Jisc briefing

Learning analytics and student success – assessing the evidence

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Overview

This briefing summarises some of the **published** evidence for the effectiveness of learning analytics initiatives. It builds on the findings of our 2016 report "*Learning Analytics in Higher Education: a review of UK and international practice*".[1]

It highlights that there is an increasing number of studies using control groups that show that retention and other measures of student success can be positively influenced by the use of learning analytics to identify students at risk, combined with an effective intervention programme.

There is a growing literature base around learning analytics and its impact on student grades and retention, often referred to as measures of 'student success'. Many institutional initiatives are still at an early stage, and it can be difficult to find concrete evidence of their effectiveness. The use of learning analytics is still relatively recent in the UK – this study therefore focuses principally on institutions in the United States and Australia, where use of learning analytics is more mature.

This document examines some of the analytics projects which have reported on their impact so far. There is anecdotal evidence that some of the most successful projects to date have been in the US for-profit sector, where it can be easier to achieve change than in more traditional institutions. However, these findings remain unpublished due to the fact that they are seen as commercially sensitive.

One caveat regarding the evidence below is that it can be difficult to isolate the influence of the use of learning analytics; it is often part of wider initiatives to improve academic achievement and develop more data-informed approaches to learning and teaching enhancement. The studies detailed below however attribute enhanced retention and student success primarily to the deployment of learning analytics products.

[1]

1 Sclater, N., Mullan, J. & Peasgood, A., 2016, *Learning Analytics in Higher Education: A Review of UK and International Practice*, Jisc. jisc.ac.uk/reports/learning-analytics-in-higher-education

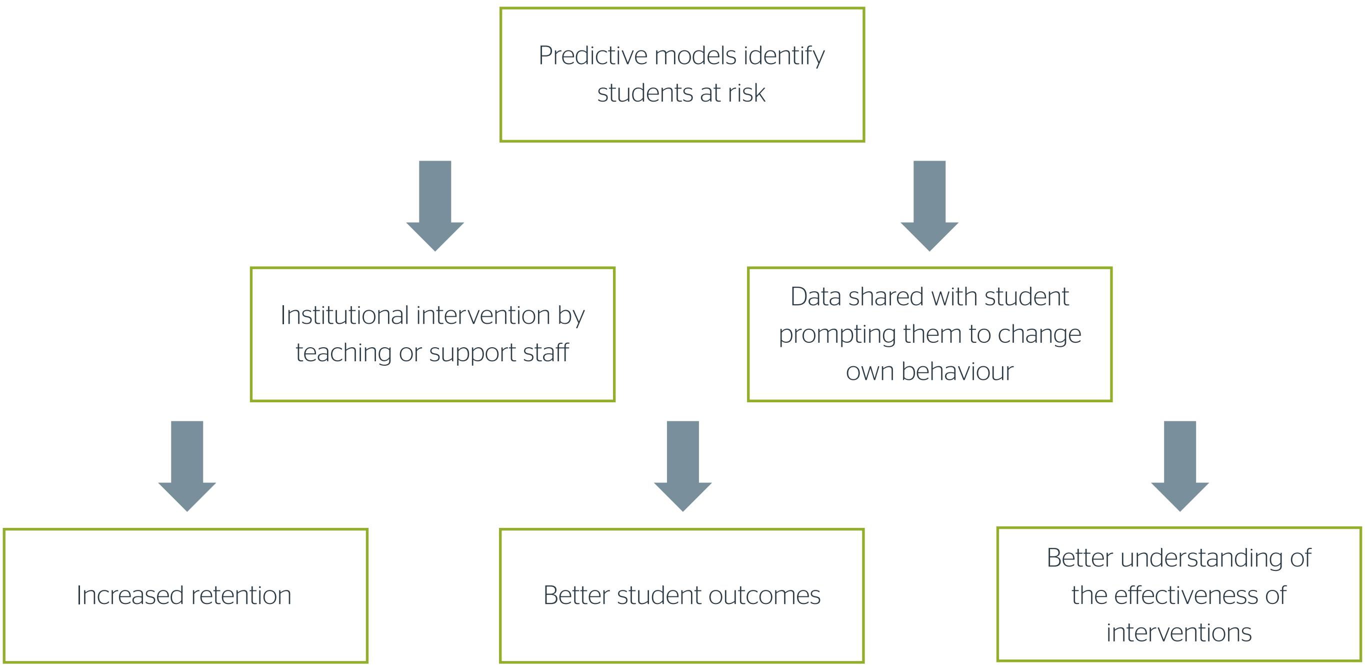
How predictive learning analytics works

Learning analytics initiatives increasingly draw data from across the institution into a single **learning records warehouse**. This might include usage data from the library and the virtual learning environment, as well as attendance records and grade data.

