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Building an evidence base for teaching and learning design using learning analytics

CASE STUDIES

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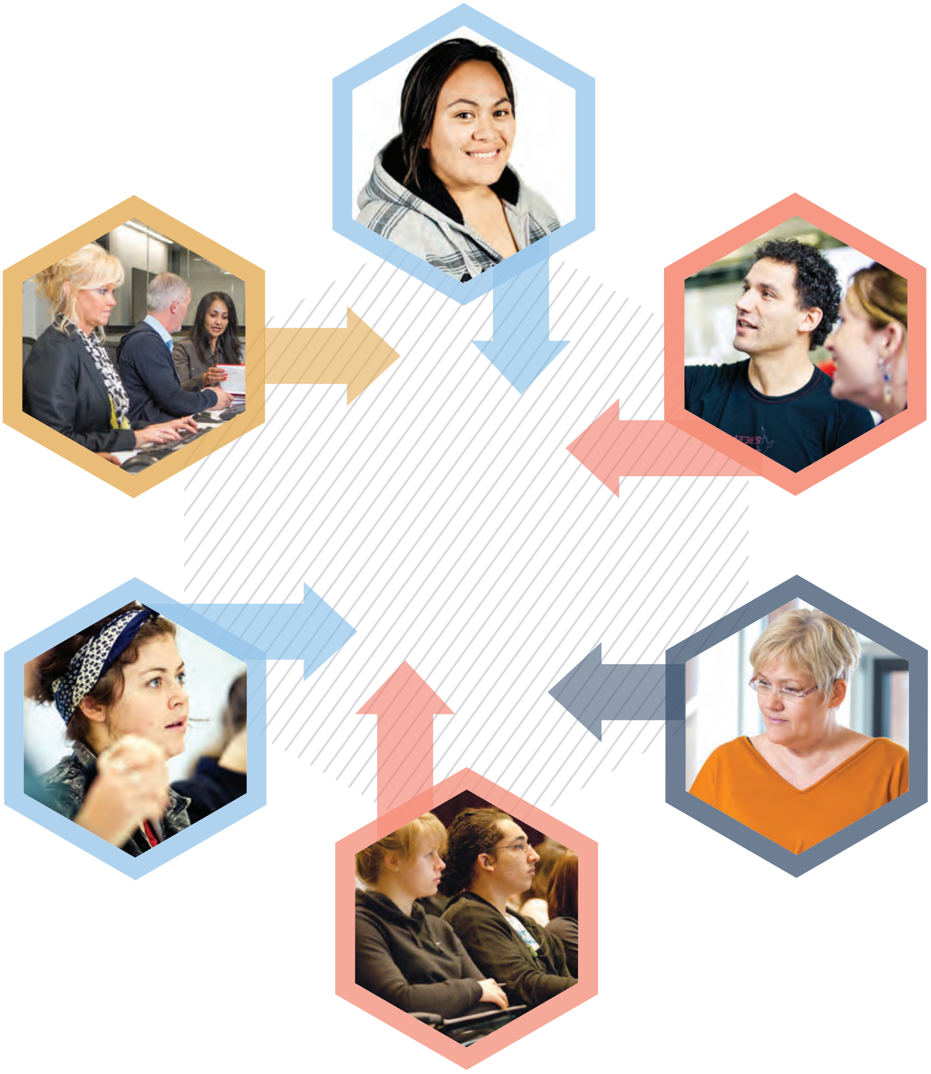

This report and related resources have been developed from the Ako Aotearoa co-funded project: Building an evidence base for teaching and learning design using learning analytics data.

More information about this project is at: www.akoaotearoa.ac.nz/using-learning-analytics

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Introduction

The six case studies and associated professional development scenarios described in this report were key outputs from nationally funded research in New Zealand, *Building an evidence-base for teaching and learning design using learning analytics data*. Early investigations of emergent learning analytics practice in tertiary education in New Zealand and internationally revealed serious gaps between research and practice. If these gaps are not addressed, learning analytics is likely to follow a well-established path from high expectations and exciting proof of concept results to another instance of technology that failed to make a significant impact on educational practice. Experience from the past sheds light on ways this undesirable outcome might be avoided.

Participatory design is one powerful strategy to ensure that the sophisticated learning analytics tools that are the result of generous investment in research and development are actually fit for the users and purposes they are intended. As the main target group for many of these tools, tertiary teachers should at least be consulted and at best involved in the design. Their input is critical for tools that produce data to answer teachers' questions about the impact of their teaching on student learning, rather than what researchers imagine they will want, and what the emergent technology is capable of doing. Our research found communication gaps between these key stakeholders, and worryingly low levels of collaboration. Few of the brilliant learning analytics initiatives we read about in the literature and discussed at specialist conferences considered professional development for target users, or invited their participation in the design process. Further investigation showed that teachers and researchers used different language to talk about learning analytics, had different expectations of purpose, and concerns about ethical matters related to the use of student data collected by online learning systems.

While acknowledging the value of high-end research and development, and being impressed by the learning analytics systems and tools that were becoming increasingly available, we were concerned that target users were not involved in critical conversations. As a result of this concern, our cross-institutional team chose to approach the research questions from the target user perspective. We used existing professional networks to identify early adopters of learning analytics practice in teaching in the lead institution, and invited them to share their experience. We surveyed potential target users and interviewed various stakeholders to understand their perspectives. This reflected a capacity development approach that aims to identify and remove barriers to progress to promote desirable change in organizations and in practice.

The case studies presented in this report reflect the authentic experiences of a sample of early adopters of learning analytics practice in New Zealand tertiary institutions. There is no reason to suppose that these experiences would be substantially different in another tertiary institution in New Zealand or elsewhere in the western world. Some institutions are more advanced with investment in, and support for learning analytics, but most, if not all have the same issues to deal with to provide a supportive environment for learning analytics practice. These issues include ethical use policies and guidelines, user-friendly data access protocols, management systems and tools, accessible and readable data reports and professional development for teachers. We hope that sharing the details of these case studies will be informative for other researchers and institutions, and for teachers and academic development teams working to promote the benefits of the data driven approaches to teaching and learning design that learning analytics is being shown to support.

This *Case Studies Report* is an addition to *Building an evidence-base for teaching and learning design using learning analytics: Project report* by Cathy Gunn, Jenny McDonald, Claire Donald, John Milne & Marion Blumenstein (2017).

Text analytics: revealing student conceptions in a large class setting
A case study in disciplinary literacy

Jenny McDonald, University of Auckland and Rebecca Bird, University of Otago

Purpose and scope of enquiry

In large-class settings, opportunities for individualised interaction with teachers, especially in relation to student written work, are limited. However, the provision of timely feedback on student writing is central to supporting academic success. Recently, there has been some progress in automatic short-answer grading but the provision of formative feedback at scale is still a long way from being widely applied in practice.

Nevertheless, computer-supported analysis (referred to as text analytics) of student written responses has the potential to directly inform teacher actions. We argue that using basic text analytics techniques to analyse student responses and provide feedback directly to the teacher is a worthy a goal. With this information, teachers can adapt their teaching and learning design in response to student conceptions.

The case-study, described here, is set in the context of one large first-year undergraduate health sciences course (~1500-2000 students) at a NZ university. The specific goals of our study were first, to provide an empirical demonstration of the theoretical link between student written responses and the teaching and learning context, and second, to develop a prototype text-analysis tool for use by teachers, especially in large-class settings.

Our case-study also provided the impetus for a much larger international research effort involving educators, social scientists, computational linguists and computer scientists and which is supported through a 5-year Canadian SSHRC Insight Grant

awarded in 2016. This larger study will explore disciplinary discourse analytics. In particular, the development of disciplinary literacy to see whether understanding disciplinary literacy development can enhance skill development and aid automatic evaluation of student written responses.

Full details of our case study have been published in a journal article: *Short Answers to Deep Questions: Supporting Teachers in Large-Class Settings* (2017) McDonald, J., Bird, R.J., Zouaq, A., & Moskal, A.C.M. *Journal of Computer Assisted Learning* http://doi.org/10.1111/jcal.12178 . We encourage interested readers to refer to this.

Background

While there has been some success in automatic short-answer grading (Burrows, Gurevych, & Stein, 2015) the automatic provision of formative feedback to students is still a work in progress (Dzikovska, Nielsen, & Leacock, 2015). In particular, these approaches may be unsuitable for analysing student written answers to questions specifically formulated to encourage deep responses (i.e. responses which are indicative of a deep approach to learning (Biggs, 1982; Biggs & Tang, 2011)).

Nevertheless, some of the same text analysis techniques, which are used to address the problem of automating analysis, also have potential to provide feedback to teachers on student understanding and support the marking process (Basu, Jacobs & Vanderwende, 2013). Furthermore, we argue that such feedback should situate student responses in context and should, where possible, identify sources of student responses from course material (e.g. lectures, course-notes, textbooks) to inform pedagogic action.

Description of development

Student volunteers were sought from two cohorts of a first-year undergraduate health science course. The course is a prerequisite for entry into professional courses (such as Medicine, Dentistry etc.). Typical enrolments are between 1500-2000 students each year. The course provides an introduction to human anatomy and physiology and is divided into five core modules. Four lectures each week are repeated, simulcast and podcast. In addition, students attend labs and are required to complete self-study modules. All course materials are made available via the University Learning Management System (LMS).

During the course there is only limited opportunity for students to practice responding to short-answer questions. Where questions are made available, they are required to check their own answers against a model answer and formative feedback is limited to that which students might seek out during laboratory or tutorial sessions. Teaching staff comment that where students are required to produce written answers in the final examination, performance is often ‘poor’.

All questions were aligned directly with the teaching materials for the cardiovascular section of the course and were designed to elicit deeper, i.e. multistructural and relational responses (see SOLO taxonomy, Biggs & Tang, 2011) rather than simple recall of facts. For example, questions typically used keywords such as explain, describe and so on.

Our goal was to analyse the written responses from student volunteers to questions designed to elicit deep responses. In particular, we sought to explore the language students used to express their ideas and to see how this related to the language used to present course materials.

Sources of data drawn on

Ethics approval was obtained for the project (University of Otago D/) and data used included student responses to the 10 ‘deep’ questions designed for the case study, transcripts of relevant lectures, coursebooks and study materials, and the course textbook.

Questions were presented to student volunteers via an online tutorial dialogue system (see http://www.ascilite.org/conferences/sydney13/program/papers/McDonald.pdf for details) and they were provided with model answers to review against their own responses. We recorded a total of 924 responses to 10 questions from 110 students; 72 from 2014 and 41 from 2015 (3 repeat students). These student volunteers represented between 3-5% of the total class size over the two years.

Actionable insights gained

To gain insight from the student response data we had to devise a way to analyse it. Our approach was twofold. First, to negotiate a coding scheme between two independent markers, a researcher and a teacher on the course; second, where patterns of response occurred, to see if we could identify these patterns in the course materials. The coding scheme we eventually devised sought to group student responses according to both alignment with the intended outcome (for example, correct or incomplete) and the language used by the student (for example, naïve or hedging). While this was largely a manual process, we did make use of simple text analysis tools to produce word frequencies, as well as bigram (word pairs) and trigram (word triples)frequencies. We also produced concordances or keywords-in-context diagrams for commonly occurring words and phrases in both student responses and teaching materials. Finally, we identified keywords from our data or corpus by comparison with a reference corpus of standard English.

