this course was experienced to have a large workload, leaving students less time to complete all surveys.

Table 5: Number of responses per survey for course 3

	Survey 1	Survey 2	Survey 3	Survey 4	Survey 5
Number of responses	118	98	90	93	96

total n=134

Table 6 shows the number of participants per condition. Not all students completed an intervention session and were thus not assigned to a condition. Therefore, the numbers do not add up to 134. The final division was quite close to our intended division as described for course 1, with slightly fewer students in the placebo condition.

Table 6: Number of responses per condition in the survey for course 3

	Control condition	Growth mindset condition
Number of participants	42	60

total n=102

Course 4

During the fourth course, a total of 153 students participated in the study. This means that 40.8 percent of the course students joined the study (in total 375 course students). Of these 153 participants, 94 completed all five surveys for this course. Other participants either dropped out, joined in later, or completed a selection of surveys. Table 5 shows the number of responses per survey. This final course shows a somewhat lower percentage of students participating than the other courses. It could be that students from other departments are less familiar with this type of research and therefore less interested in participating. In addition, there was also quite a large drop-off for the second and third surveys. Similar to the second course, students could have had a large course workload and thus less time to complete the surveys.

Table 7: Number of responses per survey for course 4

	Survey 1	Survey 2	Survey 3	Survey 4	Survey 5
Number of responses	139	116	103	103	101

total n=153

Table 8 shows the number of participants per condition. Not all students completed an intervention session and were thus not assigned to a condition. Therefore, the numbers do not add up to 153. The final division was close to our intended division as described for course 1, with slightly fewer students in the placebo condition.

Table 8: Number of responses per condition in the survey for course 4

	Control condition	Growth mindset condition
Number of participants	49	70

total n=119

3.2 Measurements

Mindsets

To measure growth mindset, an adjusted version of the original 6-item scale used by Dweck et al. (2000) was used. The original scale only uses the term 'intelligence' to measure growth mindset. However, the current study did not solely focus on intelligence and instead wanted to test a broader definition of intelligence and also include abilities, skills, and knowledge. In addition, the original scale was quite repetitive for the purpose of this study. Therefore, the original items were adjusted to include additionally these three other terms. Furthermore, an additional item was added to this scale, one item specific to the course topic (based on Hoang (2018)). For this scale, participants had to rate each statement on a 6-point Likert scale, in line with the original 3-item mindset scale from Dweck et al. (1995). We used the following items:

1. You have a certain amount of intelligence, and you really can't do much to change it.
2. Your intelligence is something about you that you can't develop very much.
3. No matter who you are, you can improve your abilities a lot.
4. You can learn new things, but you can't really increase your basic intelligence.
5. Some people are good at [neuroscience/statistics/data mining/psychology] courses and other people aren't, it's something you can't substantially change.
6. You can always substantially change your knowledge and skills.

7. No matter how much intelligence you have, you can always enhance it quite a bit.
8. To be honest, you can't really change your abilities.

For all five measurement waves, the scales reached good reliability:

wave 1: alpha=0.78
wave 2: alpha=0.84
wave 3: alpha=0.85
wave 4: alpha=0.83
wave 5: alpha=0.83

Grades

Many interim grades were determined by students' learning processes before or during the intervention. The interventions may not have affected these. Since the overall course grades are to some extent constituted by interim grades, these also are not adequate outcomes to be studied. We have chosen to take the final (written) exam grade as the outcome variable to be studied.

Being at-risk student

We describe in Report R3 in more detail what predictive model we use to identify at-risk students. Our model uses various clickstream indicators of students' use of the Canvas system during the first four weeks. With these, it predicts the students' final written exam grades with an adjusted R-Square of 44.7%. We have used the median grade of 5.4 as the cutpoint and dichotomized the predicted final written exam grades so that two groups of even size result. The group with lower predicted grades constitutes the at-risk students.

