Learning Analytics in Higher Education

A review of UK and international practice
Full report

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“Learning Analytics in Higher Education: A review of UK and international practice”

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Executive summary

Every time a student interacts with their university – be that going to the library, logging into their virtual learning environment or submitting assessments online – they leave behind a digital footprint. Learning analytics is the process of using this data to improve learning and teaching.

Learning Analytics refers to the measurement, collection, analysis and reporting of data about the progress of learners and the contexts in which learning takes place. Using the increased availability of big datasets around learner activity and digital footprints left by student activity in learning environments, learning analytics take us further than data currently available can.

This report documents the emerging uses of learning analytics in the United States, Australia and the United Kingdom. Through a series of eleven case studies it presents an overview of the evidence currently available of the impact that analytics are having on teaching and learning – and highlights some of the opportunities for the UK higher education sector. Given the current focus on teaching excellence in the higher education sector, it will be of interest to policy makers and institutional leaders alike.

A survey of Vice chancellors published last year by PA Consulting suggests Vice chancellors perceive the UK to be lagging behind, with 60% believing that the important innovations in student data analytics are taking place primarily overseas.

However, the UK is now starting to wake up to the possibilities that learning analytics provides. In their recent report, **From Bricks to Clicks**, the Higher Education Commission concluded that analytics had "enormous potential to improve the student experience at university" and recommended that all institutions consider introducing an appropriate learning analytics system.

Jisc is currently working with 50 universities in the UK to set up a national learning analytics service for higher and further education. This is the first time learning analytics has been deployed at a national level anywhere in the world, creating a unique opportunity for the UK to lead the world in the development of learning analytics.

Although, learning analytics is still at a relatively early stage of development there is convincing evidence from early adopters that learning analytics will help to improve outcomes.

The case studies presented in this report are a snapshot of some of the most prominent institution level learning analytics initiatives worldwide. Together they provide evidence that:

- researchers have demonstrated the validity of the predictive models used by learning analytics systems
- the interventions carried out with students have been effective
- there are other benefits to taking a more data-driven approach to higher education provision

Extrapolating from current practice, in the UK and internationally, we anticipate that learning analytics could make significant contributions in the following areas:

1. **As a tool for quality assurance and quality improvement** - with many teaching staff using data to improve their own practice, and many institutions proactively using learning analytics as a diagnostic tool on both an individual level (e.g. identifying issues) and a systematic level (e.g. informing the design of modules and degree programmes).

   In our response to the Higher Education Green Paper, we outlined how learning analytics could contribute to the Teaching Excellence Framework. In the first instance we expect that learning analytics data could be used by institutions as part of their submission of evidence to support applications for the higher levels of TEF. In the medium term, we will explore with the sector whether learning analytics data might be used to create appropriate new metrics.

   Similarly, we envisage learning analytics data will also be useful for institutions in demonstrating compliance with the new quality assurance arrangements being developed in England, which will require more regular review of outcomes and evidence of action taken by institutions to deal with issues.

2. **As a tool for boosting retention rates** – with institutions using analytics to identify at risk students – and intervening with advice and support – at an earlier stage than would otherwise be possible.

3. **As a tool for assessing and acting upon differential outcomes among the student population –** with analytics being used to closely monitor the engagement and progress of sub-groups of students, such as BME students or students from low participation areas, relative to the whole student body, prior to assessment results being made available. Additional support can be provided to identified individuals from underperforming groups to improve attainment. At the University of Derby, analytics are already being used to ensure that decision making on supporting black and minority ethnic (BME) students is evidence-based.

4. **As an enabler for the development and introduction of adaptive learning –** i.e. personalised learning delivered at scale, whereby students are directed to learning materials on the basis of their previous interactions with, and understanding of, related content and tasks.

Purdue University, Indiana, United States

Identifies potential problems as early as the second week of term.

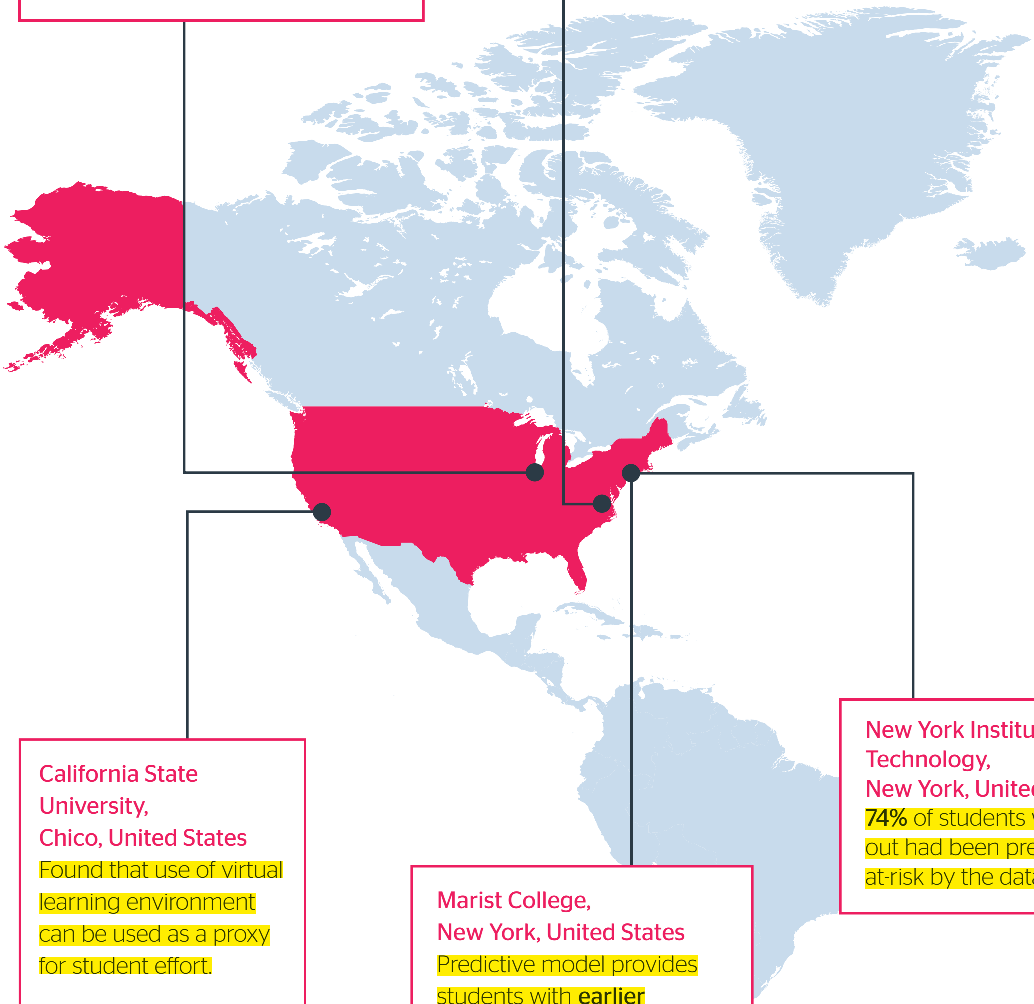
Users seek help earlier and more frequently.

Led to **12%** more B and C grades. **14% fewer** D and F grades.

University of Maryland, United States

Students who obtain low grades use the VLE **40%** less than those with C grades or higher.

Used to identify effective teaching strategies which could be deployed on other modules.



California State University, Chico, United States

Found that use of virtual learning environment can be used as a proxy for student effort.

VLE use explained **25%** of the variation in final grade – and was **four times** as strongly related to achievement as demographic factors.

Marist College, New York, United States

Predictive model provides students with **earlier feedback** - allowing them to address any issues before it is too late.

6% improvement in final grade by at-risk students who received a learning intervention.

New York Institute of Technology, New York, United States

74% of students who dropped out had been predicted as at-risk by the data model.

Nottingham Trent University, UK

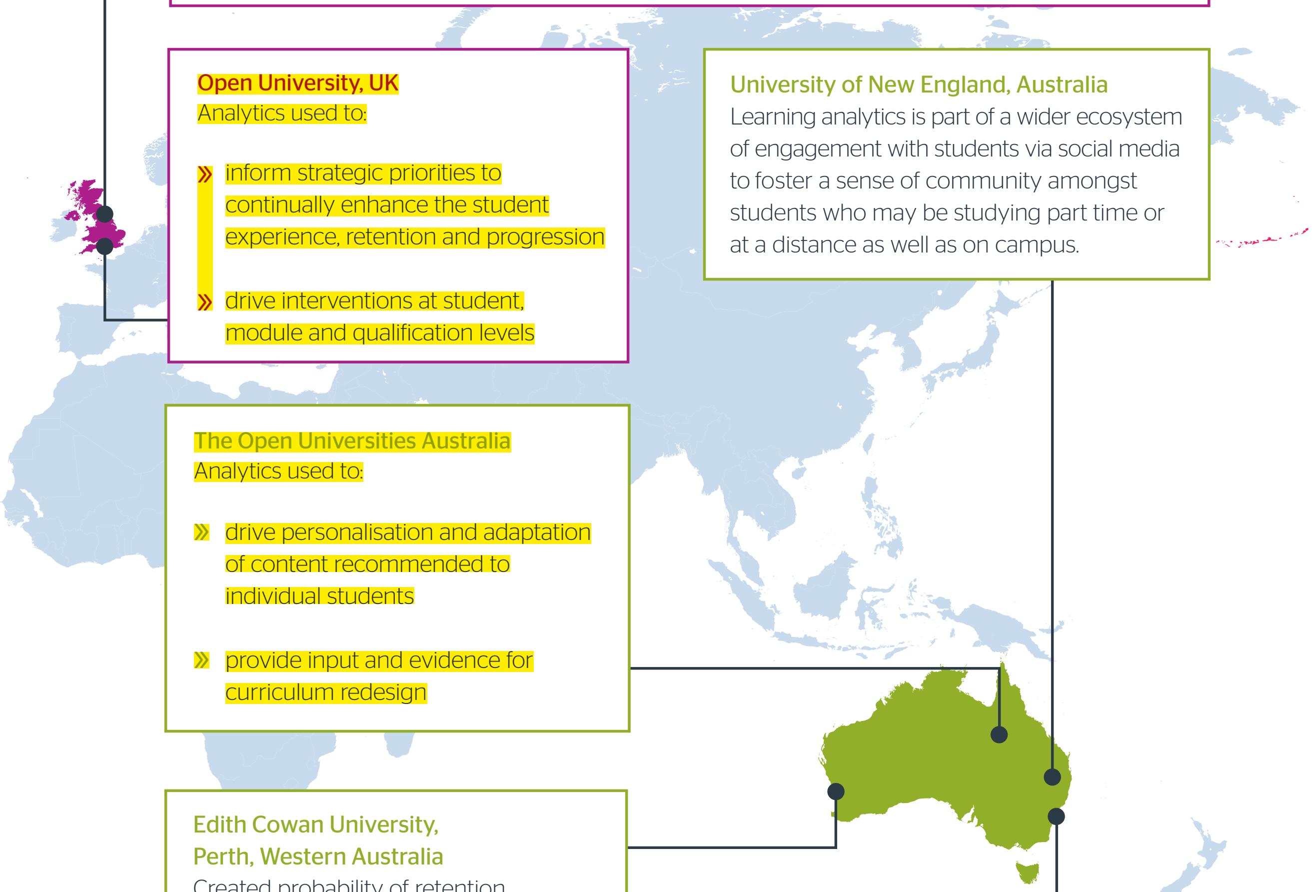
Strong link with retention- less than a quarter of students with a low average engagement progressed to the second year, whereas over **90%** of students with good or high average engagement did so.