To illustrate, the summary analysis for one question, Q6, and an excerpt from the qualitative analysis of a response pattern is provided below. For interested readers, the full analysis process is described in detail in our paper, available here http://doi.org/10.1111/jcal.12178.

Fifteen student responses to Q6 include the phrase, *'in series'*. In all cases, this lexical bundle[1] (Hyland, 2008) is associated either directly or by inference with the systemic and pulmonary circulations. Lecture transcripts revealed 24 occurrences of this lexical bundle over five lectures. This provides evidence that students are recalling a common expression (in the top 1% of all bigrams – a two-word lexical bundle – in the lecture corpus ranked by frequency) and applying it in the appropriate disciplinary context. However, it is hard to discern from the use of this lexical bundle alone whether students understand what is meant by the expression, *in series*. A short answer like this, *'it's in series'*, leaves open whether the student understands the concept compared to a more detailed answer, such as *'they are in series. all the output of [one] is the input of another'.*

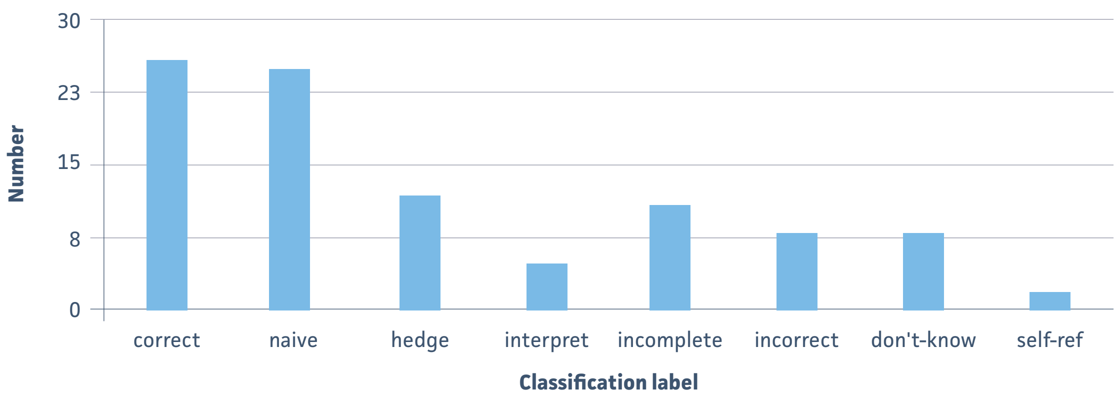
1 . . . Lexical bundle here refers to a pair of words or bigram (in + series) that occur commonly in this teaching context.

Action taken

This was an exploratory case study which sought to scope an analytic approach for further development rather than taking specific action in the classroom setting. We summarise the main findings from the case study in the discussion below as well as describe our next steps. Brief notes for practitioners are provided in the final section.

Discussion

Our case study revealed three key ideas. First, evidence of the source of student understanding or interpretation of taught concepts can often be found in course materials. Furthermore, student responses may provide clues for the teacher that additional explanations or support are required. As noted in our paper, "The extent to which the language students use 'copies' the language of the course surprised us – it is as though educator utterances or phrases are picked up in chunks and variously reapplied in appropriate or sometimes inappropriate ways" (McDonald et al. 2017, p11). Therefore, the ability for teachers to identify and address misunderstandings



Q6: *The flow of blood in the systemic and pulmonary circulations is the same. Please explain why.*

Reference answer: *The two circuts are in series which means all the output of one goes to the input of the other and vice-versa.*

Figure 1: Example analysis

before it is too late (i.e. before summative examinations), would be invaluable in supporting student understanding.

Second, grouping or classifying student responses provides an at-a-glance picture of the class. For example, it allows us to see how many students are on track, where students had interpreted questions in unanticipated ways and quickly identify students who have no idea how to respond to a question (gibberish or 'I don't know' type responses).

Finally, this type of analysis makes it possible to visualise the impact of course design on student understanding over multiple cohorts and therefore would support a cycle of teacher reflection and course development (Gunn & Donald 2015).

There are two limitations to our case-study. First, the number of student volunteers was a relatively small proportion of the total class and this is just one teaching context. It would be useful to validate this work in other contexts and with larger numbers of students. Second, the analysis suggested here only makes sense if the response analysis process can be automated. A prototype text-analysis tool, based on ideas from this case-study, was demonstrated and tested by participants attending a series project workshops during 2016 https://github.com/aggiewil/TA-Notebooks . In addition, two existing and freely available text analysis tools were presented (http://www.laurenceanthony.net/software.html and https://www.sketchengine.co.uk/). Feedback from the workshops made it clear that while interesting, all these tools presented a significant barrier to easy use by teachers. A prototype web application, suitable for use by teachers is currently under development. Please contact the authors[2] for further details.

In conclusion, our case-study suggests that text analytic techniques may provide timely and actionable insights for teachers and foster deep learning approaches for students. Our next step is to make these techniques accessible to teachers and to demonstrate that this is possible at scale.

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Notes for practitioners

- Teaching interactions, such as formative feedback, are central to encouraging deep approaches to learning and academic success.
- Formative feedback at scale is still a long way from being widely applied in practice.
- Analysis of student written responses in relation to course materials, using simple text-analytic techniques can provide insights into student conceptions and thus directly inform teacher actions.

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The Open Polytechnic Engagement Tool

Mark Nichols, Open Polytechnic researcher, September 2016

Purpose and scope of enquiry

The purpose of this case study is to illustrate the institution-wide use of high-level analytics data. The case demonstrates how the data already collected by TEIs (Tertiary Education Institutions) indicating student progress can be made available to all staff, and how support interventions can be coordinated across academic and support functions. All TEIs capture administrative data related to student progression. Data related to student demographics and assignment performance are captured as business as usual activities; these data provide a ready platform for personalising and prioritising student support.

A distance education model, multiple support services, large class sizes and the phenomena of open courses whereby multiple and overlapping cohorts of students are overseen by the same Academic Staff Member (ASM) make analytics a critical aspect of student support at Open Polytechnic. Open Polytechnic developed an online application called the Engagement Tool (ET) to provide staff with an accessible window into Student Management System (SMS) data. Three features of its development and design are critical to the success of the ET: firstly, the data is easily interrogated and manipulated; second, notes related to student contact are captured and shared through the system; third, there is an expectation that all tuition (ASM) and support roles will use the ET.

This case study addresses several key questions related to the application of high-level teaching analytics to formal education:

1. How might the data typically captured during a course through an institution's student management system be harnessed to promote student success?

2. At what points is that data most useful?
3. How can the use of the data be coordinated across different student support functions?
4. How do those using the system apply the data available to them?
5. How might the system be improved?

The provisions of this case study are relevant to all TEIs, as it makes use of data already available through normal processes to enhance interactions between students, teaching staff and the institution.

Background

Open Polytechnic is New Zealand's primary provider of open and distance education, with over 30,000 student enrolments each year. The part-time nature of the student body is reflected in that the 30,000 individual students equate to just over 5,000 Equivalent Full Time Students (EFTS). A unique feature of Open Polytechnic's provision of education is its availability of open courses. Open courses start in any month, and students have a window of 32 study weeks in which to complete. This openness provides challenges to supporting individual students across large cohorts, as the progress of each student is not easily discerned.

Open and distance education faces unique challenges for student engagement and course completions. It is widely believed that distance education necessarily has poor completions; it is more accurate to say that distance students benefit from particular approaches to education design and education support (Nichols, 2010). From the years 2009 to 2014 Open Polytechnic has improved its overall course completion rates from 62% to a steady 80% by improving various aspects of its operation (see Figure One), with only a slight reduction in overall rates to year ending 2015. One reason for this improvement is the development and implementation of the ET, used to identify specific groups of students including those yet to engage with their studies through assignment completion.[3] The ET makes use of information available through the Student Management System, and so represents a fairly simple use of high-level analytics data that is passively collected. In terms of the learning design cycles model for analytics (Gunn and Donald, 2015), the ET forms part of the teaching cycle whereby individual students are provided with customised support.

Table 1: Course completions for Open Polytechnic, 2009-2015

Year	Overall course completion rate
2009	62%
2010	63%
2011	73%
2012	80%
2013	80%
2014	80%
2014	78%

Table 2: Course completions for Open Polytechnic across priority groups, 2012-2015[4]

Year	Māori	Pasifika	Under 25s
2012	69%	74%	78%
2013 – L1-2	74%	66%	72%
2013 – L3+	74%	70%	79%
2014 – L1-2	79%	68%	76%
2014 – L3+	74%	70%	77%
2015 – L3+	70%	66%	77%

The ET was developed as the result of a student engagement strategy confirmed in June, 2011 in the context of upcoming Education Performance Indicators (one of which is concerned with successful course completion) announced by the Tertiary Education Commission. Further, across the range of Open Polytechnic courses it was clear that low completion rates were not a necessary aspect of distance education. One of the specific challenges Open Polytechnic faced at that time was providing support to students enrolled in open enrolment courses. Open enrolment courses are courses that students can enrol in at any time; in 2011 such courses had no due dates, only a final date by which all assignments had to be submitted. Supporting open enrolment students was complicated because academic staff were working with twelve intakes of students per year, and had no student progress milestones such as due dates to work with. Courses also tended to be paper-based, which means there were no online activities to measure. Subsequently it was difficult to conveniently identify which students

3 . . . The slight drop to year end 2015 is attributable to factors other than the ET.

4 . . . Note that prior to 2012 Open Polytechnic did not publicly report across these priority groups, and in 2015 L1-2 completion rates were not published across priority groups.