3.3 Other descriptive findings

The students' age ranges from 17-26 years, with a (arithmetic) mean age of 20.5 years. 44.6% of the students are female, 53.6% are male, and six students did not reveal their gender. 302 students participated in the full mindset training that was offered at survey moment 2 and survey moment 3. Of these 302 students, only 280 students participated in the final written exam of their course. 39.6% of these students (=111 students) did not pass their exam (grade lower than 5.5). 50.7% of the students achieved a grade not higher than 6. The arithmetic mean of their grades is 5.8 (SD=1.97, min=0.7, max=10). The students' mindsets are measured on a six-point scale, ranging from 1-6, with higher scores indicating a stronger growth belief. A score of 3.5 would indicate that a student neither has a growth nor a fixed mindset. At course week 2, before the mindset intervention took place, the arithmetic mean score of students' mindset was 4.3 (SD=0.63, min=2.6, max=6, n=336), indicating that the students tend to have already some belief in their capability to improve their skills and intelligence. That is, they tend to have more of a growth than of a fixed mindset. At the same time, there is a considerable amount of variation in the students' mindsets as some score rather low (tend to have a fixed mindset) whereas some score very high (tend to have a strong growth mindset). As expected, and as we will show in more detail in the following analyses, there is no difference in the initial mindset between students who have been randomly allocated either to the mindset treatment or to the Placebo treatment.

Summary of descriptive findings

Our first results show that we have reached a high response rate in all courses. The mindset scales have good reliabilities and we have enough students in our sample that could be considered as at-risk students. Students' age, gender, and mindset scores are quite varied while the average student tends to have more growth than a fixed mindset.

4. Effects of the interventions

We first present the findings for the effects on students' mindsets. The effects on students' mindsets can be analyzed at four different moments, namely at measurement moments 2, 3, 4, and (only for course 3 and course 4) at moment 5. Accordingly, we make use of a mixed model that examines whether the intervention had an effect at each of these four moments and whether the effect is stronger for the identified at-risk students.

Thereafter, we present the effects of the intervention on students' grades. In a linear regression, we test whether the intervention had an effect on final exam grades and whether this effect is stronger for at-risk students.

4.1 Effects on students' mindset

Table 9 presents the results of the effects of the intervention on students' mindset. There is no distinction between at-risk versus other students which allows us to examine the success of the intervention in general. Figure 4 presents the findings graphically, with mindsets represented on the y-axis and measurement moment on the x-axis.

Table 9

Results of mixed model for growth mindset over time (M1-M5) for the control and growth mindset intervention condition (log-likelihood = -1066.03; Wald- χ^2 *= 143.41, p < 0.0001)*

	Coefficient	Z	p
Constant	4.33	72.53	<.001
Growth Mindset Intervention	.04	.54	.59
Measurement 2	.12	2.50	.01
Measurement 3	.16	3.37	.001
Measurement 4	.08	1.69	.09
Measurement 5	.05	.82	.41
Growth Mindset Intervention x Measurement 2	.15	2.49	.01
Growth Mindset Intervention x Measurement 3	.24	3.81	<.001
Growth Mindset Intervention x Measurement 4	.26	4.27	<.001
Growth Mindset Intervention x Measurement 5	.21	2.69	.007

