An Evaluation of the Brightspace Student Success System

Introduction

I have chosen to review the Brightspace Student Success System learning analytics tool by D2L. The University of Manitoba currently uses the Brightspace Learning Management System (LMS) and this additional service could complement existing university infrastructure. As an instructional designer in the Faculty of Extension at the University of Manitoba I have an interest in improving outcomes for our learners.

The Brightspace Student Success System is an early intervention tool that promises to improve learner retention, success, and graduation rates using predictive analytics and machine learning techniques. The promotional material explains instructors are given advanced knowledge of at-risk students as well as students that could benefit from additional challenges through interactive visualizations.

Further research on the D2L website inevitably leads to dead ends with instructions to contact a sales representative. This makes information about the tool hard to find and consequently my analysis relied heavily on a user-guide in the D2L community forum. A review of the Student Success System was conducted based on an evaluation framework that blends the approaches of Cooper (2012) and Scheffel et al. (2014).

Analysis subjects, objects, and clients	Analysis subjects: students Analysis clients: course instructors Analysis objects: student LMS activity
Data origin	Private raw data is collected from the LMS. The scale of data is reasonable given that most of it is already being collected. The tool is also capable of incorporating demographic data student records from SIS. The data that is analysed is listed below.
	 course access (# of logins) content access (how often the learner accesses content topics and modules within a course) social learning (engagement in the discussion forums) assessment performance (grades) preparedness (information from SIS including admission scores and demographics data)
Orientation and Objectives	Historical data from previous offerings of a course are used to generate predictions of learners success for future offerings of that course.

Characteristics

	Orientation: this has multiple orientations including "future" facing orientation that focuses on prediction, a present orientation that includes potential alerts for interventions, and a past/reflective orientation that reviews historical course data and performs a diagnostic function. Objective type: Performance (course completion, engagement, and achievement)
Outputs	Student at risk widget for instructors identifies individuals.
	Class dashboard provides total students at risk, potential risk, and successful categories with trend arrows.
	Outputs in three predictive charts:
	 Success index is mapped on a quadrant divided into four areas On-Track/ Not at Risk Under Engagement Risk Withdrawal/Dropout Risk Academic Performance Risk - engaged but not doing well Social Learning Predictive Chart A web of connections based on interactions in the discussion tool. The learner's circle size is proportional to the amount of interaction. Assessments Compact visual of learner assessment compared to peers
Technical approach	Supervised machine learning in combination with basic descriptive statistics and dashboard visualization
Embedded theories and reality	The promotional materials for the tool do not mention pedagogy. They make the bold claim that the entire system is adaptive to the instructional approach of each course. One could presume that they are claiming this system could work in a constructivist classroom or any other approach. There is no evidence provided for this claim. The promotional materials and community resources do not include references to peer-reviewed research but there are two case-studies of success stories at other universities.

Organizational Aspects

The preparedness data (prior academic achievement and demographics) would probably not be available to input into the tool. Continuing education students do not have the same entrance requirements as degree studies and some students enter without any post-secondary experience. Demographic data from SIS would be hard to integrate because it is on a different service. The current system is quite old and is likely to be updated soon. This could be an opportunity to integrate but is also a reason to pause on choosing LA tools before the new system is selected. The predictive model would be difficult for courses that run sporadically with different instructors. Implementation across instructors and staff of this advanced LA tool would be difficult. The basic LA tools that are currently available in the LMS are not being used is a significant way or even consistently between instructors, programs, and staff.

Extended education is different from degree studies. Our students are unique and our approach to education focuses on applied learning with authentic tasks and formative feedback. Despite claiming broadly that the tool can accommodate any approach to education there was not any substantial proof that it would be appropriate for our courses. There might not be enough data for it to analyse and build a predictive model. If at-risk students are identified there might not be any useful intervention available. For example our students are typically highly motivated and those that do withdraw often have life circumstances such as a dying parent or issue at work that that an intervention will not solve.

There is one area within EE that might one day benefit from this tool. The Access program in EE provides holistic support to students that might experience barriers that prevent them from enrolling or succeeding in regular university entrance. The majority of their course work is done F2F and the role of relationships is extremely important. This type of early warning or intervention is probably inferior to the personalized instruction, advising, and counselling already in place. It may be worth exploring to see if this tool could support what they're already doing but it may be difficult to convince staff to take on an additional burden of setting up and using the system if they will not see a return on their investment.

Recommendation

The lack of transparency in the promotional materials and the missing academic rigor behind the advertised benefits make me wary of recommending this tool. The case studies provide good examples of how the tool can be used at the University of Manitoba but they are not peer-reviewed. The details are sparse and the case studies do not refer to other academic research. The claim that the tool can adapt to the individual pedagogical approach of each course seems very unlikely without sufficient evidence. The tool very well might be able to spot students at risk of failing because they haven't logged in for awhile or posted. Machine-learning is not required to reach this common sense conclusion. The existing tools in the LMS for example could be setup to notify the instructor when a student has not logged in for a week or is currently failing the course. It would be very difficult to build a case strong enough for the cost of the tool and the required time and training to get it set up.

My recommendation would be to increase the uptake of existing LA tools that we already have access to in Brightspace before purchasing additional tools.

References

Cooper, A. (2012). A framework of characteristics for analytics. *CETIS Analytics Series*, 1(7). Bolton, JISC CETIS.

D2L. (2016). Brightspace Student Success System Instructor Guide. Retrieved from https://community.brightspace.com/servlet/fileField?entityId=ka5610000090DsAAI&field=At tachment Body s

- D2L. (2019). Brightspace Student Success System. Retreived from <u>https://www.d2l.com/products/student-success-system/</u>)
- D2L. (2019). Brightspace helped Oral Roberts University improve retention. Retrieved from https://www.d2l.com/customers/oral-roberts-university/
- Scheffel, M., Drachsler, H., Stoyanov, S. & Specht, M. (2014). Quality Indicators for Learning Analytics. *Journal of Educational Technology & Society*, 17(4), 117-132.