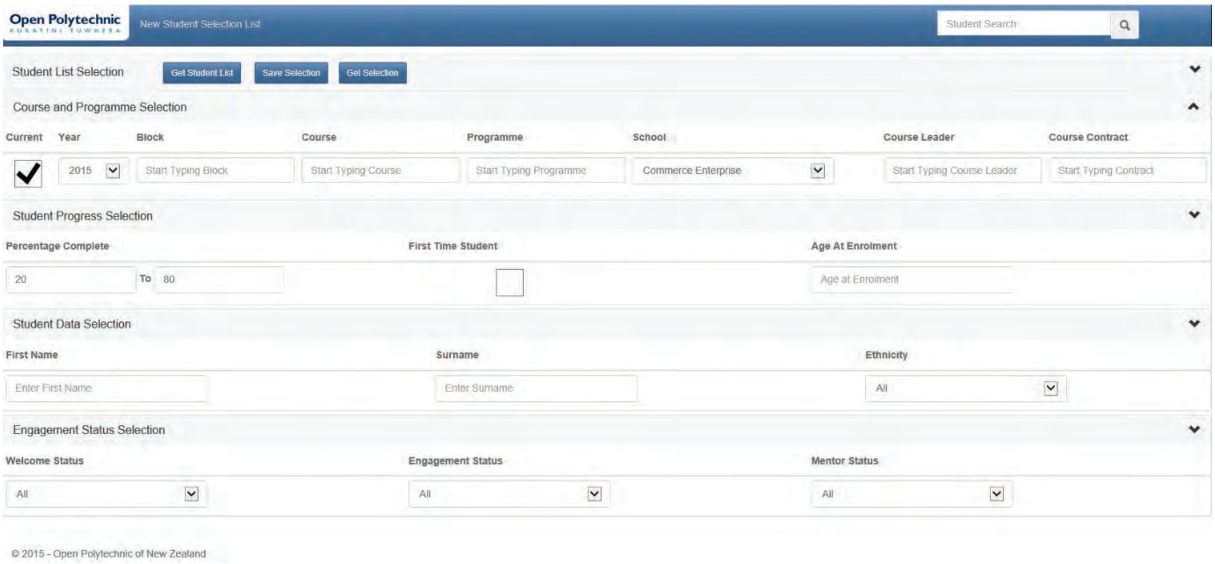

Figure 1: Student selection dashboard

might benefit from specific follow up. Students enrolled in more traditional semesterised courses work to deadlines, so any need for active support engagement is quickly determined based on initial assessment submission. The focus for the ET was initially on open enrolment courses.

Using the ET academic staff can easily access a report for their courses identifying students yet to submit, alongside each student's contact details and a place to record the outcome of an intervention (usually an email or telephone call to the student). Staff can also make a recommendation related to the student; this recommendation might involve removal from the list (student identified as engaged); hold for next report (student likely engaged); or, if the situation is consistent with the academic withdrawal criteria stipulated in the Open Polytechnic Academic Statute, a recommendation for course withdrawal. Access to student data and its use for the purposes of "providing tuition, academic advice and support" is permitted under the Polytechnic's terms and conditions of enrolment (http://www.openpolytechnic.ac.nz/assets/Uploads/2014-Terms-and-Conditions-of-Enrolment.pdf), so no additional consent is required.

Description of development / intervention

The ET was developed alongside other student engagement interventions including providing open enrolment students with more structure (including deadlines), broadening existing support strategies including referral of students to the Learning Centre, better systems aimed at contacting those students whose assignment performance was of concern, closing very poor performing programmes, and taking a more active approach toward student welcome. It is difficult to be specific about the benefit of the ET in terms of its statistical contribution to course completions however it is clear from staff feedback that support activities are better prioritised and more effective.

The main challenge of the development was to provide an easy-to-use interface for summarised data already available in the Student Management System, and to make the outcome of each intervention available to others with an interest in student support. The first iteration of the ET required data to be extracted from the Student Management System, and some manipulation of that data was necessary before it could be used. A later version linked live to the SMS. Using existing data sources meant that development time for the tool was extremely short, around 40 hours of dedicated time based on a simple set of user requirements. An initial, small-scale pilot demonstrated the usefulness of the tool and led to its widespread adoption across all staff including those concerned with trimesterised courses. The intuitive nature of the ET required very little professional development in its use. The tool was easy to use and met a clear need.

Continued use of the tool led to ad hoc improvements in implementation. It was found that a report based on 35% of study time rather than the initial 60% provided a more useful point for student contact. Separation of student lists for welcome and engagement interventions was another feature adding to the ET's usefulness. Recall that open enrolment courses would have new students added regularly; the welcome function meant that staff could identify and contact new students with a welcome message from the same interface used to contact at-risk students. Another early improvement to the ET was the automatic removal of any student who had previously been on the 'at-risk' list but had subsequently submitted an assignment. Further, staff experience highlighted the benefit of having more contextual information about the student before they were contacted. Subsequently student information related to highest qualification achieved, any previous year's study results, ethnicity, and iwi were added to the display. All student data could also be ordered by any column.

In late 2013 Open Polytechnic decided to invest in a more robust and enhanced version of the ET, which included replicating the Tool in Microsoft.Net (the tool was originally authored in Adobe ColdFusion). The enhancements added administrative functionality enabling reports to be generated on student follow-ups, and adding additional features related to student mentoring requested by the Open Polytechnic Learning Centre, Māori Office, and Pasifika Office. Any LNAAT (Literacy and Numeracy for Adults Assessment Tool) outcomes for students were also added. The approved budget for these enhancements was $55k; the project was completed on schedule and within budget, to a total of ten weeks' project and development time.

Sources of data drawn on

The ET draws on data already captured and stored in the SMS, including student notes. The latest iteration of the ET is, essentially, an interactive and user-friendly window into the SMS. The ET runs on the Polytechnic intranet. Previously student details were only available as output from a special SMS report; the ET enhances access to such data and makes it possible for student contact records to be updated across all staff.

By the second iteration of the ET the data could be interrogated as shown in the screenshot above (Figure 1). All, some, or none of the selection criteria can be added, providing maximum flexibility.

The results are listed in the following columns:

Student ID	Pref. Name	Surname	Programme	First Time Student	Ethnicity	School	Course	Block	Course Leader	Status	% of Enrolment
123456	Jane	Doe	BD121	N	Pasifika	Business	BUS101	3	John Smith	NEW TO LIST	42

Figure 2: Engagement tool data selection options

- **Student ID:** The ID number is a link to more information about the student including their contact details, address, previous year's study history, any other current enrolments, and demographic information. The student ID link also provides access to any notes about the student in the Student Management System related to that student's study and support (notes containing sensitive information about the student are withheld from ET users).
- **Programme:** The code of the academic programme the student is enrolled in.
- **First Time Student:** A toggle indicating whether the student has previously studied with Open Polytechnic.
- **School:** The Open Polytechnic School the course belongs to (note that some courses contribute to programmes based in other Schools).

- **Course:** The course number the student is enrolled in.
- **Block:** The number of the month in which the student started their course (recall that open courses start each month).
- **Course Leader:** The name of the academic staff member looking after the course, who is also responsible for follow up related to tuition.
- **Status:** A toggle indicating whether the student has previously appeared on the ET list.
- **% of enrolment:** How far the student is through their study time for the course. In the example, 42% indicates that the student is almost half way through their study period and is yet to submit an assignment.

An additional column, 'Contract', can be used to exclude some students from the overall list if they are not a typical Open Polytechnic enrolee. An example is where Open Polytechnic students are receiving pastoral care through another education provider.

A group of ET users at Open Polytechnic were interviewed, to provide insight into their experience. From the overall population of users (N=192), a total of fifteen interviews were sought using a stratified purposive approach. Of the fifteen interviewees, eight were drawn from the learning support area and the balance from ASMs. Of the ASMs four were teaching at National Qualifications Framework levels up to 4, the balance from levels 5 to 7. Courses at levels up to 4 are typically open, those at levels 5 to 7 are typically trimesterised.

Actionable insights gained

There were three key themes arising from the interviews: the apparent better return from supporting first-time students; the varying ways in which the tool is applied; and the benefit of context when supporting students.

While respondents applied the tool across multiple student groups, many agreed that first-time students particularly benefitted. One respondent pointed out that focussing on courses with lower completion rates for intervention purposes only made a real difference if the students were new to study; another commented that students beyond their first course "tend to be a bit more self-managing and know what the expectations are." First-time students were particularly appreciative of contact through the ET, sometimes because, in the words of one respondent, "there were always these basic things they wanted to find out". This level of support extended to the assistance with withdrawal in the first three weeks if the student found that study was not working for them.

Different student support services interacted with and applied ET data differently, to suit their context.

- Learning support staff used the ET to develop lists of students to contact, based on their particular interests (such as a particular course likely to have an overall low completion rate). Some support staff would deliberately contact students who were first-time in study; others would contact students in priority groups.
- Most ASMs tended to use the system to secure class and email contact lists, independent to the Learning Management System. Some ASMs and support staff working with larger classes used the ET to help identify students who would benefit from follow-up. Others would use the ET to find out more about an individual who had contacted them for assistance, before contacting the student back.
- Many users would use the ET as a means of internally coordinating student support across various functions, such as tutorial support or more generic learning support.
- While most respondents indicated their use of the ET was habitual, two users (one ASM, one learning support staff member) mentioned maintaining their own parallel spreadsheet, initially populated with data from the ET. These spreadsheets were used to track students in ways already possible from within the ET, and were used because the respondents found the spreadsheet format easier to work with. Both respondents were also confident and independent users of the actual SMS interface. Such an approach would be fine, assuming student notes are updated in the SMS. Another ASM stated that they "do not speak to a student without the Engagement Tool open… I'm putting in notes as I'm speaking to a student 90% of the time". This same respondent discussed having three monitors set up for student contact. In the middle was the ET, to the left the student's details, and to the right the LMS. This customised

setup assisted the respondent to summarise, "the Engagement Tool for me is practical, it's fast, it works."

Contextual information about the student is a particularly helpful feature of the ET. The data in the ET gives important clues as to how to better connect with the student based on ethnicity; prior study experience and grades; extensions requested and granted; disabilities; and notes from previous contact, including suggestions for the next contact. Demographic information (including previous study history) and notes were mentioned by multiple respondents.

- Demographic information is used to identify specific groups with varying support mandates, for example Māori students. One ASM respondent talked about how useful it was to be able to use a student's preferred name in communications. Another talked about the depth of information available about each student at the very start of the course, and the value of seeing "their past grades, comments, and the [other] courses that student is taking," adding that before this information was available "you had to guess [about the student's study history] based on your own previous experience with the student and most of the time we don't have any…" Further, because the ET provides alternative contact details for students, support staff were able to follow up unanswered emails with mobile phone calls and text messages. Sometimes the reason for students not responding is that their primary communication mode hasn't been used. One respondent mentioned that for "students that I'm struggling to get in touch with, maybe it's time to send them a text message saying 'hey check your emails'."
- Notes were a particularly important feature of the ET. Notes, which can be read and added to by all users of the ET, were useful for recording contact history and providing consistency and coherence of contact.[5] One respondent told how this worked in a tragic circumstance:

  I had one [call] at the start of the year where I rang the student and the student had passed away that morning, and so there was nothing that had been put up yet because they hadn't notified the Polytech yet but we were able to put it in the Engagement Tool so that no one else ended up trying to ring the student… It lets everyone know what's going on.

  Student notes also enabled later support callers to be aware of who they might be dealing with, so they could plan accordingly:

  I've had one student… He's an older student and he's quite needy. Battling with technology if you like. So with regard to students like that, I've had to take extra time to sit with them on the phone and explain to him how to copy and paste, things like that…. [from notes] I was already aware that the student was not going to be a 'problem' student but that the student might need more attention at a much lower level.

  Continuity of service is highlighted in this excerpt from another respondent:

  So it's hard when you get relentless telephone calls and enquiries to try and remember that student, but it's really important for me to recall that and to be able to understand that the student has a learning problem or an issue and obviously more care needs to be taken with that student. But also following on from that, when she finishes my block and moves onto another tutor, that tutor [and other supporters are] aware… so we can deal with that student accordingly.