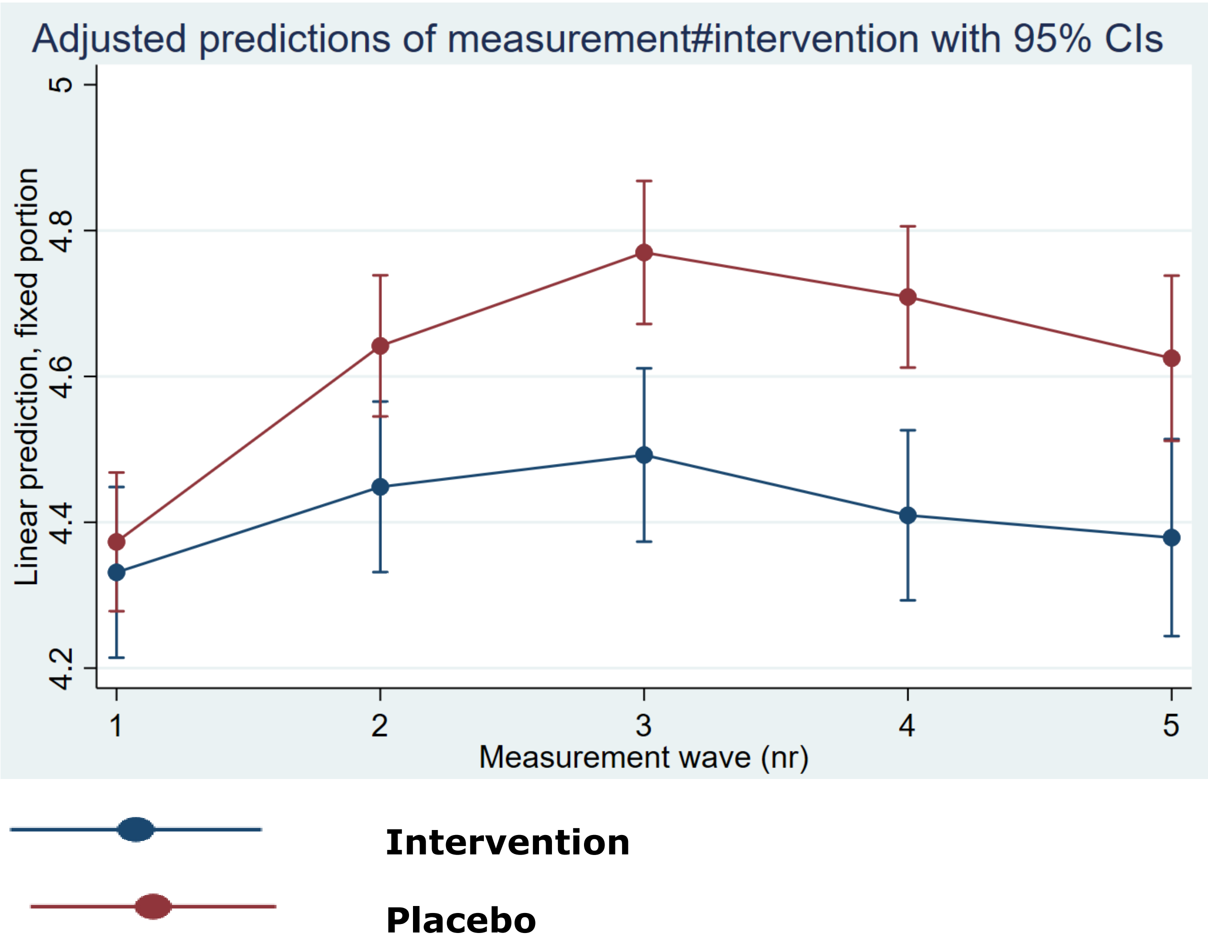
n=369, N=1442, observations per student: min=1, avg=3.9, max=5

Random-effects estimates and confidence intervals

Variance	Estimate (SE)
constant	0.36 [0.03]
Residual	0.14 [0.006]

Figure 4

Marginal estimated means of growth mindset for interaction effects of the model of Table 9 with control (blue) and growth mindset intervention condition (red), y-axis cut of at y=4.2



The findings show that while the two groups of students initially, at measurement 1 in course week 2, had very similar scores on the mindset scale, they diverged significantly until week 10 after the completion of the course. At all four moments after the start of the mindset intervention, the treatment group had significantly larger scores than the Placebo group. The difference becomes larger at moment 3 when the mindset treatment is completely finished, reaches its maximum two weeks after the treatment (measurement 4 at course week 8), and then diminishes after the course completion (measurement 5 at course week 10). We can conclude that the mindset intervention had the expected effect on students' mindsets and strengthened their belief in their potential to improve.

