Early Warning Systems for More Effective Student Counseling in Higher Education – Evidence from a Dutch Field Experiment

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Background

The absolute number of dropouts in higher education increased considerably in recent years (see for example the increase in entry and completion rates from 2001 to 2012 in: OECD 2003 & 2014). This has led to increased scrutiny of dropout in higher education and movements to hold universities accountable for graduation rates (Bettinger & Baker, 2014).

One way to reduce dropout is to improve the effectiveness of student counseling, since, for instance, proactive individual student coaching was found to improve student retention and graduation rates (Bettinger & Baker, 2014). However, student counselors often have caseloads that can span many hundreds of students (Hughes & Scott-Clayton, 2011), making individualized student counseling difficult, if not impossible.

A promising low-cost intervention that can unburden student counselors by early detection of students at risk of dropping out is an early warning system (EWS). Essentially, an EWS uses machine learning techniques to optimally predict dropout at an early stage and communicates these predictions through reporting tools, like dashboards. Currently, information student counselors can act upon (e.g. student grades) is frequently accessed at a stage in the academic year where it might be too late to rectify any problems. Providing student counselors with an EWS that flags at-risk students allows them to timely intervene, which might result in dropout reduction.

Several dashboards have been developed over the past years to support learning or teaching (Verbert, Duval, Klerkx, Govaerts, & Santos, 2013). However, not many of them are evaluated, especially not in terms of student dropout. One exception is the EWS Course Signals, which improved retention rates when it was used in at least one course (Arnold & Pistilli, 2012).

Research Objective

This study evaluated whether the implementation of an EWS at a university to assist student counselors reduced dropout or increased obtained course credits. For this purpose, a randomized field experiment was conducted.

Setting

The experiment was conducted in 2016 at the Vrije Universiteit Amsterdam in the Netherlands, which is one of the two large publicly-funded universities in Amsterdam. During the academic year, student counselors could proactively invite low-performing students for individual meetings based on the information displayed by the student analytics monitor (the EWS). At the end of the academic year, students were asked to fill in a follow-up questionnaire online and counselors were interviewed.

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Participants

In this study, 758 first-year students (57% female) enrolled in 12 study programs participated, of whom 125 (16.5%) filled in the follow-up questionnaire. In total, 34 student counselors participated.

Intervention

The intervention group received EWS-assisted counseling throughout the whole academic year, while the control group received counseling as usual. A student analytics monitor was built to inform counselors on their students' probability of dropping out. Counselors received a monitor of the intervention group students every week and were free to use this monitor in their counseling as they saw fit. The monitor showed for each student their probability of dropping out and additional information on their motivation and performance (see Figure 1). The counselors received a training on the content of the monitor. After each study term the dropout prediction was updated based on new data (obtained study results).

This probability of dropping out is based on a dropout prediction model developed on data of the first-year student cohorts of 2013 and 2014. The dropout prediction model was trained using 5-fold cross validation on 85% of the 2014 cohort data, and tested on the 15% hold out set and on the 2013 cohort data. Several models were tested and the best predictive model, the Generalized Additive Model, was selected based on its lowest mean absolute error (MAE); the smallest mean difference between predicted probability to drop out and actual dropout. At each term of the academic year, the model includes the variables that are most predictive of dropout.