Strong link with achievement - **81%** of students with a high average engagement graduated with a 2:1 or first class degree, compared to only **42%** of students with low average engagement.

27% of students reported changing their behaviour after using the system.

Received a positive reception among students and staff.

One third of tutors contacted students as a result of viewing their engagement data in the Dashboard.



Open University, UK

Analytics used to:

- inform strategic priorities to continually enhance the student experience, retention and progression
- drive interventions at student, module and qualification levels

University of New England, Australia

Learning analytics is part of a wider ecosystem of engagement with students via social media to foster a sense of community amongst students who may be studying part time or at a distance as well as on campus.

The Open Universities Australia

Analytics used to:

- drive personalisation and adaptation of content recommended to individual students
- provide input and evidence for curriculum redesign

Edith Cowan University, Perth, Western Australia

Created probability of retention scores for each undergraduate student – used to identify students most likely to need support.

Wollogong University, Australia

SNAPP visualises participant relationships in online discussion forums in real time, as a network diagram. It helps facilitators to avoid dominating the conversation and encourage greater engagement with students who are less connected with their peers in the forum.

Use and impact of learning analytics: lessons from the case studies

(1) Improving the quality of teaching

Analytics have been used to improve teaching

The value of dashboards for enhancing teaching or future course provision is also highlighted by the studies. At the University of Wollongong, Australia, social network analysis revealed interaction patterns that arise in forums that are too facilitator-centric.

At the University of Maryland, it was found that innovations which led to improvements in student performance on one course appeared to lead them to also perform better in subsequent courses.

Meanwhile learning analytics can furnish teaching staff with better information on the quality of the educational content and activities they are providing, and on their teaching and assessment processes, to enable its continual enhancement.

Obtaining better data on the student experience potentially enables an institution to identify and address issues of concern to learners such as inadequate feedback. Universities are reporting that these interventions can help to build better relationships between students and staff.

Analytics can be used by lecturers and tutors to monitor the performance of their students while the module is taking place; they can then adapt their teaching if, for example, they identify that students are struggling with a particular topic. Other analytics on student data takes place retrospectively, enabling future cohorts of students to benefit from enhancements to educational content and processes.

Wider benefits

The roll out of learning analytics may have broader institutional impacts on learning, teaching and student support. At The Open University the aim is develop an 'analytics mindset' across the institution and to base decision making increasingly on evidence. At Nottingham Trent too it is reported that the project has helped to extend a culture of data-driven decision making across the University.

Implementing learning analytics is often one strand of a wider institutional strategy, although even a small scale pilot can generate increased awareness and discussion around issues such as retention. In some implementations good practice has been identified at the individual tutor or module level that was previously invisible within the wider institution. Thus analytics can have beneficial effects beyond the immediate aims of the project, and can be part of a cultural change towards more evidence based decision making.

Dashboards may have other benefits beyond the retention of students and the enhancement of teaching: at Nottingham Trent the Dashboard is reported to have helped build better relations between learners and personal tutors.

(2) Boosting retention

A better understanding of data about learners and their learning can help universities to tackle high attrition rates, which result in adverse impacts on the lives of those affected, and wasted expense for the institutions.

Analytics can identify struggling students earlier

By merging information known about individuals in advance, such as their prior qualifications, with data accumulated about their educational progress, learners likely to withdraw can be identified earlier than in the past. At Purdue University in the United States, for example, problems are identified as early as the second week in the semester, something which simply was not possible before.

Student data analytics can be used to be predict which students will not progress to the next academic year. At New York Institute of Technology (NYIT), approximately three out of every four students who do not return to their studies the following year had been predicted as at risk by the model. Similarly, analysis of data from Nottingham Trent University showed that less than a quarter of students with a low average engagement score progressed from the first to the second year, whereas over 90% of students with good or high average engagement scores did so.

Analytics have had a positive impact on retention
Once an at-risk student has been identified, personalised interventions such as advice or support from a tutor can then be taken to help to try to retain those students.

Some examples of interventions include student-facing dashboards which contain tools that show the student's progress relative to their own goals or to the rest of the cohort. In some cases, this is found to motivate students, although other examples indicate, perhaps unsurprisingly, that the more confident and successful students tend to use the tools to a greater extent than struggling students.

At the University of New England for example **attrition was cut from 18% to 12%** during early trials of their Automated Wellness Engine.

The Signals project at Purdue University is one of the earliest and most frequently cited learning analytics implementations. Later projects have refined the modelling techniques, developed intervention strategies or transferred predictive models to other contexts. Use of the Signals system led to at 14% reduction in the number of D and F grades.

(3) Enabling students to take control of their own learning

Giving students better information on how they are progressing and what they need to do to meet their educational goals is another important application for learning analytics.

Meanwhile some universities are providing analytics-based systems to help students to select future modules, building on data about their career choices, aptitudes and grades for previous modules to provide optimum pathways through their studies.

Analytics have been perceived positively by students

Learning analytics can provide students with an opportunity to take control of their own learning, give them a better idea of their current performance in real-time and help them to make informed choices about what to study.

Learners overall seem to like having better data provided to them on their progress. 89% of students in one survey at Purdue considered Signals a positive experience, while 74% said their motivation was increased by using it. At Nottingham Trent some learners report that seeing their own engagement is a positive spur to stay engaged. Indeed, NTU have reported that the provision of learning analytics is now expected by students.

Objections by students to the use of their data for learning analytics are not widely reported in the case studies or in other literature. In the UK, the National Union of Students has been largely positive about developments in this area, described learning analytics as having "massive power and potential to tackle some of the problems and challenges that currently exist in UK higher education."

Conclusions

Learning analytics has the potential to transform the way we measure impact and outcomes in learning environments – enabling providers to develop new ways of achieving excellence in teaching and learning, and providing students with new information to make the best choices about their education. The UK should grasp this opportunity to lead the world in the development and use of learning analytics.

Learning analytics is still at a relatively early stage of development, but the processes for developing its use, and ensuring the authenticity and validity of the findings, are developing rapidly. Although not yet well understood yet across the sector, there is convincing evidence that learning analytics will help to develop more student-focussed provision of higher education, and provide data and tools that institutions will be able to use for continuous improvement. We believe that continued investment in learning analytics by the UK higher education sector will lead to better outcomes for students, universities and wider society.

1. Introduction

Across business, industry, government and other areas of human endeavour, vast amounts of data are being accumulated and processed to develop understanding of people's activities, and to optimise organisational processes and outputs.

The use of data mining and business intelligence software to analyse their customers and products is now key to the survival and expansion of organisations across many sectors. In higher education large datasets exist about learners, their learning and the environments in which they study. Universities are however only beginning to understand how to exploit this to enhance the educational experience for their students. While there are some promising examples in the UK, this country is slipping behind the US and Australia in particular, where the new discipline of learning analytics is gaining increasing prominence among educators and policy makers.

Motivations for use of student data

A number of drivers make it imperative for universities to obtain value from the rich data sources they are building up about their learners. Much of the impetus for learning analytics worldwide comes from increasingly stretched university budgets and a need for evidence based prioritisation of spending. While student fee income has to some extent alleviated financial pressures in English higher education, strong incentives remain to deploy resources spent on learning and teaching as efficiently and effectively as possible. Meanwhile students, as consumers, will increasingly, and justifiably, expect to be able to see evidence that their fees are being spent appropriately.

Many universities have unacceptably high attrition rates, resulting in adverse impacts on the lives of those affected, and wasted expense for the institutions. There is a resulting drain on the economy, not least by increasing the number of student loans which may never be paid back.

By merging information known about individuals in advance, such as their prior qualifications, with data accumulated about their educational progress, learners likely to withdraw can be identified earlier than in the past. Personalised interventions such as advice from a tutor can then be taken to help to try to retain those students. Better retention helps in numerous ways, not least in reducing the necessary expenditure on marketing and recruitment, and improving individual universities' positions in league tables (Arnold, 2010).

While not all institutions have problems with retention, educators are likely to have an interest in maximising the academic performance of their students and enhancing the overall experience of attending their institutions. This of course is likely ultimately to impact on league table positions and reputation, and thus improve recruitment.