Table 10 and Figure 5 present the results of a very similar analysis. The only difference is that we now make the additional distinction between identified at-risk students versus other students (in addition to students in the mindset treatment versus students in the placebo treatment), leading to four relevant groups.

In Table 10, the variable indicating the at-risk status of students is coded in such a way ("at-risk"=0, "non-at-risk"=1) that we would expect a *negative three-way interaction effect* between measurement x intervention x at-risk. That is, we expect that at the four moments, the mindset intervention would have a smaller effect on non-at-risk students than on at-risk students. (For clarity, the numbers representing the sizes of these four effects are underlined in Table 10.)

The findings show that none of the four interaction effects reaches significance. The sign of the interaction effects varies between the four moments measurement 2, measurement 3, and measurement 4 and none of them is significant. Accordingly, Table 10 does *not support the expectation* that the effect of the intervention would be stronger for the identified at-risk students.

Figure 5 presents the same findings graphically. We can see that the (red) group of identified at-risk students profits from the intervention as their scores increase from 4.45 at measurement 1 to 4.9 at measurement 3. However, the (orange) group of non-at-risk students also increases from measurement 1 to measurement 3 in their mindset scores. Furthermore, while the increase from measurement 2 to measurement 3 seems to be stronger in the group of identified at-risk students and in line with our expectation, the decrease from measurement 4 to measurement 5 also seems to be stronger which is contrary to our expectation. As an additional point, we can see that the group of identified at-risk students in the Placebo condition, too, tended to increase their mindset scores.

Table 10

Results of mixed model for growth mindset over time (M1-M5) for the control vs. growth mindset intervention condition and the students at-risk vs. not-at-risk (log-likelihood = -9013.68; Wald- χ^2 *= 156.24, p < 0.0001)*

	Coefficient	Z	p
Constant	4.30	41.50	<.001
Growth Mindset Intervention	.15	1.14	.26
Measurement 2	.18	2.25	.03
Measurement 3	.30	3.78	.001
Measurement 4	.04	0.53	.59
Measurement 5	.01	.13	.90
Growth Mindset Intervention x Measurement 2	.03	0.32	.75
Growth Mindset Intervention x Measurement 3	.13	1.27	.20
Growth Mindset Intervention x Measurement 4	.35	3.34	.001
Growth Mindset Intervention x Measurement 5	.17	1.44	.15
not-at-risk	.05	.36	.72
Growth Mindset Intervention x not-at-risk	-.19	-1.08	.28
Measurement 2 x not-at-risk	-.09	-.88	.38
Measurement 3 x not-at-risk	-.19	-1.80	.07
Measurement 4 x not-at-risk	.10	.97	.33
Measurement 5 x not-at-risk	.11	.87	.39
GM Intervention x Measurement 2 x not-at-risk	.19	1.41	.16
GM Intervention x Measurement 3 x not-at-risk	.12	.88	.38
GM Intervention x Measurement 4 x not-at-risk	-.14	-1.06	.29
GM Intervention x Measurement 5 x not-at-risk	.05	.28	.78