Interviews revealed that while the ET was highly valued, it was not suitable for all of the demands staff placed upon it. As an example the ET replaced an incumbent call centre database in one unit, because of the need to coordinate all contact data across a single system; this meant the loss of reporting tools useful to that particular unit, and led to various reporting workarounds. Other respondents suggested improvements to the user experience, including anticipating searches from previous use; better means of updating multiple courses a student is enrolled in at once from the same contact; and remembering a user and prioritising their courses. It was also clear from interviews that training was not effective across some user groups, and that there would be value in having users share their accounts of use.

The benefits of the ET were well understood across respondents. In the words of one, "[the ET is] creating a paper trail, it's a conversation with the student

5 . . . It is important to state that all staff are aware that the notes they add will be visible to others using the ET and SMS. Staff are trained in how to add notes, and use their discretion as to what to include in them.

right throughout the whole learning process for them, and I think it's quite critical that it's there." The overall effectiveness of the ET, though, is limited by the extent to which it is used. In the words of another ASM respondent, "I suppose it comes down to the user. If the user is using the tool properly then the students will benefit in that the students will be targeted and contacted far more frequently than with the tutors who aren't using it properly."

Action taken

The ET is, at time of writing, still in use however it will be superseded by a combination of a new SMS and enhancements to the Open Polytechnic online study platform iQualify. The experience with the ET demonstrates the effectiveness of making student demographic data and contact notes available to ASM and support staff. The combination of the two – iQualify providing learning engagement analytics, the SMS valuable demographic and notes data – will provide ASMs and support staff with knowledge of both who to specifically contact, and how to ensure their contact becomes part of a stream of student support better customised to the individual.

Discussion

Users of the Open Polytechnic ET shared various lessons applicable to other TEIs seeking to develop an analytics system for similar purposes. While the case study might seem a somewhat simple response to the potential of analytics, it clearly demonstrates the benefits of linking student characteristics and progress with an ongoing and shared picture of contact with that student. The interviews give rise to three main considerations for implementation.

Firstly, it appears that the beneficiaries of analytics interventions can be prioritised. First-time students in particular appreciated the connection with Open Polytechnic courtesy of the ET. Students yet to submit an assignment were also easily identified, and could be individually contacted by either their course ASM or another member of support staff. Ideally, analytics systems will be clear and specific on how the data gathered will assist the student.

Second, staff will use analytics data in their own ways, aligned with their responsibilities. On the one hand this is extremely positive; staff will adapt and work around those features of the tool that may not absolutely meet their needs. On the other hand, it means that beyond initial training, good practice is not necessarily disclosed and shared. Neither are different practices, which might be evidence of either poor design or inadequate features, able to assist in further development. Initial training provides familiarisation and basic terms of use; later, users should be encouraged to share their good practice and the challenges they encounter.

Third, analytics should do more than just identify patterns of student use. Ideally, analytics systems will also provide access to each student's demographic information and the support history. In online and distance education, where students are likely to encounter multiple support service options, previous contact notes assist in the coherence and customisation of each communication. Such contact notes provide a further dataset in their own right, which might be later interrogated to provide meta-themes of service improvement across the institution.

As a further point, it is clear that Open Polytechnic was able to implement the solution across all staff quickly. The provisions of the Polytechnic's terms and conditions of enrolment legitimised the use of student data, and additional policy limits the use of private student data to the purposes of employment responsibilities. Requiring all units to make use of the ET in their communications with students led to a system made more useful to all.

Conclusions

Analytics data must be embedded across an integrated system of student contact and refined practice. The Open Polytechnic case study clearly demonstrates how the data typically already gathered by TEIs can be made useful as analytics. Openly sharing data related to student demographics and course performance, and further enriching it through a contact notes system, creates an accessible and effective student support network. The ET does not draw from the LMS, and required a single developer only one week to initially design. A later version with enhanced features was delivered to its budget of $55k.

Returning to the five questions posed at the beginning of this case study:

1. How might the data typically captured during a course through an institution's student management system be harnessed to promote student success?

By making student data accessible through a user-friendly interface, and linking all student support staff to that same system. Adding a notes feature adds further value to the data.

2. At what points is that data most useful?

   For first-time students, and after assignment grades are returned. Data might also be used to identify students with specific characteristics to help in prioritising their support.

3. How can the use of the data be coordinated across different student support functions?

   Through a student notes system, and removing the option for alternate tools.

4. How do those using the system apply the data available to them?

   Variably, but effectively on the whole. Some begin and end with class lists, though others use the ET as the central means for student contact.

5. How might the system be improved?

   Some user experience features might be added, and staff using the system would benefit from sharing ideas of good practice.

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Setting students up to pass:
A first year experience initiative

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Purpose and scope of enquiry

A Faculty of Education initiative to facilitate the transition from school to university used learning analytics to inform blended learning design and a student-mentoring and support program. A multi-disciplinary First Year Experience Team combined student information from institutional and faculty databases with online activity logs and performance data to monitor learners' progress. Course designs had built in learning milestones, or checkpoints at which lecturers would review student progress. These included the date of students' first log in to the course in the learning management system (LMS), online activity logs and performance on assessment tasks. A review of learner progress at these milestones triggered contact with students who were not participating as expected, and may thus be at risk of failing. Under an existing faculty programme, all first year students were assigned mentors to support any aspect of their studies. The aim to offer timely, individual support to students was part of a strategy to reduce a high non-completion rate in first year courses. The ability to monitor learner activity throughout a course provided useful feedback to teachers on their learning design decisions. A further aim was to explore the possibility that a relationship might exist between students' physical and online presence, and their overall performance and final grades. At a general level, the project team was aware that the ability to access, combine and interpret different types of data about learners and learning had grown in recent years, and wanted to explore any further benefits this might offer to learners and teachers.

Background

The First Year Experience initiative[6] took place in the Faculty of Education of a large, campus based and research focused university with around 40,000 students. Trends of increasing class size, blended learning and student diversity had all gathered pace at the institution in recent years. These changes required new ways of teaching and interacting with students, as previous methods had been designed for a very different set of circumstances.

6 . . . http://www.education.auckland.ac.nz/en/for/first-year-experience/about-fye-programme.html

The transition from school to university is known to be challenging for many students (De Clercq, Galand & Frenay, 2017), and the first year of teacher education is no exception. The problem had become more acute as class sizes grew and blended learning was adopted as a pedagogical strategy to combine coursework and practicum within the degree programme. Teachers found they were unable to provide the individual attention they could when classes were smaller and on campus with a more homogenous student population. High drop out and failure rates in the first year were attributed largely to these changes. As part of a three-year strategic plan, and in common with many other Australasian universities (Krause et al 2005), the faculty set up a First Year Experience Programme to address these specific challenges.

Early trials using student data from a combination of sources produced positive results in terms of the teachers' ability to monitor learner activity (engagement) and performance, and to trigger timely and individualized support for students. Online activity reports offered insights into learner presence and performance on the course. Failure to meet set criteria was a trigger for action by the lecturer or a student mentor. The use of learning analytics data for initiatives such as these has become increasingly common in recent years (Arnold & Pistilli, 2012). It is hoped that disseminating the results will encourage more teachers to adopt a data driven approach to course design and support strategies for their students. Adoption will depend on the availability of easy to use data access protocols, analysis and reporting tools.

Development of the intervention

The project was a collaborative initiative involving a First Year Experience Team with course directors and teachers, and faculty based learning designers. The team also included student administration staff, a data analyst, and high performing second or third year students who acted as mentors and role models. The Māori Academic Support Service and Pasifika Success were involved to support students from these priority groups.

This multi-disciplinary team worked together to design and test sustainable ways to support students through the transition to university, and to promote high success rates in a changing context. The range of roles provided a holistic view of each situation encountered, and allowed the team to design solutions that were coordinated across all aspects of the student experience. Initial trials involving two first year courses allowed the project team to explore what insights the combined sources of data were able to reveal, what correlations they might look for, and how to produce readable activity reports with useful features such as heat maps, activity spikes as indicators.

The shift to blended learning meant more activities were mediated online so relevant learning analytics data was easy to collect. The main source of student activity data was the Moodle learning management system (LMS), though system logs from other common elearning tools were also used. Tracking included student log ins to the course site, frequency and type of online activity, and performance on assessment tasks. Specific course features were designed to allow useful data to be collected in a timely manner. This reflected the critical contributions of experienced learning designers, and teachers who were willing to try new ways of working. Student profile information from the faculty database was an important factor in generating actionable insights from the activity data.

A first action following identification of an inactive and potentially at risk student was to alert the peer-mentor. The peer-mentoring initiative ran across all faculty programs to pair first year with successful second or third year students in the mentoring role. A five-point matrix was used as the trigger for intervention, and learning analytics data was an integral part of this process.

- DELNA score (A standard English language ability test)
- Physical tutorial attendance
- Assignment submission
- Assignment performance
- Online behaviour / presence

The mentors ran focus groups to address the specific issues identified as potential problems. As well as checking in on learner progress, peer-mentors were able to aid the transition to university by guiding new learners to faculty-based support services.

In addition to identifying students who may be at risk of failure, learning analytics data provided teachers with clearer understanding of student learning and behaviour. This afforded them better control of the course and allowed them to respond in timely and appropriate ways, for example, by revisiting tricky concepts or picking up topical threads from online discussions. This kind of immediate feedback was not previously available to teachers in regular or accessible format, and provided useful insights on how students were responding to various aspects of the course design.

Who was involved?

The Associate Dean Teaching and Learning, members of a faculty based learning design unit, course directors and teachers and the First Year Experience Team worked together to adjust the design of the courses, and to develop assessment strategies and appropriate ways to use the LMS. The course design drew on performance data from previous years, and on prior experience of student behaviour combined with teachers' pedagogical knowledge.

What tools were used?

Basic e-learning tools were used as the source of activity data, i.e. the LMS, Mahara ePortfolio, a software tool called Go soapbox and the faculty database which records tutorial attendance as well as student profile information. Data logs of presence online were combined with physical attendance records from lectures.

Sources of data

Weekly class attendance and online activity reports were provided to teachers. These reports included formative assessment results, but because some data is sensitive, they did not include all the combined data on the metrics that the First Year Experience Team was able to produce. Although this was not included, many teachers find student profile data useful in deciding on a course of action, and believe it should be widely accessible. At this time, however, the issue of open access remains a topic for further discussion. While the issue is being resolved, there is no technical problem combining student demographic information with online activity data and grades across courses. However, all the metrics were sourced from different databases, so a major part of the task was combining them into a single, readable report. Management of this data required a certain level of competence, but advanced statistical analysis capability was not necessary to monitor learner progress or look for relationships between activity data and end of course results.