Learning analytics can furnish teachers with information on the quality of the educational content and activities they are providing, and on their teaching and assessment processes. Some analytics are used by lecturers to monitor the performance of their students while the module is taking place; they can then adapt their teaching if for example they identify that students are struggling with a particular topic. Other analytics on student data takes place subsequently, enabling future cohorts of students to benefit from enhancements to educational content and processes.

Benefits for learners

Learners themselves, particularly when beginning higher education, often have little idea of how they are performing in comparison with others, have gaps in prerequisite knowledge, and lack key study skills. Giving students better information on how they are progressing and what they need to do to meet their educational goals is an important application for learning analytics. This has the potential to transform their learning and their understanding of how they learn by giving continual formative feedback as they progress through their studies. It also enables them to compare themselves to peers, adding a competitive element (an important motivator for many students) and a check that they are keeping up with the group or with the progress of successful students in previous cohorts. Meanwhile some universities provide analytics based systems to help students select future modules, building on data about their career choices, aptitudes and grades for previous modules to provide optimum pathways through their studies.

Adaptive learning systems are emerging to help students develop skills and knowledge in a more personalised and self paced way. These too may depend on data about a student's aptitude and performance, together with fine grained details of their clickstream, enabling the educational content to be tailored to their level of understanding as they progress through it. While these systems may be inappropriate for certain aspects of higher education, particularly the development of higher order research and communication skills, they are set to revolutionise the teaching of basic skills and the provision of educational content. This data can also provide better understanding for educators of how their content is being used and how effective it is, and enable its continual enhancement. The student activity data can in turn be aggregated and combined with other educational data to give a richer picture of the effectiveness of learning programmes at successively higher levels in institutions, to programme managers, deans, senior management and ultimately education authorities and government.

Developments in the UK

A number of institutions in the UK are deploying learning analytics in different ways and for a variety of reasons. A study was commissioned by Jisc in late 2014 which analysed the innovations in learning analytics in the UK (Sclater, 2014). The research found that early adopters were driven by a desire to enhance the student learning experience for reasons such as improving achievement and reducing the number of resits, providing better feedback, and empowering students to become more reflective learners. Some institutions had significant issues with retention and saw learning analytics as a way to identify students at risk of dropout; for others retention was not a significant problem. Providing students themselves with better information on their progress was also mentioned as being an important driver.

An issue several institutions raised was the requirement to provide information on the attendance of foreign students to UK Visas and Immigration. This required capturing attendance data in various ways, which can be an effective proxy for student engagement and hence bring the additional benefit of being able to identify students, both foreign and local, who are struggling. Another clear external driver mentioned by some institutions was the National Student Survey; obtaining better data on the student experience potentially enables an institution to identify and address issues of concern to learners such as the provision of feedback. Manchester Metropolitan University attributed a nine per cent increase in student satisfaction over two years to its efforts to reorganise its curriculum based on better analysis of student requirements.

Learning analytics is seen by some universities as a way of enhancing teaching, in particular by encouraging more timely marking of student work, and helping to build better relationships between students and staff. For several institutions the focus was on putting the analytics tools in the hands of staff who work directly with learners, and providing them with actionable insights into student performance. At Nottingham Trent University it was found that tutors were putting effort into supporting students who requested help but missing those who most needed it. A key aim of learning analytics there was to help identify students at risk before it was too late to intervene.

A number of institutions mention varying levels of achievement among different ethnic groups or genders and describe how they are using analytics to identify and attempt to provide additional support to individuals from underperforming groups. The University of Derby used analytics to ensure that its decision making on supporting black and minority ethnic (BME) students was evidence-based. It developed a handbook of good practice for academic staff which appeared to have improved the performance of BME students. Nottingham Trent aimed to develop more fine-grained understanding of the factors which lead to a particular minority struggling. A group may have more difficulties with one subject than another, and individuals within a group do not necessarily conform to its characteristics, so the aim was to develop a highly personalised approach to the provision of student support.

As well as a few high profile institution level deployments there are various examples of small scale initiatives in UK higher education to analyse data on students and their learning activities. These often fail to scale up, however interest among senior management in the potential of learning analytics to address strategic issues appears to be growing rapidly. A recent study by the UK Heads of Elearning Forum (HeLF) of 53 institutions found that the main focus of interest around learning analytics in UK universities is on retention and the enhancement of learning, with equal importance being placed on both.

The same study found that nearly half of the institutions surveyed have not implemented learning analytics at all, roughly a third are working towards implementation and a fifth have partially implemented it. The report also mentions that three quarters of senior management had limited understanding of the benefits of learning analytics and that awareness and understanding vary widely across departments within institutions (Newland et all, 2015).

2. Learning analytics: a new and rapidly developing field

Defining learning analytics

Learning analytics combines expertise from different academic disciplines such as educational data mining and predictive modelling. In 2007, Campbell et al discussed the opportunities for 'academic analytics' to address some of the growing challenges in US higher education such as poor retention rates. Learning analytics began to coalesce as a discipline its own right around 2010 (Ferguson, 2012), while academic analytics is now regarded as being more concerned with aspects of institutional business such as recruitment, and less related to learning itself. The Society for Learning Analytics Research (SoLAR) was formed, and adopted probably the most oft-quoted definition of learning analytics:

> *Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs.*
> **Siemens & Gašević, 2012**

There are overlaps across the three rapidly developing fields but educational data mining, learning analytics and academic analytics are increasingly diverging. Educational data mining is focused primarily on the technical challenges of extracting value from learning-related big data. Learning analytics is concerned with enhancing aspects of learning, while academic analytics focusses more on utilising data for marketing and administrative purposes (Ferguson, 2012; Long & Siemens, 2011). The field of learning analytics is influenced by a wide range of disciplines including education, psychology, philosophy, sociology, linguistics, learning sciences, statistics, intelligence and computer machine learning/artificial science. The two most dominant disciplines (by far) of the key researchers in the field are computer science and education (Dawson et al, 2014).

Can analytics predict academic success?

The idea that measurement of student participation through VLE accesses, submission of assessments and other data can be used as a proxy for learning and hence likely academic success is one of the key concepts of predictive learning analytics. Many studies confirm the assumption that those students who participate more are likely to perform better. A model produced at St Louis University in Missouri, for example, showed that student access to learning content and the gradebook correlated with their final grade. However, this was considered an unsurprising finding which did not provide any useful insights which could be used to support learners (Buerck & Mudigonda, 2014). Some reports have even suggested that the highest levels of participation do not correlate with the best results; sometimes the most engaged students appear to be the weaker ones who are working particularly hard to try to improve their performance (e.g. see the Nottingham Trent case study - A9 - in this report).

A report by SoLAR, funded by the Australian Government's Office for Learning and Teaching (Siemens, Dawson & Lynch, 2013), contains ten brief case studies from some of the most prominent learning analytics initiatives in Australia, the US and the UK. It is notable that few of the projects yet claim any significant impact from learning analytics – and many seem still to be at early stages of implementation. One exception is Queensland University of Technology's early intervention programme which the report states "has resulted in significant improvements in retention for those students who have been successfully contacted". However, no data is provided to back up this claim.

One of the case studies in the SoLAR report however has some concrete data and significant outcomes: 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. The dearth of such data overall in the literature and rigorous, empirical, replicable studies however makes it difficult yet to justify any grand claims for the impact of learning analytics. The case studies provided in this report highlight the work of some of the leading institutions which have provided evidence of effectiveness.

Papamitsiou & Economides (2014) attempt systematically to analyse the empirical evidence for learning analytics and data mining by examining the literature on case studies between 2008 and 2013. They identified 209 relevant papers in international journals and conferences but narrowed these down to forty based on the number of citations, the degree of innovation, the quality of the methodology and adequate presentation of the findings.

From this they created an analysis of the strengths, weaknesses, opportunities and threats identified in the literature.

» **Strengths** include large volumes of available educational data, the ability to use powerful, pre-existing algorithms, the availability of multiple visualisations for staff and students, increasingly precise models for adaptation and personalisation of learning, and growing insight into learning strategies and behaviours

» **Weaknesses** are the potential misinterpretation of the data, a lack of coherence in the sheer variety of data sources, a lack of significant results from qualitative research, overly complex systems and information overload

» **Opportunities** include using open linked data to help increase compatibility across systems, improving self-reflection, self-awareness and learning through intelligent systems, and the feeding of learning analytics results to other systems to help decision making

» **Threats** discussed are ethical and data privacy issues, “over-analysis” and the lack of generalisability of the results, possibilities for misclassification of patterns, and contradictory findings

3. How learning analytics works

As educational activity moves online, and content accessed by students is increasingly digital in format, the data sources available to analyse learning are expanding.

Data sources

Much of this is 'big data', datasets which are regarded as being too large for standard database systems to handle (Manyika et al., 2011). The main source being used for learning analytics is the VLE, where students increasingly have to go to view timetables, assessments and course information, access learning materials, interact with others through forums, and submit assignments. The use of the VLE varies considerably across modules, courses and institutions. Where it is used as the primary means of course delivery in for example distance learning programmes or MOOCs it is likely to provide a rich source of data.

Learning analytics can still however provide useful insight on student engagement in courses which do not use a VLE. The second major data source is the student information system (SIS), which contains data about students such as their prior qualifications, socio-economic status, ethnic group, module selections and grades obtained to date. This is all potentially valuable information to bring together with VLE activity data in order to predict academic performance. Data from the VLE and SIS is frequently supplemented by other information. In some institutions attendance monitoring systems are in place which record campus visits by students or their presence in particular locations such as lecture halls, libraries and refectories. This can be captured from swipe cards, proximity cards and other entry systems, or from accesses to institutional Wi-Fi services by students.