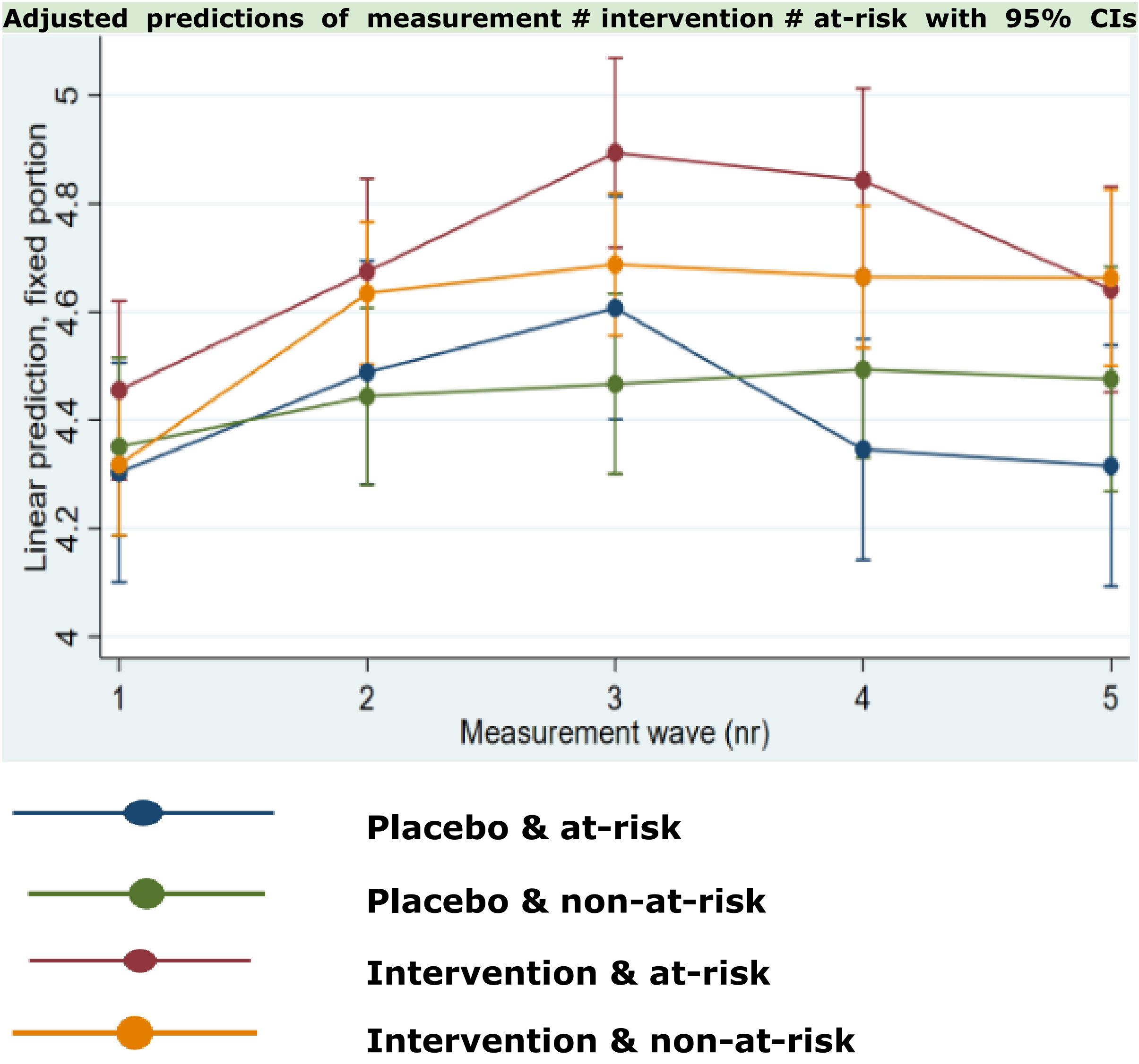
n=316, N=1244, observations per student: min=1, avg=3.9, max=5

Random-effects estimates and confidence intervals

Variance	Estimate (SE)
constant	0.37 [0.03]
Residual	0.14 [0.006]

Figure 5

Marginal estimated means of growth mindset for interaction effects of the model of Table 9 with control & at-risk (blue), control & non-at-risk (green), growth mindset intervention condition & non-at-risk (orange), and intervention condition & at-risk (red), y-axis cut of at y=4.0



4.2 Effect on students' grades

As described earlier, we have 280 students who participated in the final written exam. We use the data of these students to test whether there is a main effect of the intervention on grades and whether the intervention effect differs for at-risk versus other students.