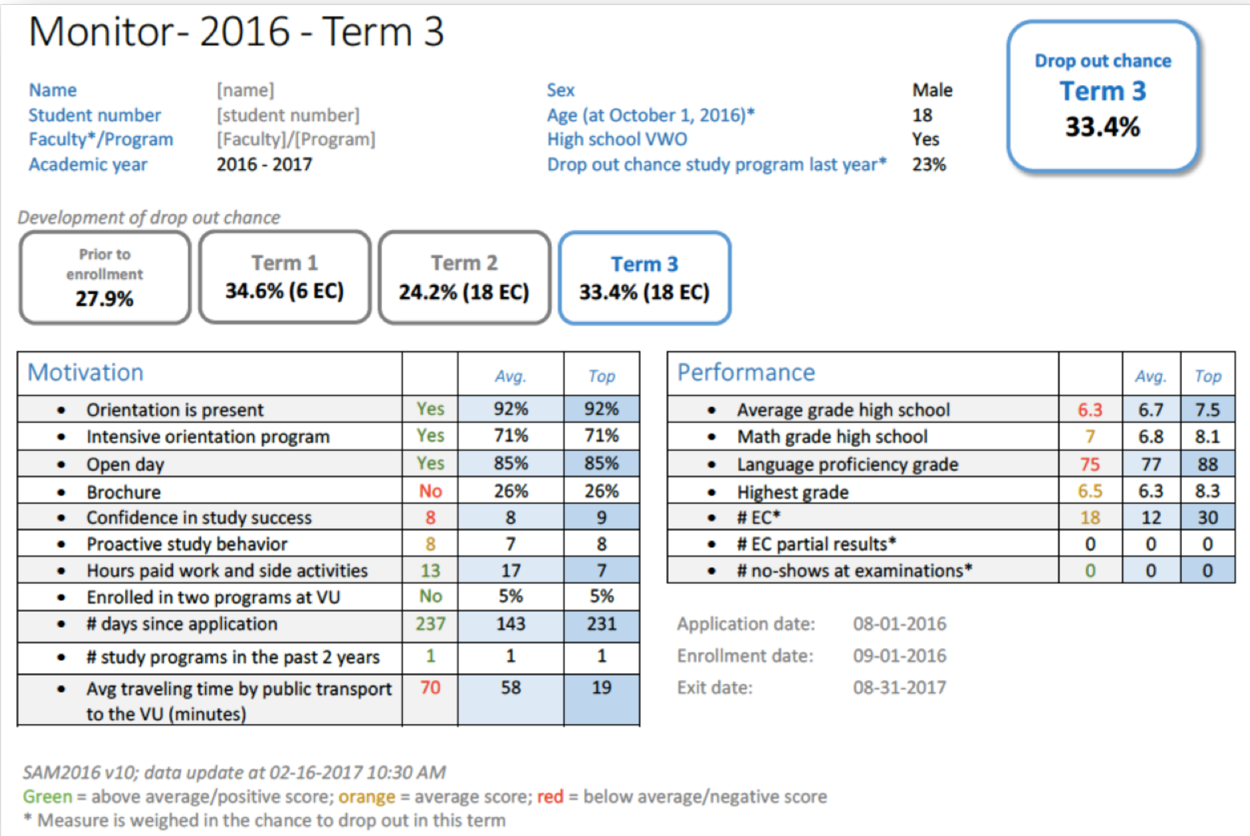

Figure 1. Example of the student analytics monitor.

Research Design

To obtain an unbiased estimate of the effect of EWS-assisted counseling, the participating students were randomly assigned to the intervention or control group as follows. For each study program, all students were ordered descending on the exact moment of consent. Per study program, either a 1 or a 0 was randomly sampled with equal probability. If the drawn number was a 1, the first student was assigned to the intervention group, the second student to the control group, the next to the intervention group, and so on; if the sampled number was a 0, the first student was assigned to the control group, the second student to the intervention group, and so on.

Thereafter, all students were individually informed within one week by e-mail about their assignment. Counselors were informed on which students were assigned to the intervention group, but not on students assigned to the control group.

Data Collection and Analysis

We use register data to monitor study progress (e.g. obtained credits, and retention). Additionally, we use student characteristics and study program controls to get a more precise estimate of the intervention effect, and we use survey data to examine students' experiences with counselors and whether they acted on the counselors advise.

To test the effect of EWS-assisted counseling on both dropout and obtained credits we will perform OLS regressions and cluster standard errors by participating study programs. We will step wise add student and study characteristics to the models, to increase precision of the intervention effect estimate.

Results

Table 1 shows that EWS-assisted counseling did not have an effect on dropout, and Table 2 demonstrates no effect on total obtained credits at the end of the academic year. These findings suggest that EWS-assisted counseling has no effect on student retention and educational attainment.

The follow-up questionnaire demonstrated no differences between the intervention and control group. For instance, no differences were found in number of meetings with a counselor. Interviews showed that student counselors did not pro-actively invite students at risk of dropping out, because they either had not enough time or mentioned that they expected students not to show up.

	(1)	(2)	(3)
EWS-assisted Counseling	0.041 (0.033)	0.047 (0.035)	0.048 (0.036)
Constant	0.224*** (0.019)	0.322*** (0.044)	0.249*** (0.035)
Student Controls		✓	✓
Study Program Control			✓
R^2	0.002	0.145	0.160
N	758	758	758

Table 1

*Three OLS regressions - when (1) no controls are included, (2) student characteristics are included, (3) student and study characteristics are included in the model - to determine the effect of the treatment (EWS-assisted counseling) on dropout. */**/*** denote significance at a 10/5/1 percent confidence level (two-sided). Standard errors are given in parentheses.*

	(1)	(2)	(3)
EWS-assisted Counseling	-1.970 (1.401)	-2.420* (1.471)	-2.431 (1.495)
Constant	44.668*** (1.337)	40.452*** (2.349)	45.383*** (1.553)
Student Controls		✓	✓
Study Program Control			✓
R^2	0.002	0.228	0.274
N	758	758	758

Table 2

*Three OLS regressions - when (1) no controls are included, (2) student characteristics are included, (3) student and study characteristics are included in the model - to determine the effect of the treatment (EWS-assisted counseling) on total obtained credits. */**/*** denote significance at a 10/5/1 percent confidence level (two-sided). Standard errors are given in parentheses.*

Conclusions

The findings suggest that providing student counselors timely with information about students' risk of dropping out together with students' background characteristics does not reduce dropout or increase obtained credits. Early identification of at-risk students is useful as it can support student counselors, but risk identification does not imply that the underlying problem that causes poor performance is identified. Moreover, the results show that the number of interactions does not become higher in the presence of an EWS.

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