Library data too can be added to the mix. Information such as a students' library visits, records of book borrowing and access to electronic journals is provided to personal tutors in some institutions on dashboards for facilitating conversations with individuals or groups. For example analytics of historical data for a module may show that success is associated with frequent access to library resources. If analytics on the current cohort show that fewer students than expected have so far visited the library, an instructor can bring this to the group's attention, with the intention of modifying the students' behaviour. They can back up their suggestions with evidence from previous students.

Main data sources being used by UK universities

In the UK the main data sources being used or planned for use by institutions are the VLE, SIS, and library systems. The SIS may include much useful information such as details of a student's financial situation, the number of hours they spend working, and their prior academic attainment. End of module surveys and other questionnaires completed by students can provide a rich source of data for learning analytics too.

Attendance monitoring and swipe card access to buildings, lecture capture and media streaming systems are also being considered (Newland et al, 2015). Wherever digital technologies are deployed in the learning process, data can potentially be captured from those systems to help understand student engagement, to provide additional assistance to students who require it, or to inform enhancements to the content. Other examples include:

» E-book platforms which record learners' interactions with the materials, monitoring frequency of use, the pages they access and even the annotations they make to the text

» Intelligent tutoring systems which assess student understanding, and adapt the content provided to them accordingly

- Videos, including those captured from traditional lectures, those recorded specifically by lecturers for online teaching, and other educational videos. Again the data can show to what extent students are engaging with the materials. One study has even suggested the optimum length for a video clip, based on the amount of time most users will watch a clip for before moving on
- Serious games, used to motivate learners and encourage deeper engagement, providing useful information about the choices they make and a large amount of clickstream data, showing how they interact with the software

Learners not only consume content provided by their institutions but also create increasing amounts of data themselves, again potentially valuable in assessing their engagement and progress. As well as assignments and examination responses, students may write blogs, develop e-portfolios and create video or audio content or software, all of which can be processed automatically. End of module questionnaires and other survey data can also be valuable sources of data for learning analytics.

Jisc is developing a student app for learning analytics, influenced by some of the increasingly popular fitness monitoring software applications such as Google Fit. This enables students to set targets for their study activities, record them and compare their progress and results with others. Use of the app itself provides yet more data which can be used to refine algorithms for predictions of student success.

Technical infrastructure

One issue for institutions wishing to invest in learning analytics is the nascent state of the relevant technologies and the lack of consolidation in the marketplace. A battle for commercial dominance is taking place between vendors of VLEs (e.g. Blackboard), SISs (e.g. Tribal), business intelligence and visualisation software (e.g. IBM Cognos, Tableau, Qlikview) and emerging bespoke learning analytics packages (e.g. Civitas Learning). The HeLF survey (Newlands et al, 2015) found that institutions were considering a great variety of different solutions, including their own in-house developments. This echoes Jisc's findings of very little common ground in the systems being deployed for learning analytics across the thirteen leading institutions it interviewed (Sclater, 2014).

One of the main requests coming from the higher education community in the UK was for a basic learning analytics solution which institutions could use to start to experiment with learning analytics.

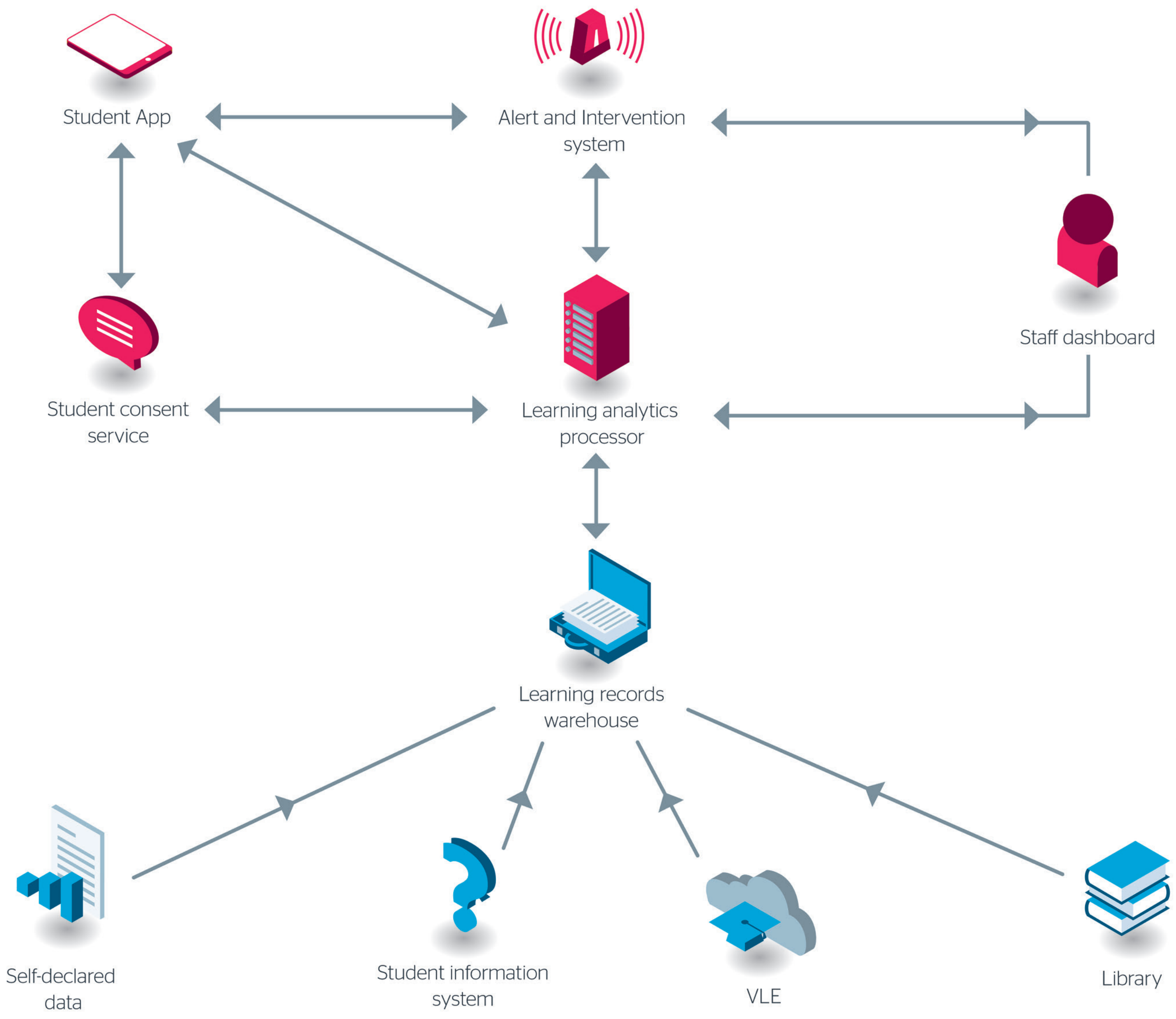
The resulting architecture is shown in Figure 1 opposite.

This shows how data from sources such as the VLE, the SIS, library systems and students' own 'self-declared' data feed into the **learning analytics warehouse**. At the heart of the architecture is the **learning analytics processor** where predictive analytics are carried out, and lead to action coordinated by the **alert and intervention system**. Visualisations of the analytics for staff are available in a series of **dashboards**, and a **student app** allows learners to view their own data and compare it with others.

The **student app** provides students with data on how their engagement and attainment compare with those of other students, enabling them to plan and set targets for their learning and to receive positive reinforcement through the app when they meet these targets. Meanwhile a **student consent service** helps to ensure privacy by enabling students to give their permissions for data capture and use.

This software is being provided freely to institutions for the first two years as a combination of commercial and open source systems, hosted as an open, multi-tenanted, cloud-based solution. This allows institutions to share the same highly scalable architecture but maintain complete control over their own data. They can also select individual components if they do not wish to deploy the whole solution.

Figure 1: Jisc's learning analytics architecture



The benefits of an open collaborative approach

There are a number of advantages in institutions working together through this open approach:

1. With IT directors reportedly being bombarded with approaches from vendors to select their analytics systems, a suite of nationally tried and tested products can help institutions in their procurement decisions

2. Jisc is able to negotiate better rates for products which are provided to multiple institutions under the architecture

3. The predictive models can be made available for inspection openly and transparently, facilitating greater trust by end users than closed commercial models. There may also be opportunities for a trusted broker to validate proprietary metrics and algorithms on behalf of the sector.

4. Expertise can be shared across institutions in many ways e.g. the identification of appropriate metrics, the development of predictive models, and the deployment of the systems themselves. At the moment innovations are happening on a small scale, often at departmental level, and experience is not being shared adequately, resulting in duplication and a waste of resource.

5. Universities which decide to outsource aspects of their learning analytics provision require contracts with service providers to ensure compliance with data protection legislation. Jisc is working with institutions and suppliers to provide guidance and draw up model contracts, reducing costs and the burden on institutions

6. There is potential to share learning analytics data anonymously with other universities in order to benefit from cross-institutional comparisons and benchmarking

7. Student data can be handled under rigorous compliance with data protection legislation, building confidence among stakeholders that the possibility of security breaches is minimised

8. Any commercial exploitation of the data could be handled under strict conditions, agreed by the universities, ensuring appropriate anonymisation and avoiding the surrendering of data ownership to purely commercial entities which do not have the interests of learners at heart

9. New products can be integrated with the architecture easily, encouraging competition and innovation from commercial providers, and boosting the overall market for learning analytics solutions

The Jisc initiative is being watched with interest in other countries, particularly in North America, Australasia and a few European countries, notably the Netherlands and France. No other country has yet put in place a national infrastructure for learning analytics, however the Predictive Analytics Reporting (PAR) framework in the US has been set up to share data, analyses and findings across institutions. One of its main achievements has been the creation of a set of common data definitions, defining common variables across US higher education institutions. It has now built up a database of two million de-identified student records, which it claims can identify at-risk students with 90 per cent confidence (PAR, 2015).

4. Findings and impact – lessons from the case studies

Most of the large scale, systematic implementations of learning analytics to date are in the USA.