Actionable insights

Weekly course engagement reports allowed teachers to control teaching better by knowing how students were progressing with their studies, specifically, whether or not they were accessing course resources and engaging with formative assessment tasks, and how well they performed on those tasks as individuals and as a group. Inactivity in the course and / or failure to meet milestones proved to be a simple but effective way to trigger action by teachers and / or mentors. Such moves are becoming common across courses, disciplines and institutions. Caution is required in interpreting data of this type[7], however, as there can be many reasons behind it. For example, if a student does not log in until the second or third week of a course, this does not necessarily mean they are at risk of failure. They may be working, overseas or busy elsewhere and planning to devote full attention to later weeks of the course. Similarly, failure to access resources through the LMS may mask the fact that they have acquired them in another way. The choice of action to take depended on consideration of multiple factors, such as presence in other courses, academic background etc., with the most important information coming from the students in response to personal communication. In this case, the learning analytics data created opportunities for teachers to intervene before students incurred an academic penalty, which would be detrimental to future prospects and may weigh heavily on their minds.

Online quizzes were provided but not always formally assessed. Students who completed them performed better than those who did not, suggesting that formative assessment is a useful addition to a course. Advising students of the positive impact of taking these quizzes was therefore considered to be a helpful strategy.

Another insight gained from the data was no significant difference between those students who viewed lecture recordings and those who did not. The resulting action was not to stress the importance of this aspect of the course. Further investigation of this finding may follow.

The FYET considers it important to analyze the same datasets year on year to see if results recur, and as an indicator of whether different interventions are effective across cohorts.

7 . . . For a broader discussion of reasons to be cautious with data interpretation see https://eandt.theiet.org/content/articles/2016/09/beware-of-the-gaps-in-big-data/

Discussion

A summary of case study findings is presented in the following sections.

1. Impact on learning

Some metrics were found to have a stronger relationship with academic performance than others. The strongest relationship was between physical attendance in class and at tutorials and strong academic performance. This is perhaps not surprising, and the practice now is to explain this observation to students to encourage them to develop good study habits. Students who didn't access the course site in the learning management system in the first two weeks were less likely to perform well academically. Making students aware of this and making early contact with late joiners can be simple but effective interventions. In contrast, the observation that there was no significant difference in performance between those students who did and those who did not access lecture recordings means this may not be a critical element of these courses. Further investigation to identify the users and perceived impact of these resources may be a useful future project.

During the course of the project, pass rates were observed to be 10% higher than in previous years, and submission rates for assignments were the highest on record. Although there may be other reasons for this, it is likely that timely support, scaffolding student learning through formative assessment and mentoring as a form of individual support all contributed to these increases. It will, however, be necessary to analyze these results over several iterations to produce evidence that the approach has been a success overall. Caution is required when interpreting learning analytics data or exploring possible relationships between activity and performance. For example, when students are not active in an online course there can be many reasons for this. Reasonable knowledge or access to relevant advice on statistical methods supports sound interpretation.

While it is not too surprising that the strongest relationship was between physical presence and academic results, this is important to note in a context where blended learning is being promoted. The question remains, what positive action can result from this information? The course design implications were an ongoing discussion topic for the project team.

Another actionable insight was to accept that some students were simply on the wrong course or on the course for the wrong reasons. The use of data and metrics made it possible to identify these students and decide whether the best course of action was to offer additional support, steer them towards more appropriate choices before a ‘did not complete’ result went on their academic record, or walk them off the course before they became a drop out statistic.

2. Access to data

This case study was conducted as an ethics approved research project and a collaborative venture involving people with role based access to student data as well as the requisite skills for data analysis and interpretation. A statistician was required to ‘crunch’ the numbers and design reports to combine information from different databases for use by non-data specialist teachers. Aggregated data from different sources processed by automated systems and presented visually in easy to read reports was ideal for most purposes.

It is not safe to assume that an individual teacher wishing to adopt learning analytics practices would have similar skills and resources to hand, so working with a team may be helpful. Access to student data is a sensitive issue with the growth of the big data movement and the growing demand for learning analytics data. There is some evidence that access is getting more rather than less restrictive in tertiary institutions. Role-based access is an important matter for institutions and staff to consider, so relevant information can be made available to the right people at the right time, while data security and protection are maintained. Access rights are a matter of policy and it is easy to see why nervous institutions might tend to err on the side of caution. However, the benefits of being able to close a critical feedback loop for teachers and learning designers, and to monitor student progress in order to offer timely, individualized support must be weighed against the risks of unauthorized access or improper use of data when determining a policy framework for learning analytics.

3. Collaboration and professional development

Designing courses with built-in milestones to facilitate monitoring of student progress was a key enabling strategy, not just to check on presence but also to use formative assessment as evidence of knowledge development. While many teachers may be familiar enough with these pedagogical approaches to adjust their own course designs, others will benefit from working with experienced learning designers as the ones in this case did. To make a project like this work, teachers must be willing to try something new and to change their course design to build in the necessary milestones. If the plan is to scale up, this may lead to resistance for any number of reasons, e.g. workload or external pressure to change the way that they teach. The move to a new learning management system during the project was both a challenge and an opportunity because change had to be made. This was an obvious time to introduce further change, although the capacity of the new LMS to produce the necessary data was yet to be explored.

Similarly, some teachers may be familiar enough with datasets and analysis techniques to make their own interpretations. Others may need assistance, particularly if they are not involved in a collaborative initiative with a multi-skilled group such as the FYET. Collaboration among people in different roles related to the course was a critical success factor in this case. Different perspectives, priorities and skill sets were brought to the table to review the data, discuss insights and consequent actions, and consider the implications for teaching, student support and administration functions.

Rich sources of data were available and it was important to spend time analyzing them to gain useful insights. It wasn't always necessary to identify individuals or particular groups to understand what the data revealed. Specific research questions may have different parameters however, and it may be important to identify priority groups or individuals. These different levels of engagement with learning analytics data are all technically possible, provided the necessary permissions can be put in place.

It is our belief that many teachers would benefit from a guided process through learning analytics data collection and analysis, with advice on which metrics matter, how to monitor them at given points in time, and what possible courses of action they could take. Mapping the process and offering trails to follow based on the initial experience of the case study project team would be helpful. Basic data literacy skills may be an issue to address, and ways to raise awareness of the relevant systems and databases and how they can contribute to actionable insights is a matter for further consideration.

Setting students up to pass, that is, to develop successful study strategies, to know how to approach assignments and call on support services when necessary were all key elements of an initiative where learning analytics data was just one important factor. Course design to facilitate data collection and generate insights was equally important, and so were the multiple perspectives of the project team members.

Conclusions

This case study describes one type of response to the pressures of increasing class size and student diversity that benefitted from the affordances of new technology. Although it was a costly exercise, the investment of time and resources in the first year was justified because habits and behaviours of students in later years can be traced back to their experience in first year (Tinto, 2006). While it may be hard to justify a similar level of investment for smaller numbers, such initiatives may not be necessary where classes are small enough for teachers to know each individual student and to be able to monitor their progress. However, if data capture and reporting systems are put in place for larger scale operations, it would be a missed opportunity not to encourage all teachers to adopt the evidence based teaching practices that these tools can support.

In terms of measuring the actual effects of different intervention strategies, the complexity of teaching and learning situations makes it difficult to link any particular change to an effect as many elements are interconnected. However, each change, such as the increased use of formative assessment, was made for a well-considered and contextualized reason. If the overall outcome is positive, it may be less important to separate effects and attribute causes. This reflects an ongoing problem for educational technology research where the only real solution is to repeat processes over a number of years to see if results are replicated, and to constantly search for other variables that may be influential. Comparative studies are not usually appropriate in educational contexts. They may be impractical to set up, and run the risk of unfairly disadvantaging students in either group.

In this case however, the data did provide clear answers that previously had not been available to teachers, and it was useful for students to have the apparent relationships between behaviour and academic success explained. It was considered important to advise teacher education students of this to inform their evolving practice as teachers.

For learning designers, the ‘holy grail’ of constant reflection, re-evaluation and revision of a course design can be supported. Using learning analytics data in the ways described here can ‘close the loop’ by providing direct and objective feedback on their learning design decisions. While reasons may still need to be sought through qualitative methods, the data provides useful indicators of where to start an investigation. This case study describes a manageable way to achieve this, with the promise of a ‘low barriers to entry’ access route for teachers, as easy to follow processes and tools can be provided.

While specific learning design features and data analysis procedures were defined in collaboration with other team members, it was important for the questions to be answered by the combined sources of data to be defined by teachers. Regular conversations within the project team helped to shape the direction of the work.

Another point to note was that learning analytics data was only one aspect of a collaborative initiative that also involved course design, teaching and learning strategy, collaboration among key stakeholders, and the use of additional data from existing sources. Although not widely available in this case, it was noted that intelligence could be shared across courses to good effect. This would be a new practice but there would be clear benefits to teachers from knowing how individuals or groups of students were performing in other areas.

As mentioned above, access to data is a complex issue to be dealt with at institutional level to facilitate productive use at practice level. For this to happen, leadership support is required, as it is to support all teaching and learning innovations. It is important to involve potential users in the design and development processes so the resulting systems are flexible enough to accommodate other types of use. Leadership skills are required to foster collaboration and to disseminate and operationalize new systems. Adoption needs to be made easy for those who are not the originators of the ideas through easy to follow processes, mapped activities, examples and accessible reporting formats. The importance of policy guidelines and a code of practice for learning analytics cannot be understated. These are all leadership issues. In this case, preliminary work by a Student Tracking Working Group went some way to informing a learning analytics strategy at institutional level. Development of an institutional framework is part of the ecology of a holistic business intelligence practice. The work of early adopters can help to drive an institutional agenda where their successful initiatives provide examples that are scalable and useful. However, their contributions are often undervalued and easily overlooked in this context.

Another contribution that may be undervalued (though not necessarily in this case) is the critical role played by the faculty’s central learning design unit. These units are often significant drivers of multi-disciplinary collaboration, provide learning design, technical and project management expertise, and are well placed to disseminate new knowledge and offer teacher professional development following successful trials. The research focus of some units is an important contribution to innovation. However, in many institutions, their unique ability to drive strategic change in a way that supports a leadership vision while adapting to the local context of faculties and departments is not acknowledged.

By the end of the project, a successful pilot study was ready to scale, with due consideration of all the different pressures, activities and requirements that this would involve. To provide incentives for teachers, it is helpful to explain the benefits in concrete terms. Results that suggest improved course management and outcomes while saving time and effort are a good place to start. Further evidence will be gathered from future iterations of these and other courses, both as incentives and examples to follow.

It was important to keep an open mind as unexpected findings could arise from the data or from the experience. Some form of computer-based analysis that looks for relationships without having to set parameters for specific questions would be a useful research tool in this context. More sophisticated analysis tools are under development and will no doubt be used more widely in the future.

In the final analysis, collaboration is key, as each group and individual brought something of value to the table. This can be compromised by staff changes, particularly in the early stages of a project, if essential skills are lost. However, the remaining members of a strong team are well placed to bring new talent up to speed.

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Early alerts to encourage students to use Moodle

John Milne, Massey University, January 2017

Purpose and scope of enquiry

There were two aims of this study. The first was to explore if learning analytics data could be used to help encourage students who appeared to be not engaged in their study. The project used indicators such as low use of the learning management system (LMS) to identify students who may be at risk and in need of extra support. The Paper Co-ordinator emailed these students to encourage them to seek support if they needed it. The second aim investigated how learning analytics data could help teachers design more effective teaching strategies. The aim was to enhance outcomes for learners through better design.