A t-test shows that there is no significant direct effect of the intervention on students grade (mean1=5.83, SD1=.19, n1=113, mean2=5.85, SE2=.15, n2=167, t=.09, p[one-sided]=.53). The treatment group scored only 0.02 grades higher than the Placebo group. The difference corresponds to Cohen's d=0.12. From a statistical point of view, this is between a small and a very small effect size and our sample is not large enough to detect such small effects.

Next, we test whether there is a significant difference in the treatment effect for the group of at-risk versus other students.

Table 11

Results of linear regression on final exam grades (Adj R-Square=.251, F(3.263)=30.78, p < 0.001)

	Coefficient	t	p
Constant	4.67	17.81	<.001
Growth Mindset Intervention	-.30	-.87	.39
Non-at-risk student	1.92	5.69	<.001
Non-at-risk*Intervention	.27	.61	.54

n=267

The results of Table 11 show that only the effect of being non-at-risk is significant. Students who after four weeks have been identified as being not at risk have a significantly higher grade in the final written exam than the at-risk students. The difference in grade scores is 1.92 which is very large. Neither the main effect of the intervention nor the interaction effect is significant.

5. Summary and general discussion

5.1 The problem

Blended and online learning suffers from several limitations that make learning for students more difficult than necessary. First, many elements of traditional courses that motivate students are missing. Students need to develop and maintain a regular schedule, motivate themselves, and persist in their learning activities. Therefore, students' self-regulation of their learning is much more relevant in online courses (Cho & Shen, 2013). Second, teachers are less aware of whether students are on track in meeting the course learning goals and of how they experience the teaching. This lack of insight makes it hard to adjust the teaching and quickly intervene when students fall behind in their learning progress. The PerActiLA/PAELLA project aims at helping university teachers to solve this issue. A promising strategy to empower students consists of interventions that allow for more personalized or differentiated learning. These take into account students' personal deficiencies and difficulties and are expected to be much more effective than general interventions (van Eck et al., 2015).

In this project, we tested the idea of combining Learning Analytics with mindset interventions to create more personalized (mindset) interventions. Mindset interventions are known to strengthen students' motivation, engagement, and grades. Furthermore, there is evidence indicating that mindset interventions have stronger, more beneficial, effects on at-risk students (Burnette et al., 2022, Sisk et al., 2018). A limitation of earlier research is that the identification of at-risk students is not systematically and inconsistently done. Therefore, we tested the idea that a Learning Analytics-based identification of at-risk students in ongoing courses might be useful. Learning Analytics research has shown that it is possible to identify such students early in ongoing courses.

5.2 Our approach and findings

In a nutshell, we proceeded as follows:

As described in Report R1, in line with suggestions from our students, we re-designed four courses to make sure that students are stimulated to engage with the Canvas LMS. The Canvas learning environment was set up to make sure that students generated much clickstream data within the first four course weeks before the intervention took place. The clickstream data was pre-processed to create various variables that could be indicative of different aspects of students' learning processes. Several variables were aggregated per student over the complete course as well as per course week (see Report R2). Most of all, the clickstream indicators of the first four weeks were of potential interest for the generation of predictive Learning Analytics models that could predict at-risk students. In report R3, we describe in more detail how we generated several predictive models. Originally, we planned to use data of the last year of the same course to develop the predictive models. In a second step, these could be used in the actual course with the new data as predictors of at-risk students. Unfortunately, it turned out that this approach did not create models with a high predictive power. Therefore, we decided to model student performance post hoc with the data of the actual courses. We were able to generate a model that could predict the final written exam grade after four weeks with an R-Square of 44.7%. We used this model to identify at-risk students. Furthermore, as described in Report R4, we created online versions of mindset interventions that were tailored to our groups of students. In line with the suggestions of our students (see Report R1), we created for the four courses four course-specific online mindset interventions that "trained" students to strengthen their growth beliefs. The training requires a 40-minute investment of students and can easily be adjusted to the needs of students of other courses (see Report R4). In the final step, we executed the interventions in a randomized field experiment, including a Placebo treatment, to find out whether the interventions had stronger effects on at-risk students. We focused on two potential effects, namely a strengthening of their growth beliefs and their final written exam grades.