Various universities in Australia and Canada are also rapidly gaining experience in analysing data about students and their learning at an institutional level, particularly with the aim of enhancing retention. Documented case studies in other countries elsewhere in the world, other than in the UK, are scarce.

The brief case studies presented in this chapter report on institution (or multi-institution) level deployments of learning analytics. They represent some of the most prominent examples of innovations taking place in the field worldwide; five are from the USA, four from Australia and two from the UK. Most provide evidence either for the effectiveness of the methodology or of the intervention strategy. Full versions of the case studies are included in the appendices:

The following abbreviations are used for each of the institutions and their associated case studies:

1. **Purdue** - Traffic lights and interventions: Signals at Purdue University
2. **UMBC** - Analysing use of the VLE at the University of Maryland, Baltimore County
3. **NYIT** - Identifying at-risk students at New York Institute of Technology
4. **CSU** - Fine grained analysis of student data at California State University
5. **Marist** - Transferring predictive models to other institutions from Marist College
6. **ECU** - Enhancing retention at Edith Cowan University
7. **UNE** - Early Alert at the University of New England
8. **OU** - Developing an 'analytics mind set' at the Open University
9. **NTU** - Predictive analytics at Nottingham Trent University
10. **Wollongong** - Analysing social networks at the University of Wollongong
11. **OUA** - Personalised pathway planning at Open Universities Australia

Reflecting the current emphasis in the field on identifying students at risk of attrition, and hence enhancing retention, most of the case studies concentrate on predictive analytics.

Learning analytics is not however solely concerned with reducing attrition rates, and here the Australians are engaged in some of the most interesting innovations. One of the studies relates to the use of **social network analysis** to enhance learning and teaching at Wollongong. Another examines how analytics can be used to **help students plan pathways through their modules** at Open Universities Australia (OUA).

What impact has student data analytics had?

The early identification of at-risk students is an aim common to most of these initiatives. At Purdue problems are identified as early as the second week in the semester, something which simply was not possible before Signals. However, interventions with students deemed to be at risk may have unintended consequences. At Marist it is accepted that the analytics might have encouraged some to withdraw from courses who would not ultimately have failed.

Analysing the data may help to discover factors relating to student success which can then be revealed to future cohorts to encourage them to change their behaviour. For example students who obtain D or F grades at UMBC use the VLE around 40% less than those with C grades or higher, a finding which remains constant, year after year. The caveat here is that the more confident or successful students may tend to use the VLE more than struggling students, so correlation between VLE usage and grades has to be interpreted with caution. CSU found that analysing the type of activity within the VLE gave more useful results than bulk data about VLE use in general. However providing students with the profile of a successful learner may help to encourage the right behaviours.

The value of dashboards for enhancing teaching or future course provision is also mentioned by some of the studies. At Wollongong, social network analysis revealed interaction patterns that arise in forums such as discussions that were too facilitator-centric. Analytics also helped identify a particularly effective teaching strategy using a specific VLE tool at UMBC. Here too, interestingly, it was found that innovations which led to improvements in student performance on one course appeared to lead them to perform better in subsequent courses as well.

Dashboards may have other benefits beyond the retention of students and the enhancement of teaching: at NTU the Dashboard is reported to have helped build better relations between learners and personal tutors, and its provision is now expected by students. At UNE too, learning analytics is part of a wider ecosystem of engagement with students via social media to foster a sense of community amongst those who may be studying part time or at a distance as well as on campus. Qualitative feedback from students also shows that sharing their experiences of study increases their motivation.

Implementing learning analytics is often one strand of a wider institutional strategy, although even a small scale pilot can generate increased awareness and discussion around issues such as retention. In some implementations good practice has been identified at the individual tutor or module level that was previously invisible within the wider institution. Thus analytics can have beneficial effects beyond the immediate aims of the project, and can be part of a cultural change towards more evidence based decision making. This is highlighted at NTU, where analytics is giving the University insight into ways to improve processes in many aspects of institutional business. At NTU too it is reported that the project has helped to extend a culture of data-driven decision making across the University. At the OU the aim is develop an 'analytics mindset' across the institution and to base decision making increasingly on evidence.

It is important to note that many of the implementations described in these case studies are at a relatively early stage. Processes for reviewing the use of learning analytics, modifying the way it is used institutionally and ensuring the authenticity and validity of the findings, are not well-represented here. Also, there may be wider implications for each institution, as staff learn how to use evidence in their day to day activities and reveal opportunities and challenges which were previously hidden.

Predictive learning analytics models – are they accurate?

Development of predictive models

At this early stage in the development of learning analytics, the creation and refinement of predictive models is one of the main activities being undertaken by institutions.

Some implementations are explicitly based upon educational principles or an ethos consistent with the institution's aims e.g. programmes at OU and the UNE. Others appear to be based upon a normative or deficit model, identifying behaviours that do not match the cohort or expectations of the course. Predictive models use a range of mathematical approaches to analyse factors that were chosen as likely indicators of students at risk of attrition (NYIT, CSU). These factors were identified from staff experience, from published literature about retention, and by training models based upon data available within the institution.

Bringing in the knowledge at an early stage of specialist staff who will be taking interventions can be essential: at NYIT the expertise of counselling staff who support students was deployed to help define the model for identifying at-risk students.

Data sources

While the student is learning, the VLE can generate large volumes of detailed data; the challenge then is to identify which measures are useful and link them to student behaviours and success. Other data, such as library access, attendance at class and submission of assignments is helpful in giving a more rounded picture. Simple measures such as a drop off in a student's use of the VLE, or a change in mood evidenced by their choice of emoticons on the student dashboard, as shown at UNE, may be sufficient to indicate where support is needed.

At NYIT data on previous students was used to train the model using four different mathematical approaches. Extensive work was carried out at ECU to identify which student variables predicted attrition using their own institutional data, a decision based upon an extensive review of the literature and other models. NTU calculates engagement scores from VLE access, library usage, door access card swipes and assignment submissions. A number of the institutions describe how they plan to extend and develop their models by adding more data in subsequent versions.

Many predictive systems use demographic and pre-enrolment data in their models. When designing a model to identify new students at risk, the lack of data about each student's behaviour is a problem that may be addressed by modelling across cohorts. Other data sources can be gathered from direct contact with the student, such as student surveys or data about the student's financial situation or emotional state. A major challenge is the analysis of fragmentary data from multiple sources. Each item of information may have contextual idiosyncrasies and interact with other information in multiple ways (e.g. Personalised Adaptive Study Success - PASS at OUA). Meanwhile some models incorporate semantic or other qualitative data to enhance the validity of the model.

Key metrics used

The review identifies some of the most common and most important metrics to predict student success.

» At Purdue the Signals' predictive algorithm is based on performance, effort, prior academic history and student characteristics. At NYIT key risk factors include grades, the major subject and the student's certainty in their choice of major subject, and financial data such as parental contribution to fees

- John Whitmer at CSU finds that variables relating to a student's current effort (particularly use of the VLE) are much better predictors of success than their historical or demographic data. This is confirmed by NTU, which finds engagement in current studies to be a stronger predictor of success than the student's background characteristics

- Similarly at Marist College the most important predictor of future academic success was found to be partial contributions to the final grade. In other words, with every assignment handed in or test taken, the predictions of final grade become more accurate, and "a student with average intelligence who works hard is just as likely to get a good grade as a student that has above-average intelligence but does not exert any effort" (Pistilli & Arnold, 2010)

Whitmer also finds that predictions of student success are more accurate when using multiple demographic variables than single ones. He suggests too that predictive analytics is better performed on categories of usage (e.g. engagement or assessment) than at the level of individual VLE tools. His analysis of CSU students finds that **Total hits** is the strongest predictor of student success, with **Assessment hits** coming a close second, again appearing to confirm the finding from other studies that what you do as a student is a more important predictor of your future academic success than who you are or what you did in the past.

So how valid are the models? Do they successfully predict attrition and academic achievement?
Many implementations test the models thoroughly against historical data from the institution. Much of the work in developing the models concerns the weighting of risk factors and adjustment of parameters to optimise the match with student behaviour. Generally, the greater the range of data sources and the more options tested, the more valid the resulting models, though research at CSU and Marist shows that some data sources make minimal impact on the predictions.

At NYIT recall of the model is 74%; in other words, approximately three out of every four students who do not return to their studies the following year had been 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. Although many institutions developed their own specific models rather than adopting those developed elsewhere, a key finding of the Open Academic Analytics Initiative led by Marist College is that the predictive models developed at one institution can be transferred to very different institutions while retaining most of their predictive abilities. Open Analytics is a movement within the analytics community which may offer an effective approach in future.

Alternatives to predictive models

Social network analysis
In contrast to predictive analytics, other systems aim to increase the effectiveness of student engagement in real-time. For example, Social Networks Adapting Pedagogical Practice - SNAPP at Wollongong - focusses upon the quality of discussion in online forums, as these are a common feature of courses. The underlying principle is that greater engagement in discussion leads to enhanced student success. Social network analysis is used to visualise interactions between participants in forums, showing patterns typical of an active peer to peer discussion or less desirable patterns of isolation or dominant individuals. This can inform learning design and the staff development of forum facilitators.

Personalisation of learning
Personalisation of learning, and guiding the student along a learning pathway that meets their specific needs, are other uses for learning analytics. Here, the data is used to generate recommendations for learning activities, to indicate progress towards learning outcomes and to route the student into alternative modules, depending upon their current situation. PASS at OUA aims to personalise the study experience

for each student, especially the path through the curriculum. A combination of statistical and qualitative data is drawn from the student profile, learning profile and curriculum profile, as well as data from discussion forums and responses to open-ended questions.

How have analytics been used?

Dashboards and interventions

Some of the institutions profiled are still at the stage of reporting on the development of metrics and the rolling out of their initiatives. However it is only when actions are taken with students on the basis of the data that the true value of learning analytics can become clear, so those studies which report on interventions and their effectiveness are of particular interest.