The Moodle LMS collects information on student use of the system. Each click is recorded to show what the students are viewing or doing and timestamped to show when they are doing it. Teachers can use this information to check that students are using the LMS including who has logged into the system and what activities they have engaged in. There is potential to use this information to help students who may need extra support and also to help the teachers create more effective student experiences.

Learning analytics includes the analysis of usage data to understand what students are doing and allow teachers to connect with students to help their learning. The data in this case study is about the use of the activities and resources in the LMS and identifying if students are using the material. The teachers used the information to encourage students who were not as engaged as others. The findings were also used as a basis to refine the course design.

Background

New Zealand tertiary organisations want to improve the number of students who complete courses. This will have financial benefits for the student and the educational organisation. There are also emotional benefits such as improvements in self-esteem for the students (Chemers, Hu & Garcia, 2001). A key part of improving completion rates is to improve student engagement (Zepke, & Leach, 2010). Teachers can use learning analytics data to do this by improving communication with students and through refining course design.

There is some convincing evidence of the impact of learning analytics on student success. In the well-known Purdue course signals study the courses that used the learning analytics tool had improved student retention and some at-risk students moved to a lower risk category after they were sent intervention messages (Arnold and Pistill, 2012). Sclater and Mullan (2017) summarise some of the evidence for using learning analytics to improve student success. They found that learning analytics can identify at-risk students and those that were provided with an intervention did better than those who were not. Liu, Froissard, Richards and Atif (2015) investigated the Moodle engagement analytics plugin and found

that it can predict academic performance. They found that the system could predict success although there was a margin of error especially early in the course.

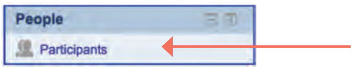
The case study was based on a first year health science course that is an introduction to scientific concepts relevant to human health. It is a foundation course for nursing, health science and sports and exercise degrees. There were a number of data points that the lecturers were interesting in using. In the LMS these included the pattern of student use, especially lack of use, access to recommended resources such as the course guide, and use of activities such as quizzes and forums. In addition attendance roles for the laboratories were recorded on paper, entered into the computer and combined with the LMS data.

Learning analytic tools within Moodle

There are a number of learning analytics functions within Moodle. These tools give the teacher information about overall student use of the system. The data can be limited to the use of a tool or operate at an overall course level.

Overall student usage

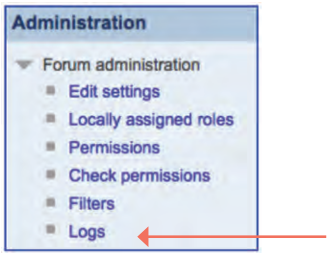
This tool shows a list of students with their last use of Moodle. This is accessed this from the 'Participants' link in the 'People block'. This can be useful at the start of the course to identify students who have not yet logged in. Teachers can contact these students to ask how it is going and if they need any help or information.



Name	ID number	Email address	City /town	Country	Last access
Sam Smith	12345678	s.smith@gmail.com	Nelson	NZ	36 secs
Alex Arnott	12345679	a.arnott@spark.com	Gore	NZ	5 days 8 hours
Jo Jones	12345680	j.jones@massey.ac.nz	Napier	NZ	Never

Use of Moodle tools to track progress

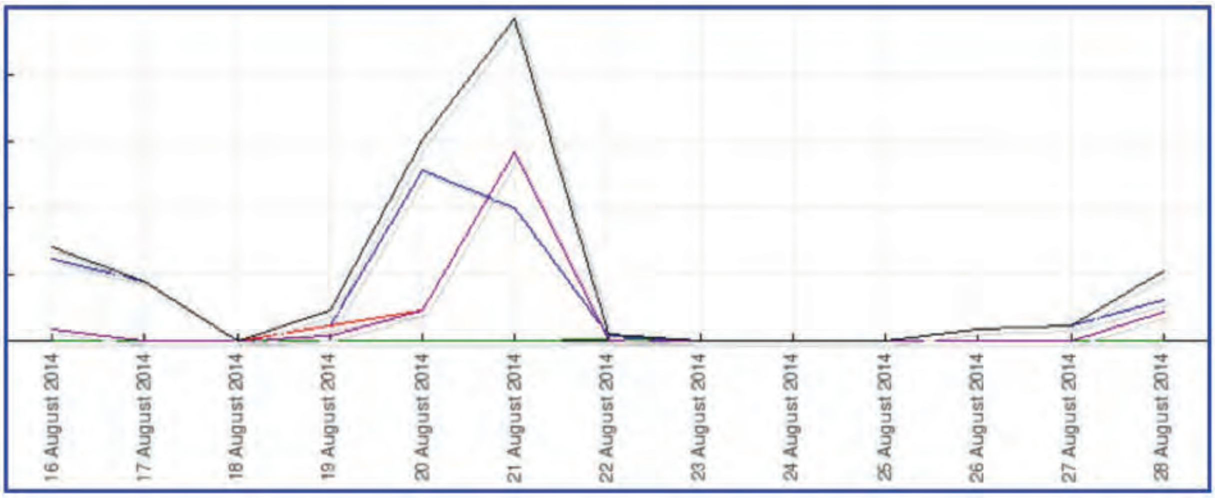
The log data is available for many Moodle tools such as forums, quizzes etc. This is accessed when a tool is selected. In the example below the teacher has accessed the Forum. The logs are available from the 'Logs' link in the 'Administration block'. This link provides a list of the date and time with the students' action.



Time	IP address	User full name	Action	Information
Mon 28 May 2016, 10:00 AM	130.123.206.156	Sam Smith	Forum veiw	Assessment info
Mon 28 May 2016, 10:10 AM	130.123.206.156	Sam Smith	Add post	Due dates
Mon 28 May 2016, 1:30 PM	130.123.222.167	Jo Jones	Forum view	Introduce yourself

Overall use of Moodle course

The data for all of the use of the course is available in a number of reports and in the raw log format. This data is available from the 'Administration block' in the Reports section. These reports tell teachers what activities students have been accessing in Moodle. The logs available are: Course completion, Activity report, Engagement analytics, Logs, Course participation, Activity completion, Statistics. An example of the statistics report is below. This shows the usage by student and teacher over time.



Activity	Views	Last access
Feedback on session	30	Thursday, 4 August 2016, 2.44 PM (21 days)
Lesson – Kaupapa Māori research methods	194	Monday, 9 August 2016, 12.14 PM (16 days)
Wiki – commend and recommend	48	Thursday, 4 August 2016, 2.44 PM (21 days)
Learning Guide – library, writing, Stream	185	Friday, 1 July 2016, 10.41 PM (51 days)

The activity report gives the total views for each tool. From here teachers can find out what students used and so may adjust what they provide for the next offering.

These learning analytics tools within Moodle help teachers in various ways. At its simplest the tool of overall student usage can help teachers identify who has not used Moodle. This can be very helpful at the start and throughout the course so the teacher can send a message to the students to encourage them to get back into the activities in Moodle. Similar techniques can be used on to track progress in specific tools. The tools to visualize or review use of the course can provide information on the overall course design and could be used to discuss with colleagues what the data would mean to them and the implications for teaching and learning.

Description of development / intervention

The Health Science course was campus-based with a face-to-face component of lectures and laboratories with a LMS component to support learning and provide some of the assessments. The online components include quizzes, forums, resources, short videos of lecturers outlining key points, links to relevant websites, assignment submission and feedback, and course administration such as grades. The assessments were two online tests, a group presentation and a final exam. The course had 159 students and of these 123 passed, 12 withdrew and 24 failed. This pass rate of 77% is similar to other offerings.

At three times during the semester at week 2, 5 and 8 the data points were investigated. The students who were considered to have low engagement scores were sent an email. The email was from the lecturer and asked them if they needed any help and suggested contacting the lecturer or going to the Centre for Teaching and Learning.

The at-risk students were selected using a combination of data. First the lecturers identified activities and resources that they wanted the students to access on the LMS. These included items such as the course guide and the use of quizzes in week 2. These data points were crosschecked using the previous cohort's use of the LMS. This indicated associations between the regular use of the LMS and the use of quizzes and the final marks. The lecturers wanted to include the laboratory attendance records as they consider the face-to-face experience to be an essential part of the course and those who do not attend to be at-risk.

Table 1 outlines the items that made up the data points in the case study. These items were formed into a risk rating for each student. The students who got high risk ratings generally did not use the LMS or had low assessment scores.

Table 1: Components of the risk rating during the semester

Week 2	• Total use of LMS • More than 5 days since last use of LMS • Low use of course guide • Low use of Quiz • Absent from laboratories
Week 5	• Low total use of LMS • Days since last login • Score for first assignment • Absent from laboratories
Week 8	• Total use of LMS • Days since last login • Score for formative tests • Absent from laboratories

The components were analysed and decisions made on cut off points. The cut-off point varied depending on the distribution for the class. For instance in week two we examined the days since the last login and used a cut-off point of more than five days since last use of LMS. A different cut off point was used in week 5.

Sources of data drawn on

The data is mostly from the LMS and identifies if students are using the material. Some data on laboratory attendance was also used.

Actionable insights gained

This section will outline insights on the impact of the email intervention on those in the at-risk category, the implications of the learning analytics data for the course design and some discussion of the ethical issues of practical use of learning analytics data.

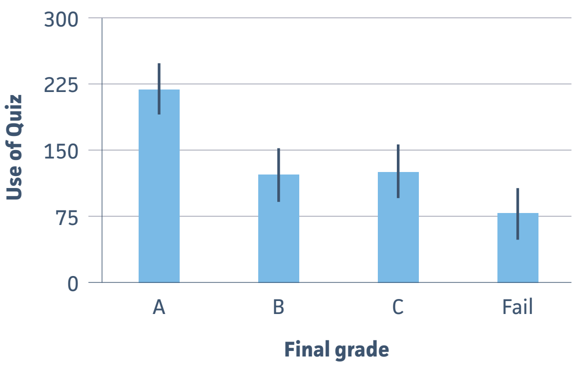


Figure 1: Graph of the LMS quiz tool use grouped by final grade

There are associations between the data used in the risk rating and the student final mark. For example Figure 1 shows the use of the quiz for the categories of final grade. Students who received an A grade used the quiz tool more than those who failed. This is a loose association as the difference between the C grade and fail is small.

Students were given a risk rating and those who had high-risk scores were sent an email to encourage them and to seek support. The association of final marks to risk group was examined and the percentage of students who passed is displayed in Figure 2. Those who were identified as at-risk had lower pass rates than those who were not. As the semester progressed those in the at-risk group had a lower pass rate. For example 68% passed who were in the at-risk group in week 2 while 38% of the at-risk group in week 8 passed.