A **learning analytics processor** then compares data on individual learners with current and historical data to identify any students who might be at risk of attrition or not meeting their full academic potential. This data can be made available to teaching and support staff, students themselves and on an aggregate level to management.

Jisc provides an open learning analytics architecture to higher and further education institutions in the UK, including a learning records warehouse, which will enable institutions to benchmark their data. Vendors of leading analytics systems are now integrating their products with this architecture.

Learning analytics can lead to improved student outcomes in a number of ways – summarised in this diagram, and explored in more detail in the text below.



Accurate predictive models identify students at risk

Learning analytics systems enable universities to track individual student engagement, attainment and progression in near-real time, flagging any potential issues to tutors or support staff. They can then receive the earliest possible alerts of students at risk of dropping out or under-achieving.

Researchers have demonstrated that the predictive models used by learning analytics systems can be valid. The models are developed with historical data from previous cohorts of students, examining their patterns of activity and how these correlate with subsequent academic achievement.

» At New York Institute of Technology, **recall of their predictive model is 74%;** in other words, approximately three out of every four students who do not return to their studies the following year are predicted as at risk by the model. This high recall factor is reported to be due to the choice of model, careful testing of alternatives and the inclusion of a wider range of data than other similar models: financial and student survey data were included in the model as well as pre-enrolment data[2]

» Civitas Learning reports from a study of 23 institutions using their products that **student engagement with the virtual learning environment (VLE) is highly predictive of success**, even in the institutions where most courses are offered primarily face-to-face. The type of activity that is predictive varies between institutions – in some the use of forums is important, while in others views of course content are more relevant. In one institution they found that the most significant predictor of student success for first year students was the percentage of days that they logged onto the VLE during the first 14 days of the term[3]

» VLE use is considered a proxy for student effort, which is why it is such a strong predictor of final grades. At California State University Chico it was found that **VLE variables were more than four times as strongly related to achievement as demographic ones such as gender, race and income**[4]

» Although many institutions develop their own specific models rather than adopting those created elsewhere, a key finding of the Open Academic Analytics Initiative led by Marist College, New York was that **the models developed at one institution can be transferred to very different institutions, while retaining most of their predictive abilities**[5]

Monitoring of sub-groups of students

Learning analytics is also being used as a tool for assessing and addressing differential outcomes among subgroups of the student population – with some institutions monitoring the engagement and progress of eg BME students or students from low participation areas. The University of Derby, for example, has used analytics to ensure that its support of black and minority ethnic (BME) students was evidence-based – developing a recipe book of interventions for academic staff which appeared to have improved the performance of BME students.[6]

[1]

2 Agnihotri, L. & Ott, A., 2014, Building a Student At-Risk Model: An End-to-End Perspective, *Proceedings of the 7th International Conference on Educational Data Mining.*
3 Civitas Learning, 2016, Emerging Benchmarks & Student Success Trends From Across The Civitas, *Community Insights*, 1(1).
4 Whitmer, J., 2012, *Logging On to Improve Achievement: Evaluating the Relationship between Use of the Learning Management System, Student Characteristics, and Academic Achievement in a Hybrid Large Enrolment Undergraduate Course*, University of California, Davis, p 90.
5 Jayaprakash, S. M. et al., 2014, Early Alert of Academically At-Risk Students: An Open Source Analytics Initiative, *Journal of Learning Analytics*, 1(1), p 41.
6 Sclater, N., 2014, *Learning Analytics: The current state of play in UK higher and further education*, Jisc, p 23.

Effective institutional interventions

It is only when actions are taken with students on the basis of the data that the true value of learning analytics becomes clear.

» At the University of Nebraska-Lincoln **the four year graduation rate increased by 3.8% in four years** after a student success system (Hobsons Starfish) was deployed. The Chancellor believes the product was "a 'game changer' for transforming UNL's climate for undergraduate advising and academic support services."[7]

» Similar results are reported at Columbus State University College, Georgia, where **course completion rates rose 4.2% (and 5.7% for low-income students)** after the deployment of Starfish.[8] Meanwhile, at Youngstown State University, Ohio (where 56% of students are first generation higher education students, and 88% receive financial aid) **completion rates increased from 81.1% to 86.8% in three years**, after the same product was implemented[9]

» At the University of New England, New South Wales, **the drop-out rate was cut from 18% to 12%** during early trials of their "Automated Wellness Engine", which analyses data from seven corporate systems every night and runs a model based upon 34 triggers identified as suggesting at-risk behaviour[10]

Control group studies

A number of institutions have carried out studies involving control groups, which appear to demonstrate some of the most convincing evidence for learning analytics to enhance retention and other measures of student success.