In the cases using predictive analytics, the output is commonly a dashboard or alert system for staff with responsibility for supporting students. Many of these work in real-time on a daily or weekly cycle to identify students at risk of attrition, so staff can make proactive interventions to support those students. Interventions are usually initiated by an email or text message from staff to student, although some systems enable staff to put indicators onto the student's home page. Generally, proactive support from staff is more effective than waiting for students to ask for help. There are, however, some issues reported, such as students who appeared to be 'immune' to intervention and others who feel that interventions are demotivating or confusing, especially when communicated multiple times across a range of media (Purdue).

At the OU, a range of dashboards, tools and on-demand reports is being developed for students and staff at all levels within the University, working over timescales from days to months or years, in terms of organisational and curriculum change. At OUA customisable dashboards are provided for students, facilitators and instructional designers. Some of the dashboards reported on in these studies show a surprising amount of detail: at NYIT support staff can see whether each student is predicted to return to their studies the following year, the percentage confidence in that prediction from the model and the reasons for the prediction – this then provides a basis for discussion with the student.

However, complex data visualisations, dashboards and other support for learners may not be necessary. Marist's experience of directing at-risk students to a sophisticated support environment suggests that simply making them aware that they are at risk may suffice. Apparently confirming that a simple notification may be all that is required, at Purdue it has been found that students who use Signals seek help earlier and more frequently.

There are also appears to be an impact on grades for those students who are able to view data on their engagement and progress. At UMBC 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. Another reported positive impact on grades was at Marist where on one course there was a significant improvement in final grade (6%) with those at-risk students who were subject to an intervention compared with the control group who were not. Some improvements to retention as a result of interventions are also documented in the case studies. At UNE for example attrition was cut from 18% to 12% during early trials of the Automated Wellness Engine.

The role of teaching and support staff

Involving the support staff in the problem definition for the implementation is helpful in ensuring that the technical and organisational systems are developed in parallel. At CSU, the support staff team was reorganised to establish new roles and working practices alongside the new dashboard designed to support that work. The impact upon support staff of increased workload due to an alerting system needs to be considered, especially at busy times such as induction.

The expertise of student-facing staff is important to ensure that interventions are appropriate and genuinely helpful to the student. At the OU, student support staff use learning analytics to inform proactive interventions across the cohort, based upon agreed criteria, in addition to reactive support and other existing initiatives.

At Purdue, students are given feedback through traffic lights, however human mediation is considered important as well, though: messages are tailored by the instructors. This is important too at NTU, where tutors are prompted to contact students when their engagement drops off.

Student perceptions

Some examples include student-facing dashboards which contain tools that show the student's progress relative to their own goals or to the rest of the cohort. In some cases, this is found to motivate students, although other examples indicate that the more confident and successful students tend to use the tools to a greater extent than struggling students. In one case study, the increased student performance due to the use of analytics on one course appears to impact upon the same student's performance on subsequent courses.

Learners overall seem to like having better data provided to them on their progress. 89% of students in one survey at Purdue considered Signals a positive experience, while 74% said their motivation was increased by using it. At NTU some learners report that seeing their own engagement is a positive spur to stay engaged. Objections by students to the use of their data for learning analytics are not widely reported in the case studies or in other literature.

In many cases, the organisational culture is an important factor in the acceptance and uptake of learning analytics. Ethical and privacy issues are addressed in a variety of ways, depending upon the institutional context. In particular, it is reported to be helpful to involve students and staff in the approval and adoption of open and transparent codes of practice and policies for the use of learning analytics. These policies can be supported using existing institutional governance and consultation structures. A Policy for the Ethical Use of Student Data was agreed with students and staff at the OU through the usual governance and consultation channels. Openness and transparency are key principles, which take this policy beyond the legal requirements. At NTU, transparency and a close partnership approach with students are regarded as having been critical to the success of the initiative, and have addressed ethical concerns about the use of student data.

5. Case study summaries

The full case studies, with references, are at http://bit.ly/1WczdOn

A. Traffic lights and interventions: Signals at Purdue University

The institutional aim at Purdue University, Indiana was to use business intelligence to enhance student success at a course level, thus increasing retention and graduation rates. The Signals system aims to help students understand their progress early enough to be able to seek help and either increase their likely grade or take a different path.

Signals mines data from the SIS, the VLE and the gradebook to produce a 'traffic light' indicator showing how at risk each student is considered to be. A range of interventions can then be taken by the instructor. The predictive algorithm is based on student **performance** (points earned so far), **effort** (interaction with the VLE), **prior academic history** and **student characteristics** (e.g. age or credits attempted). These components are weighted and fed into the algorithm which produces the appropriate traffic signal. Red indicates a high likelihood of being unsuccessful, yellow potential problems, and green a high likelihood of success.

Potential problems are identified as early as the second week in the semester. Instructors can then decide to intervene in various ways such as posting the signal on the student's home page, emailing them, texting them or arranging a meeting. Positive feedback is sent as a green traffic signal, which the instructor can reinforce with a positive message. Negative feedback can be sent with a warning message. 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 Cs and Ds obtained than Ds and Fs. Meanwhile students receiving the automated interventions sought help earlier and more frequently than those who did not receive them.

Results were monitored for two years, and appeared promising. In a biology course, the signals pilot produced 12% more B and C grades than among students not involved in the pilot, and 14% fewer D and F grades. There was also a 14% increase in students withdrawing early enough for their grade point average (GPA) scores to be unaffected. It also 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.

A key benefit of Signals was that students who used Signals took greater advantage of subject help desks and additional tutoring sessions, which were often poorly-attended. Signals also appeared to improve communication between students and instructors. Instructors meanwhile agreed that students tended to show improvements in engagement after using Signals, and were thinking about their assignments earlier.

Learners' opinions on Signals were also sought. More than 1,500 students were surveyed anonymously across five semesters to gather feedback on their use of Signals. Most felt that the automated messages and warnings sent to them were a type of **personal** communication with their instructor, which reduced their feelings of "being just a number". They found the messages and the traffic lights informative and helpful in changing their behaviour, and would have liked even more detailed information on how to improve.

B. Analysing use of the VLE at the University of Maryland, Baltimore County

The University of Maryland, Baltimore County (UMBC), a public research university with 12,000 students, had growing VLE usage but no evidence that it was improving learning. An institutional research project was carried out to investigate the correlations between VLE data and final grades and how best to use the predictions to support students. The research also explored potential interventions and how to identify effective teaching practices from the data.

As a first step, it was found that students with C grades or higher used the VLE 39% more than lower scoring peers. If lower performing students had been made aware of the difference in VLE use, would they have changed their habits? To help answer this the Check My Activity (CMA) tool was developed for students to compare their own VLE activity on a course with a summary of the whole cohort's activity. After a pilot, the tool was rolled out across the institution, with a publicity campaign and a link from the VLE gradebook. In one year there were 45 000 visits to the CMA tool page. In a cohort of students new to UMBC, 92% used the VLE and of those 91.5% used the CMA tool. Those who used the tool were 1.92 times more likely to get a grade C or higher than those who did not use it. The students may be paying attention to feedback from the CMA tool that they might not hear or accept directly from a member of staff. Additionally the tool may be able to build on students' "obsessive status-checking tendencies" to provide them with frequent feedback (which is not cost-effective if staff are involved). As a note of caution, there may be an inherent bias, in that successful students tend to adopt new tools to a greater extent than struggling students.

Examination of the VLE log files in more detail revealed one instructor who had particularly high levels of student participation. He used Blackboard's 'adaptive release' feature, so students had to take quizzes about course content before they could access the assignments. Students on the adaptive release sections typically scored 20% higher than on other sections. Also, when those students moved onto their next course they performed better than those who had not used adaptive release. So analytics revealed effective learning design and a generalisable conclusion: effective implementation of a VLE tool on a prerequisite course may lead to enhanced performance not just in that course, but in subsequent courses. It was suggested as well that particular types of VLE activity may encourage better engagement, which in turn results in better grades.

Future developments have been suggested, in particular a consent process to address privacy concerns by adding two checkboxes to the tool: 'It's ok to track my usage of this site' and 'It's ok to follow up with me for an informational interview'. Other planned enhancements include a view of the frequency and duration of VLE tool usage compared with others; and alerts sent to individuals when their VLE activity drops below the level commensurate with their target grade (modelled from the rest of the cohort). Also it is intended to provide a facility to allow students to share the information with staff, and to give them permission to intervene when their VLE activity drops below a certain level.

C. Identifying at-risk students at New York Institute of Technology

New York Institute of Technology (NYIT) is a private higher education institution with 13,000 students in the USA and overseas. By developing its own predictive model in collaboration with counselling staff, NYIT has been able to identify at-risk students with a high degree of accuracy. The aim was to increase retention of students in the first year of their studies by creating a model to identify those most in need of support, and to provide information about each student's situation that would assist support counsellors in their work. The process included mining the data, running the analytics and producing the output in a format that was helpful to the counselling staff. There were two reasons for this approach: however powerful the predictive model, it would be useless unless the counselling staff were willing and able to incorporate it into their day-to-day work; and the model needed to work quickly and automatically, without time-consuming manual intervention.

The problem definition originated from the users: the counselling staff responsible for supporting students. An external IT solution provider worked with NYIT staff to identify the relevant data, deploy and evaluate the model. The design process was an iterative cycle, with NYIT counselling staff involved at each stage. The model was built in-house at NYIT, so the database, prediction models and front end used by the counsellors were all on the same platform.

The model used four data sources: admission application data, registration/placement test data, a survey completed by all students, and financial data. The latter was included because it was known to influence student completion rates. The model was trained on a set of records from previous NYIT students. In total, 372 variants of four mathematical approaches were compared, to see which performed the best in modelling the risk as a function of the other attributes (incoming grades, finance, etc).