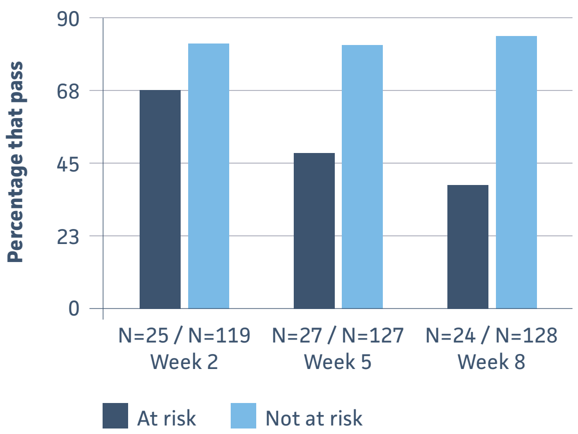


Figure 2: Percentage of students who passed the course grouped by risk rating at week 2, 5 and 8

The impact of the email was compared to the previous year where the risk rating was calculated but no emails were sent. The risk rating calculation did not use the laboratory attendance component but the other categories were consistent. It was hypothesised that the impact of emailing the students would encourage students to spend more time on their work and then they would be more likely to pass. Those students in the previous cohort (Figure 3) were hypothesised to have a lower pass rate than those who were sent an email. This did not occur.

The impact of the emails

We examined the impact of the emails to at-risk students by analysing the use of the LMS two weeks before the email and two weeks after it. The at-risk

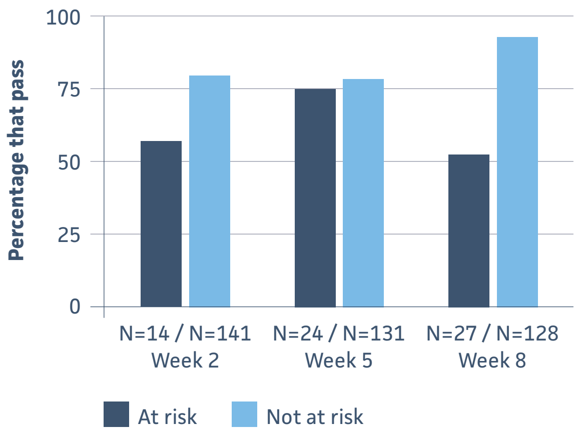


Figure 3: Percentage of previous cohort of students who passed the course grouped by risk rating at week 2, 5 and 8

group was compared to the students in the not at-risk group (Figure 4). Each column of data in Figure 4 shows the average use of the LMS two weeks before the date of the email in white and after the email in grey. All scores before the email were lower than after.

In week 2 and week 5 students in the at-risk group had a low level of use but after the email there was a marked increase in LMS activity. In week 5 the at-risk group had an average use of the LMS of about 20 downloads and this increased to about 100 downloads after the email. This indicates that the emails may encourage students to make more use of the LMS.

Impact on course design

Teachers can use the learning analytics data to inform the course design. An extract from the LMS activity report shows the activity with the total number of times the students viewed the components of the activity (Table 2). Some of the activities such as the assessment guide were viewed a lot while others were viewed less such as the student café forum. This indicates that the student café forum may not be needed or students need to be given a more useful purpose for using them. A quick review of the messages in the forum will provide further evidence of the value of the forum and if it should be removed. The online test quiz is a summative assessment that counted for the final mark and was used a lot. The treasure hunt quiz was used far less and its inclusion should be reviewed. It could be replaced by a quiz that helps students prepare for the summative online test quiz.

Table 2: Extract from the activity report

Activity	Views
Administration Guide	2851
Assessment Guide	6956
News forum	1510
Ask a Question forum	1294
Student Café forum	33
Treasure Hunt Quiz	153
Online Test Quiz	5847
Learning Guide	1308

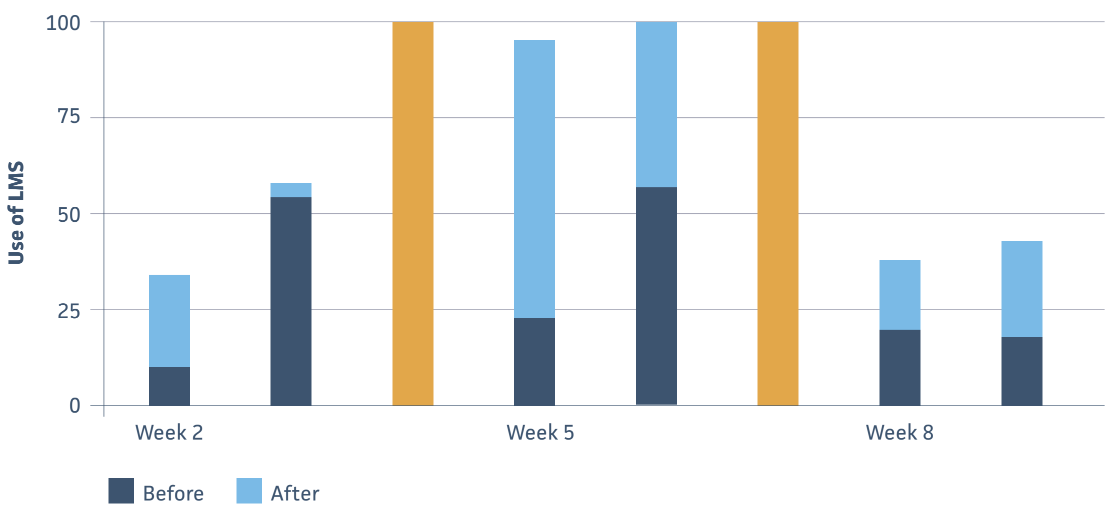


Figure 4: Use of LMS before and after email to at risk students

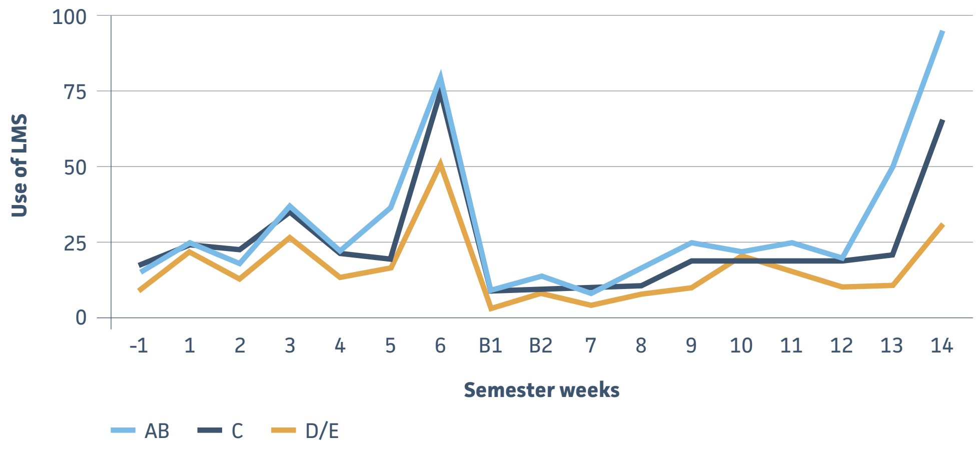


Figure 5: Student use of LMS over the semester grouped by student final grade

The student use of the LMS varied over the semester (Figure 5). The site was available before the semester started so students could become familiar with what was expected of them and to help them prepare for the semester. The semester had a two-week break midway through and there were twelve teaching weeks. The peaks in use are associated with assessments that occur in week 3, 6, 9 and the final exam in week 16. The assessment in week 12 was a group assignment that did not require online use.

The overall pattern of use may help the teachers to understand their teaching. For instance teachers may expect students to use the system a similar amount before the assessment in week 3 and 9. The use in week 9 is lower so the teachers may review the material at this time to ensure it is relevant.

Ethical issues

The ethical issues in this study were around student consent to access data. For normal educational business student permission is not needed for some aspects of using data. For example student can expect teachers to collect grades and the teacher does not require permission to collect this data. The student can expect that this information be used carefully. For instance students can expect that their individual grades are not shared with other students, although it is acceptable to share the average grade to the rest of the class. In a LMS data is collected automatically as it has always been so does not require student permission.

The usage data collected by the LMS is part of the normal teaching process. It was not imposed by the research project so if students felt any discomfort it was not additional to what they are exposed to. The data was reported in groups so it will not be possible to identify individuals.

This case study was reviewed and approved by the Massey University Human Ethics Committee. This included getting permission to use data from the owners of the data. The JISC code of practice for learning analytics guides the project on the ethical use of data (JISC, 2015).

A main consideration is that transparency is important. Tell staff and students what is happening. Be clear about your purpose – to say that you are collecting learning analytics data is too vague and students may not understand what is meant. A good way to review the ethical issues is to discuss what you want to do with a colleague. This process will help to make sure you are clear when you tell students what you are doing.

Action taken

The learning analytics data helped to target students who needed extra support so contact could be made to encourage them to get back on track with their study. The case study indicated that the process did encourage students to make greater use of the LMS.

The learning analytics data identified what students were using in the LMS. This evidence can guide the design of the course by identifying LMS tools that are not used and rethinking how they are presented. The learning analytics data should be checked with other evidence such as asking the students how they used certain tools, and whether or not they found them useful.

Discussion

The focus in this case was to understand how to use learning analytics data and provide it in the form of practical information that teachers can use. This case study looked at ways to encourage students who need extra support and using learning analytics data to refine the course design.

Teachers aim to provide high value learning activities that help learning. Learning analytics offers teachers the opportunity to identify how the students are progressing and to offer extra support to those who may need it.

Students need to do meaningful activities to learn. The approach used in this case study of learning analytics is that data may indicate what the students are doing (or not) and thus give the teacher an insight into their learning. Checking that students are making use of the learning opportunities that are offered will give one measure of effectiveness. If the activity has low use the teacher could discuss with students how to make the activity more relevant.

The laboratory attendance data was collected manually and was difficult to process. The records were on paper and so had to be transcribed to fit with the LMS data. The data was messy with students changing sessions, lecturers sometimes forgetting to take a role, and it was time consuming to process. In comparison the data from the LMS was much easier to work with.

The data processing tools within Moodle were limited. The risk ratings were processed using pivot tables within a spreadsheet. Once a list of students who were identified as at-risk was obtained a mail merge process was used to send out the emails to students. This was a time consuming process and tools such as the Student Relationship Engagement System tool (McDonald et al., 2016) would make this a far more efficient process.

There are limitations to the approach of using learning analytics data. The data tells what the student viewed but not what they did with it. Counting the number of times a quiz question was attempted does not tell you how engaged the students were in their attempt at an answer. The analytics are one measure but not a definitive indicator of student engagement. The data does give useful insight from which actions can be taken to help students.

Conclusions

Teachers can use learning analytics to help students succeed. The data offers opportunities to improve contact between teachers and students and insights into the impact of the course design. Staff need support to integrate learning analytics into their teaching. Organisations can help with effective policies to help staff be clear about the purposes and benefits of learning analytics and the processes involved. Organisations can setup the infrastructure so that teachers can access and use the data, and then provide training on how to use the technology. When this is in place the benefits of learning analytics will flow into the learning.