The results of the evaluation of the interventions showed the following. The intervention successfully strengthened students' growth beliefs. However, it did not directly improve students' final exam grades, as the grade difference between students in the mindset versus Placebo condition was (almost very) small.

We further tested whether the effects differed between at-risk versus other students. The multivariate analyses did not support our expectation of larger effects for at-risk students, neither for the impact on mindsets nor for the effects on students' grades.

5.3 Discussion and Conclusions

The mindset interventions strengthened students' growth mindsets. Furthermore, as shown in other analyses (Tossaint, 2022), they increased students' learning engagement. The effect on grades was small and, because of the limited sample size, non-significant. Our found effect size on grades (d=.12) is near to the effect found in a recent meta-analysis of Burnette et al. (2022) that reports an average effect size of d=.09. We have too little power.

The analyses distinguishing between at-risk and other students indicate that the interventions worked quite well for both groups. The lack of evidence for stronger effects on at-risk students' mindsets is unexpected. We offer the following potential explanations:

It could be that there is no difference in effects. Earlier research defined at-risk students rather inconsistently and sometimes ad hoc. This might have led to the impression that there are stronger effects for some groups while in reality there are none. Others have criticized inconsistent decisions across studies as well (Macnamara, & Burgoyne, 2023). Further research in the field of mindset research has to conduct more cumulative research on this question.

It could also be that the lack of evidence is the result of insufficient predictive power of the Learning Analytics-based models. The model that we were able to generate after four weeks, predicted 44.7% of the variance in students' final exam grades correctly. It is difficult to judge whether this is already "enough". There are different ways to go to increase the predictive power:

One could decide to wait a bit more with the execution of interventions so that more clickstream data is available. Delaying the intervention is likely to lead to better discrimination between at-risk and other students, but the interventions may then not have enough time to be beneficial within the ongoing course.

Another way to increase the predictive power might be to use more fine-grained data. We aggregated many indicators per week, but a different aggregation level leading to more nuanced clickstream indicators might be better. Also, the video data that we used were aggregated across videos. Measuring a student's viewing behavior per video may be better.

A third way would be to increase the complexity of the statistical models by using other Machine Learning approaches. We used linear and logistic multiple regressions regression trees (sometimes random forest models) and it turned out that the more complex models tended to be somewhat more powerful. Maybe other Machine Learning approaches would increase predictive power. We will continue with further research and will try out the latter two approaches.

5.4 Other beneficial effects of the educational innovation project

The project generated other insights: An important learning point is that seemingly small changes in the course design prevented us from using the last-year instance of a course for the model development. The subsequent instances of the course were too different from each other. Teachers and course designers need to be very careful with such changes.

Apart from the issue of whether different student groups may have different benefits, the educational innovation project demonstrated how it is possible to combine predictive Learning Analytics with educational interventions. University teachers may want to concentrate some educational interventions on at-risk students simply because they do not want to bother other students who do not urgently need additional support.

Related to this, the educational innovation project created another learning point and an educational output that both are important for the further development of our education not just in our department. The use of Learning Analytics-based interventions requires a well-coordinated and intensive collaboration between the ICT department on the one hand and the teachers and researchers on the other hand. We (the research team in our department) developed such a collaboration that turned out to be very fruitful for the advancement of other Learning Analytics applications at our university. To strengthen the sustainability of this advancement, we produced an online tutorial for teachers who are interested in the application of Learning Analytics-based online interventions. The tutorial is not limited to mindset interventions but is applicable to all kinds of educational online interventions and should be of interest to many university teachers. It will be distributed (via SURF, 4TU.CEE, and TU/e) as an Open Access tutorial. In this tutorial, university teachers are walked through the different steps that are needed to apply a Learning Analytics-based educational intervention. We hope that this tutorial helps to improve higher education.

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