The models were tested for precision and recall, which measure the match between the actual and predicted student behaviour. The best version of the model had 74% recall and 55% precision. This compares very favourably with a similar model developed independently at Western Kentucky University (WKU), which had a 30% recall. The WKU model was based only upon pre-enrolment data. The enhanced recall of the NYIT model however is considered to be due to the inclusion of financial and student survey data and the type of model used. It means that for every four students not returning to study the following year, three of those students will have been correctly predicted as at risk by this model.

The results were shown on a dashboard designed with and for the student support staff. It is a simple table, with one line for each student, showing whether they are predicted to return to their studies the following year, the percentage confidence in that prediction from the model and, importantly, the reasons for the prediction. The counsellor then has the basis for a conversation with each student about their situation and future plans.

D. Fine grained analysis of student data at California State University

John Whitmer's doctoral research project examined student activity on a course at California State University, Chico. This is a mid-sized campus in the North West of the state which had 14,640 full-time students in 2010. Whitmer, now Director for Platform Analytics and Research for Blackboard, analysed the complete population of 377 students on a course which had recently been redesigned to integrate much deeper use of learning technology. His research attempted a more fine-grained approach to the factors leading to student success than the cruder measures used by some other researchers. He believed that existing learning analytics initiatives tended to ignore most of the data in the VLE and there was minimal justification for why some variables were included and not others. He grouped VLE use measures into broader categories e.g. he categorised posting to a discussion as an engagement activity. He also looked at nine student characteristic variables including gender, whether in a minority racial/ethnic group, income, high school grades, and whether the student was the first in family to attend college.

Whitmer points out that earlier studies consistently found that combinations of student characteristics correlated much better with student success than single demographic variables do. In other words, if the student's ethnicity/race, income level and gender are used, the predictions should be considerably more accurate than simply using one of these variables. Seven of the nine student characteristic variables were found to be statistically significant. However VLE use was a better predictor of student success than the demographic and enrolment data traditionally used to identify at-risk students. It was also found that use of individual VLE tools varied widely between students but that there was less dispersed use within the categories which had been defined i.e. administration, assessment, content and engagement. Whitmer recommends therefore that predictive analytics should not be performed at the level of individual tools.

Total Hits is the strongest predictor of student success, with **Assessment Activity Hits** coming a close second. In his conclusions Whitmer suggests that using total VLE hits is an excellent starting point for predictive modelling and early warning systems. A multivariate regression was carried out using all the above variables except **Total Hits**. It was found that these explained 25% of the variation in final grade. Including all the student characteristic variables in the analysis added another 10% to the predictive relationship with course grade.

Overall Whitmer made the not unexpected finding that use of the VLE is related to student achievement. What his research does do though is to quantify the difference the various types of VLE usage can make, and therefore enable instructors to monitor the efforts of their students and have at-risk students flagged to them. He found that VLE variables were more than four times as strongly related to achievement as demographic ones. VLE use is a proxy for student effort which is why it is such a strong predictor of final grade. It suggests that what students do on a course is more important than their background or previous results. Another finding was that VLE use is less effective for at-risk students: there was a 25% reduction in impact from VLE use by at-risk students (based on under-represented minority status and income) compared with not at-risk students.

E. Transferring predictive models to other institutions from Marist College

The Open Academic Analytics Initiative (OAAI) led by Marist College, a liberal arts institution in New York State, developed an open source early alert solution for higher education. The predictive model was successfully transferred to different institutions, and intervention strategies to help at-risk students were evaluated. The technologies are now being deployed at UK universities as part of Jisc's learning analytics architecture. The initial predictive models were based on data from Marist College. Building on Purdue's approach, data sources included demographic details such gender and age, aptitude data such as high school scores, and various aspects of VLE usage. The models were deployed at two community colleges and two state universities with high numbers of ethnic minority students with low retention rates, to investigate how portable the models were and the effectiveness of the interventions with at-risk students.

Researchers discovered that the three most significant metrics for predicting student success were **marks on the course so far, grade point average and current academic standing**. The model was trained with data from Marist College and rolled out to the partner colleges and universities. It was found to transfer well, with around 75% of at risk students being identified in three out of the four institutions. The researchers expected a much larger difference in how the institutions compared with Marist, given the difference in student cohorts, type of institution and teaching practices. They believe that theirs was the first project to identify **partial contributions to the student's final grade**, as entered in the VLE gradebook tool, as the key indicator for determining at risk students. This enables instructors to take action much earlier in the semester than has been done previously.

Reports were produced showing the students deemed to be at risk, who were then subjected to one of two different intervention strategies. The first group was sent a message stating that they were at risk of not completing the course, and providing guidance on how they could improve their chances. The second was directed to the online support environment where open educational resources were provided in areas such as study skills, time management and stress reduction, as well as subject specific content in algebra, statistics, writing and researching. There were also mentoring opportunities from peers and support staff. Both interventions involved standardised text which becomes more serious in tone with every message.

Two different cohorts of 1,739 and 696 students in 2012 were divided into three groups: students who were sent a message, those who were directed to the support environment and a control group which received no interventions. No differences were found between the two treatment groups overall however there was a 6% improvement in final grade for those subjected to an intervention over the control group in one course. Another finding was that withdrawal rates were larger in the intervention group than among control subjects. The differences may be explained by students preferring to withdraw early rather than running the risk of failing later. The Marist researchers conclude that the predictive model helps to provide students with earlier feedback on their progress, allowing them to address any issues before it is too late. They also note that there are some students who appear to be "immune" to interventions. They found that very few students who failed to respond to the first intervention improved after the second or third.

F. Enhancing retention at Edith Cowan University

Edith Cowan University (ECU) in Perth, Western Australia has a diverse student population, largely from non-traditional backgrounds. The strategic priorities are to maintain a strong track record in teaching quality, and to focus on supporting students in order to improve retention, via an institution-wide predictive learning analytics initiative, Connect for Success (C4S). The C4S technology automatically identifies students likely to need support. The organisational system enables support staff to contact a large number of students and manage a series of interventions for each one. A phased programme over two to three years included governance, control processes, organisation, communications and risk management. This allowed time for the development of the technologies and a change management process to support staff involved and to establish new roles in the student-facing teams.

The University invested in extensive work to identify which student variables were most effective in predicting attrition. Although the research review identified some common factors in student attrition at other institutions (including grades, university entrance scores and language skills), the reasons for students leaving or staying are multi-faceted and the factors may be interdependent. Hence ECU decided it was important to gather and analyse institution-specific data to accurately identify students most likely to need support. Statistical models were developed for the first three semesters of a student's time at ECU, based on over 200 student variables. The models used data from ECU's SIS, including demographic and progress information, split into undergraduate and postgraduate courses. In total, six models were developed to predict retention. As a result, ECU has a probability score for each new and continuing student enrolled in an undergraduate course.

The predictive model identifies students who may require support, in a regular report. This is triaged by two staff who make sure that no student is contacted twice or too often. Personalised emails are then sent to the identified students offering assistance. If students do not reply to the initial email, they are contacted by telephone with a similar message. A dashboard enables support staff to log and manage contacts and support for each student. They can create an action plan, agreed with the student, which may include referrals to specialist support services, other appointments or interventions.

Critical success factors included: trained and knowledgeable support staff, partnerships with institutional stakeholders, knowledge of clear roles and boundaries with other ECU services, procedures that work (on a day-to-day basis), and strong executive support. The challenges included: integrity of the data (manual collation was involved in the early stages, interpretation of it was an issue), resourcing the programme at peak times (for example during Orientation), integration of information systems at an institutional level, and 'student suspicion'.

Around 700 students were contacted via email and/or telephone and given the opportunity to opt into a case-management initiative to support their studies. 20 per cent of students opted in, which the institution reports is in line with take-up rates for similar programmes at other universities.

G. Early alert at the University of New England

The University of New England, New South Wales, Australia has around 18,000 students, with high numbers of part-time and external or mixed mode undergraduates. 20% of students are of low socio-economic status. The main driver was the need to identify students who were struggling, so they could be offered timely support. Previously, identification of students who were 'at risk' tended to occur after they had failed to submit an assignment or attend a class. It was also difficult to observe the many students who were off-campus. The aim was to develop a "dynamic, systematic and automated process that would capture the learning wellbeing status of all students". There were three strands:

e-Motion

Every student has a set of emoticons and a text box on their student portal page. They can opt in to record how they are feeling each day (happy, neutral, unhappy, very unhappy), linked to their current module. All students recording a negative emotion are contacted within 24 hours by the Student Support Team. 17%-20% of students recording 'unhappy' or 'very unhappy' are case managed by the team. Of those, 33% require multiple contacts.

The Vibe

Students' comments in the text box alongside the emoticons are aggregated into a word cloud, which is updated every ten minutes, so the entire student cohort can see what their peers are saying. This word cloud acts as a barometer for student wellbeing and normalises student experience, because the larger the word, the greater the number of students experiencing the same thing. The text entries on each student's portal page also give the support team a daily update on the issues and concerns of the students.

The Automated Wellness Engine (AWE)

Analyses data from seven corporate systems every night and runs a model based upon thirty-four triggers identified as suggesting at-risk behaviour. These indicators are based upon behaviours, not demographics. Data sources include e-Motion student input, class attendance, previous study history, prior results, assignment submissions, and access patterns for the student online portal and other university websites. Previous AWE scores are also included. Both daily time series and trend analysis are used to assess a score for intervention. So, even if a student does not provide direct input via e-motion, the AWE can still run the model. Each morning, the student support staff dashboard is updated to identify which students need support. An automated email is used in the first instance, followed by phone calls and other support as necessary.

During initial trials of the AWE, attrition was cut from 18% to 12%. Qualitative feedback from students showed that Early Alert was successful in increasing the student's sense of belonging to a community, and that sharing their experiences of study increased their motivation. Feedback from students has been "overwhelmingly positive", showing that they value the proactive support. Other aspects of the system are successful in motivating students with automated feedback to the cohort, rather than direct staff intervention.