» In one course at Marist College there was a **significant improvement in final grade (6%)** with those at-risk students who were subject to an intervention compared with those in the control group, who were not[11]

» At Strayer University, Virginia contact with **the students identified as most at risk in one learning analytics pilot resulted in a 5% increase in attendance, 12% increase in passing and 8% decrease in attrition – compared to a control group**[12]

» At the University of South Australia 730 students across a range of courses were identified as at risk. **Of the 549 who were contacted, 66% passed with an average Grade Point Average (GPA) of 4.29. 52% of at risk students who were not contacted passed with an average GPA of 3.14.** This appears to be a significant finding, implying that intervention strategies with struggling students could be extremely important for institutions: if you are identified as at risk but left alone you are not only considerably more likely to fail but your result is likely to be much worse too[13]

[1]

7 Hobsons, 2016, Starfish Results [Presentation file provided by Hobsons].
8 Ibid.
9 Hobsons, 2016, Youngstown State University: Connected Support Results in Improved Course Completions starfishsolutions.com/client/youngstown-state-university
10 Davis, D., 2015, Altis Consulting: HE Information Management Specialists. Presentation to the UK Learning Analytics Network, Edinburgh, UK, April 2015. http://bit.ly/effective-learning-analytics
11 Jayaprakash et al, Early Alert of Academically At-Risk Students: An Open Source Analytics Initiative.
12 Civitas Learning, 2016, *Learning Brief: Strayer University*. http://ji.sc/civitas-learning-space
13 Siemens, Dawson & Lynch, *Improving the quality and productivity of the higher education sector: Policy and strategy for systems-level deployment of learning analytics*. p 20.

» In another study, Purdue University's predictive analytics system, Signals, was evaluated on *student performance*, measured by final grades, and *behaviour*, indicated by interactions with the VLE and help-seeking behaviour. Using two semesters of data it was seen that, in those courses which deployed Signals, there were **consistently higher levels of Bs and Cs obtained than Ds and Fs**.[14] Meanwhile, in a biology course a Signals pilot produced 12% more B and C grades than among students not involved in the pilot, and 14% fewer D and F grades[15]

In addition, it appeared that when students became aware of their risk level, **they tended to alter their behaviour**, with resulting improvements to their performance. **Students in pilot groups sought help earlier and more frequently than those not taking part.** Even after the interventions stopped, these students were seeking assistance 30% more often than those in the control group.[16]

Improving the efficacy of interventions

Once a student has been flagged as being at risk, learning analytics can also help universities understand which interventions work best. By using proxies to measure student engagement in near-real time, institutions can examine how effective an intervention is proving with each individual soon after commencement of their studies.

At a time when there is increasing focus on the efficacy of spending on access and student success, this can help institutions to review and demonstrate the effectiveness of their student support. We expect learning analytics data will inform improvements to the guidance and support available across the board to whole cohorts of students, as well as interventions offered to students at risk.

[1]

14 Pistilli, M. D., Arnold, K. E., 2010, Purdue Signals: Mining Real-Time Academic Data to Enhance Student Success, About Campus, p 24.

15 Arnold, K., 2010, Signals: Applying Academic Analytics, EDUCAUSE Review, 3 March.

16 Ibid.

Student awareness of risk can lead to changes in behaviour

One report proposes that complex data visualisations, dashboards and other support for learners on the basis of learning analytics may not be necessary.

Experience at Marist College of directing at-risk students to a sophisticated support environment suggests that **simply making them aware that they are at risk may suffice**.[17]

There also appears to be an impact on grades for those students who are able to view *comparative* data on their engagement and progress. At University of Maryland Baltimore County **students who used a tool to compare their VLE activity with that of other students were 1.92 times more likely to be awarded grade C or higher compared with students who did not use it.**[18]

At Nottingham Trent University, in a survey of first year students, **27% said that they had changed their behaviour in response to data** on their learning analytics dashboard. Some students carried out more academic activities, eg independent learning, although this is not measured in the dashboard. Others competed with each other to have the highest engagement score.[19]

[1]

17 Jayaprakash et al, Early Alert of Academically At-Risk Students: An Open Source Analytics Initiative.
18 Fritz, J., 2013, Using Analytics at UMBC: Encouraging Student Responsibility and Identifying Effective Course Designs, Louisville, CO: EDUCAUSE Center for Applied Research.
19 Foster, Ed, 2015, What have we learnt from implementing learning analytics at NTU? Jisc Learning Analytics Network, Nottingham Trent University. http://bit.ly/Foster-Ed-2015

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