The value of learning analytics within a wider social media strategy is another important feature of Early Alert. A sense of community and the presence of support staff as routine (not just for times of crisis) is built through multiple channels. The staff use Facebook, Instagram and a blog to communicate with students on a daily basis, as well as using the AWE to intervene when necessary. Students seem to be more receptive to intervention because they know the staff by name.

H. Developing an 'analytics mind-set' at the Open University

The Open University, UK has over 200,000 students studying part time degree, postgraduate and sub-degree qualifications. The institution is investing heavily in a strategic learning analytics programme to enhance student success by embedding evidence based decision making at all levels. Due to funding changes, retention on a qualification has become a strategic issue for the institution; retaining students is particularly demanding when they are geographically scattered, studying part-time and typically take several years to obtain a degree.

The University is developing its institutional capabilities in ten key areas to strengthen the foundations for the effective deployment of learning analytics. These are organised into three main strands: the availability of data, the analysis and creation of insight, and processes that impact upon student success. At the macro level, aggregation of information about the student learning experience informs strategic priorities to enhance continually the student experience, retention and progression. At the micro level, analytics are used to drive short, medium and long-term interventions at the student, module and qualification levels. One of the aims is to develop an 'analytics mind-set' throughout the University, so staff incorporate evidence-based decision making into their routine work.

Understanding the impact of interventions is a major goal. Within the University there is a wide variety of interventions. Previously, it was difficult to identify how a single intervention impacted upon student success, so the learning analytics strategy is intended to create a more coherent picture. Data is drawn from the SIS, VLE and other platforms. Multiple dashboards, reports and tools are under development to provide easy access to analytics outputs for a range of users, including senior management, student support staff, academics and students. The support staff dashboard for example enables staff to manage a structured programme of interventions. A student dashboard will enable students to track their progress and make better choices about their study path. Predictive analytics are being developed to model student progression at individual module level and institutional level, based upon previous cohorts on similar modules.

At the curriculum level, faculty staff use analytics to inform updates to the learning design and assessment of modules. Analytics can also identify successful learning designs, enabling the sharing of best practice. The University sees the use of learning analytics as an ethical process, with the focus on the student as an active participant. The 'Policy for the Ethical use of Student Data for Learning Analytics' goes beyond legal requirements. This approach also recognises that however good the models, a student is more than a set of data, so there will always be aspects of the student experience that lie outside the domain of learning analytics. The pilot projects and study support implementation are not yet at a stage to produce clear evidence of effectiveness. The key factors that impact upon student success are now understood sufficiently well to inform priorities in strategic planning. The impacts of the various interventions will take some time to appear and interpret, given the complexity and scale of the activities being undertaken.

I. Predictive analytics at Nottingham Trent University

In one of the most prominent learning analytics initiatives in the UK, Nottingham Trent University (NTU) has implemented an institution-wide dashboard to enhance the academic experience of its 28,000 students by facilitating dialogue between students and staff. The specific goals were: to enhance retention, to increase a sense of belonging to a community, and to improve attainment.

Earlier institutional research found that up to a third of students had considered leaving at some point during their first year. These 'doubters' were less confident, less engaged, formed weaker relationships with peers and tutors, and were ultimately more likely to withdraw early. Tutors were supporting students who asked for help, rather than the 'doubters' who most needed it, but did not ask. There are four key dashboard features designed in response to these goals: students and staff see precisely the same information; the dashboard sends an email alert to tutors when student engagement stops for two weeks; the dashboard enables tutors to make notes about agreed actions as they work with students; and demographic data is not included, only data about student engagement whilst on course. The tool itself is easy to use, with low impact on academic time for training and use; this was important for its adoption.

Demographic data was deliberately not used in the model, because a student can only alter their behaviour, not their background, and the dashboard is there to motivate students. Each student receives one of five engagement ratings: High, Good, Partial, Low and Not Fully Enrolled. The dashboard enables students to check their engagement against their peers, and tutors to discuss the students' performance with them. Two visualisation charts show a progress line indicating engagement, comparing individual students with the rest of the cohort, and showing the student's engagement rating. The tutor can drill down to the level below the rating to gain a better understanding of the student's recent engagement.

The pilot showed that greater engagement was positively related with both progression and attainment, based on four courses. Analysis of a far larger dataset for first year students, showed that a student's engagement was a far more important predictor of progression than data such as background characteristics or entry qualifications. For final year students there was a strong association between engagement and a final degree classification: 81% of students with a high average engagement graduated with a 2:1 or first class honours degree, whereas only 42% of students with a low average engagement did.

In a survey of first year students, 27% said that they had changed their behaviour in response to data on the dashboard. Some students did more academic activities, e.g. independent learning, although this is not measured in the dashboard. Others competed to have the highest engagement score. There is a possibility of bias however here, because the dashboard may help those students who are already articulate and engaged. NTU will be exploring these issues in much more detail in the coming years.

Another impact is that tutors are changing how they work with students because of the analytics. They find that the improved information on individuals allows them to target their interventions more appropriately. Most tutors in the initial pilot used the dashboard once per week with a minimal impact on their workload; one third of tutors contacted students as a result of viewing their engagement data.

J. Analysing social networks at the University of Wollongong

The University of Wollongong, New South Wales, Australia is a public research university with over 30,000 students. The central premise of the Social Networks Adapting Pedagogical Practice initiative (SNAPP) is that collaborative learning is important to promote student understanding. SNAPP analyses conversations in online student discussion forums to show patterns and relationships in real time as social network diagrams. Typically, these forums are moderated by the instructor whilst students tackle specific learning tasks or have general conversations about the subject or administrative issues. The timing and quality of interventions by the instructor can have a significant impact on the student learning experience. Some of these forums may have hundreds of participants, making it difficult for an instructor to keep track of the activity.

Instructors can track the evolution of the relationships by comparing diagrams over time. The SNAPP software can be used a diagnostic tool to help instructors identify students who are isolated from the main discussion, or to see how the overall pattern is progressing (Are a few students dominating? What is the extent of peer discussion?) Because it operates in real time, this gives the instructor an opportunity to intervene in the discussion. Instructors may also use the visualisation to reflect upon the learning design and perhaps redesign the task for a future cohort.

Although intended primarily to facilitate real-time intervention, teachers predominantly used SNAPP for reflection after course completion. This was helpful for professional development, because the network patterns indicate different styles of moderation, e.g. if an instructor responds to individual students rather than encouraging wider discussion. In real time, SNAPP was felt to be useful for identifying isolated students, especially in large forums at busy times. Some instructors showed SNAPP network diagrams to their student groups, as a part of a discussion about how to contribute to an online forum.

It was recommended that SNAPP should be promoted as a reflective teaching tool and that the importance of learning design in professional development should be emphasised. It was felt that there needed to be a greater awareness of common interaction patterns among staff, and a greater understanding of how to intervene, as a facilitator, in a discussion which shows undesirable patterns of social interaction.

The SNAPP project revealed a strong correlation between students' 'learning orientations' and the types of forums that that they frequent. For example, those with a strong **learning orientation** preferred discussions about learning and resource-sharing. Students with a **performance orientation** focussed on administrative and assessment forum discussions.

The SNAPP software is a web browser extension which automatically extracts data from the selected forum and displays the relationships as social network maps. SNAPP targets student interaction data as an indicator of engagement and creates a isualisation system that works across multiple third-party platforms and versions. This approach could be used to add other nctionalities to a VLE.

K. Personalised pathway planning at Open Universities Australia

Open Universities Australia (OUA) is a distance education consortium owned by seven Australian universities. Study materials are entirely or partly online, or with a mix of print, CD and DVD. Qualifications are offered as modular courses. Students can choose how many units they study at the same time but planning a route through the modules necessary for a qualification can be difficult. Personalised Adaptive Study Success (PASS) enables personalisation of the study experience for each student, especially in terms of their path through the curriculum. It aims to support struggling students by suggesting alternative modules, more appropriate to their needs, as well as offering support. Students at risk are also identified.

In a traditional linear path through the curriculum, poor performance on one module impacts upon student outcomes for subsequent modules, and a struggling student may not have an opportunity to catch up with the rest of the cohort. In contrast, PASS supports a personalised and adaptive learning path. A student with a weakness in a particular topic can study extra modules to strengthen that area before re-taking the original module. PASS can recommend an alternative study path at any point where the student is deemed to require help.

PASS draws upon data from a wide range of sources, including customer relationship management systems at OUA and partner universities, the learning management system and the curriculum profiles for each unit and program. In essence, the analysis is based upon three profiles: the student profile (location, socio-demographic factors, prior knowledge etc.), the learning profile (use of online content, assessment, online forums etc.) and the curriculum profile (requirements of the module and program, alternative paths etc.) A combination of statistical and qualitative data is analysed by the learning analytics engine, which feeds into the reporting engine and into the personalisation and adaptation engine (producing recommendations and other feedback for students and tutors). This is intended to enable intervention at the micro, meso and macro level, for example, suggesting an extra mathematics module to a student or providing evidence for redesigning a section of the curriculum.

PASS uses the output from a learning analytics engine to inform a personalisation and adaptation engine, and a reporting engine. The personalisation and adaptation engine feeds recommendations for content and activities to the student dashboard in the online learning environment. Dashboards are provided for students, facilitators and instructional designers. These can be customised by adding and moving tiles with different functions, such as summaries, recommendations and alerts.

One of the conclusions of the project is that the preparation of stakeholders for applying insights from learning analytics in meaningful ways is vital. A major challenge for this project was the interaction and fragmentation of information as well as its contextual idiosyncrasies. The models combined numerical and qualitative data to build a more rounded picture of the learner's situation. In particular, semantically rich data from discussion forums and responses to open-ended assessments, for example, enable a better understanding of learners' knowledge and needs.

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