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The Student Relationship Engagement System (SRES)

Marion Blumenstein, The University of Auckland

Purpose and scope of enquiry

The purpose of this case study is to illustrate a cross-institutional initiative to improve teacher-student connections at scale via personalised messaging. The case demonstrates how learner data collected from various sources can act as indicators of student engagement with course materials and how this data can be utilised by teachers to inform actionable insights for optimising teaching and learning. Student related data are captured as business as usual activities and provide a wealth of information for personalising and prioritising student support. At the University of Auckland faculties are concerned with very large classes, particularly in the first year, ranging from around 800 to over 2000 students per class. Thus, initiatives are concentrated around the first year experience to optimise student retention and success. One important aspect is the teacher-student relationship which is not always easy to maintain in very large classes. SRES is aimed at filling this gap; a simple to use learning analytics tool that lets teachers apply filters based on their own criteria of student engagement to reach out to those who are in need of further support through personalised text and email messages.

SRES was initially developed at the University of Sydney. However, version 1 was specific to the local IT architecture at Sydney. To make SRES accessible to other tertiary institutions required redevelopment and an open-source model was agreed with the original developers. A cross-institutional collaboration between the universities of Auckland, Sydney and, in the initial stages of development Otago, resulted in the current version (SRES v2). Development of SRES v2 is ongoing and experiences and expertise shared between the University of Auckland, University of Sydney and Otago Polytechnic. More recently, the tool is being further developed at Massey University to suit their local context of very large classes in business studies comprising thousands of students.

Two features of its development and design are critical to the success of the SRES: Firstly, a collaborative approach to developing the tool involving developers, IT systems specialists, learning designers and teachers from the beginning; secondly, manipulation of SRES data sources needs to be user friendly without requiring expert data analytics skills. The key questions that arose during this case study were:

1. What steps are necessary to develop and implement a learning analytics tool to fit the local context of a tertiary institution? This raised questions about data governance, IT architecture, and professional development.
2. How might the data typically captured during a course be harnessed to connect students and teachers in large class settings to improve student engagement?
3. At what points is that data most useful?
4. How might the SRES system itself be improved?

Background

At the University of Auckland, in common with many leading universities worldwide, large class sizes are relatively common at first-year level and require either simultaneous video-feeds of live lectures or team teaching efforts where students are streamed into parallel sessions. Moreover, many first-year papers are compulsory and a prerequisite for progression to the next level. This presents obvious challenges not only for students new to university but also to teachers, for example, capturing and holding students' attention and creating opportunities for genuine engagement between teacher and student as well as fostering student-student interactions. Students new to tertiary study often feel disconnected and overwhelmed in the first year (Krause, 2005).). In fact, the retention and progression of diverse, first-year student cohorts is an issue for many higher education institutions worldwide (Tinto, 2006; West et al., 2015). Krause (2005) suggests targeted support could help to alleviate this and regular, personalised communication and feedback between teachers and students may be central to enhancing student engagement and success (Chickering & Gamson, 1987; Kift, Nelson, & Clarke, 2010). Fundamentally, this should never just be about the at-risk cohort or for the purposes of retention, but rather improving the experience for all students. The challenges for teachers to connect to their students in a climate of massification of tertiary education motivated the development of a simple to use learning analytics tool transferable to local teaching contexts: The Student Relationship Engagement System (SRES). The SRES was first developed by Dr Danny Liu at Sydney University, Australia, and collaboratively redeveloped by a group of NZ institutions, under an Ako Aotearoa grant, led by the University of Auckland, to suit broader integration across a wide range of tertiary education providers. It is a web-based system adaptable to local teaching context and IT architecture via shared open-source code available in github under public licence (see details below). SRES combines the capability of a central student data repository and utilisation of these data at scale to personalise support and interactions with students via messaging (McDonald et al., 2016). It has previously been reported that persuasive text and email messages targeted at individual students or student groups have positive effects on learning and study success (Goh et al., 2012; Dodge et al., 2015).

The emergence of learning management and classroom response systems in recent years enabled a more widespread adoption of learning analytics utilising student generated data to understand and optimise student learning. However, our research revealed barriers for teachers to gaining insights from learning analytics defined as 'the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs'(SoLAR, 2012). For example, the complexity of systems do not always allow easy access to learner data and a lack of expertise in data manipulation may be an issue for making learning analytics accessible. Therefore, the aim of SRES is to provide teachers with user-friendly tools to enable actionable intelligence from data and the adoption of learning analytics without the need for expert data analysts. Its strength lies in the usage of "local data", i.e. information collated from several sources such as the learning management system, student services, and other context-specific information that may be different for different instructional contexts. Thus, data can be easily collated and combined into the SRES by teaching staff for a range of purposes. The overall goal is to connect teachers with all students, not just those at risk, via personalised messages based on teacher-criteria. Underpinning the SRES is a belief in 'bottom-up' learning analytics, empowering teachers to gain actionable insights from their own local data instead of having learning analytics delivered to them from centrally-controlled services.

Description of development / intervention

Based on the teacher-centred approach of a learning analytics tool a key initial step in SRES v2 development was to establish a flexible system architecture that could easily be customized and at the same time simple to use by teachers. The core database architecture therefore consists of the collections of courses (papers), users (students and teachers belonging to courses), columns (belonging to courses), and student related data (information in the columns). SRES v2 affords cross-institutional collaboration and application, and as such is licensed under the GNU Public License v3. The SRES v2 source code is freely available at https://github.com/atomsheep/sres. The similarly-licensed supporting mobile app (leveraging the Phonegap platform for device agnosticism) is available from https://github.com/atomsheep/sres-app. Anyone interested in using the SRES within their institutional LMS is advised to integrate it in consultation with their institutional IT architects and respective data security policies.

The first version of the SRES, built at Sydney University with limited ability to scale in other enterprise level environments, was a pilot project with transferability to other institutions as a stated outcome. Moreover, this approach lent itself to bringing new partners into the project, sharing the development load, ensuring sustainability and increasing the benefits for all. From the beginning of the collaborative redevelopment, it became clear that IT specialists, learning designers, teachers and university management needed to be involved early on as too often educational technology failures tend to result from "too little attention being paid to the pedagogical, organisational, cultural and other factors that determine what fails, what works and what

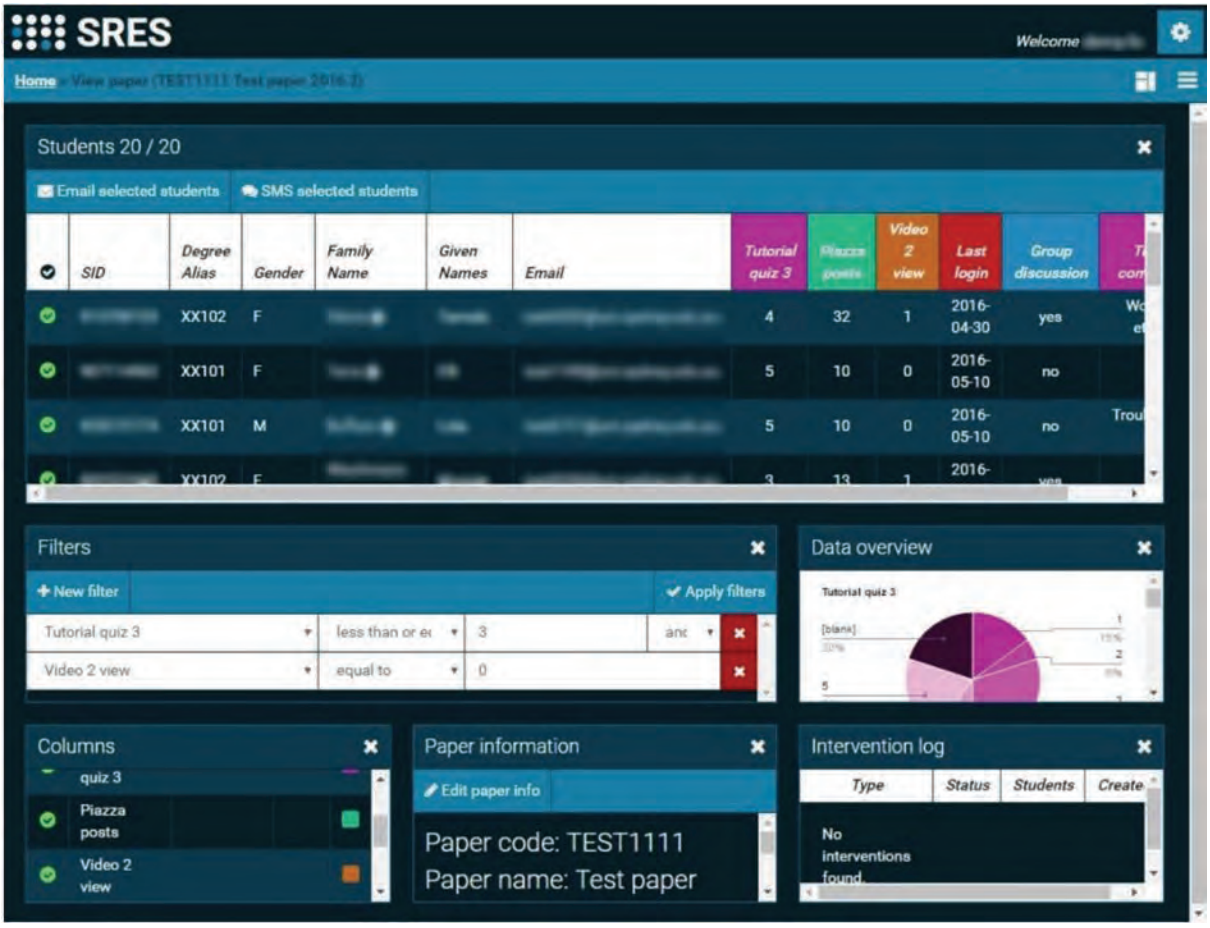

Figure 1: Main SRES v2 interface showing student list, filter functionality and overview panels

transfers successfully into other contexts" (Latchem, 2014, p. 5).

The user interface guides the user, step by step to setting up a course, , importing or entering data, selecting students according to pedagogically-informed criteria and customising email templates. The main SRES interface revolves around the student list which consists of rows of students and columns of data, which is familiar to all teachers (Figure 1). From this interface, teachers can directly apply 'filters' to the data to generate a subset of the list, and then contact the filtered students. These filters are based on simple operators such as 'equals', 'less than', etc. This dashboard also has simple visualisations which display the relative frequency of data in each column, as well as a log of the messages (interventions) that have been delivered to students.

Teachers can write personalised messages addressed to individual students or groups of students and include specific data about that student (Figure 2). When teachers compose messages to students, any data that are stored in the list can be brought into the message. Messages can be further personalised using the 'conditional paragraph' function in SRES targeting only a subset of students, when teacher-specified conditions are met (see below). The aim is to allow teachers to connect with all students, not just those at risk, by efficiently collating and processing student data related to course engagement and performance supporting students at scale.

Sources of data drawn on

SRES allows a lecturer, or any member of the teaching or support team, to efficiently target students based on their individual performance, engagement with course materials, and/or participation in learning activities (e.g. quizzes, discussions) using highly personalised email or text messages. Its strength lies in the usage of local data which are collected from several sources such as the learning management system, student services, and other context-specific information that may be different for different instructional contexts. SRES provides flexibility because the input data structure is simple (one row

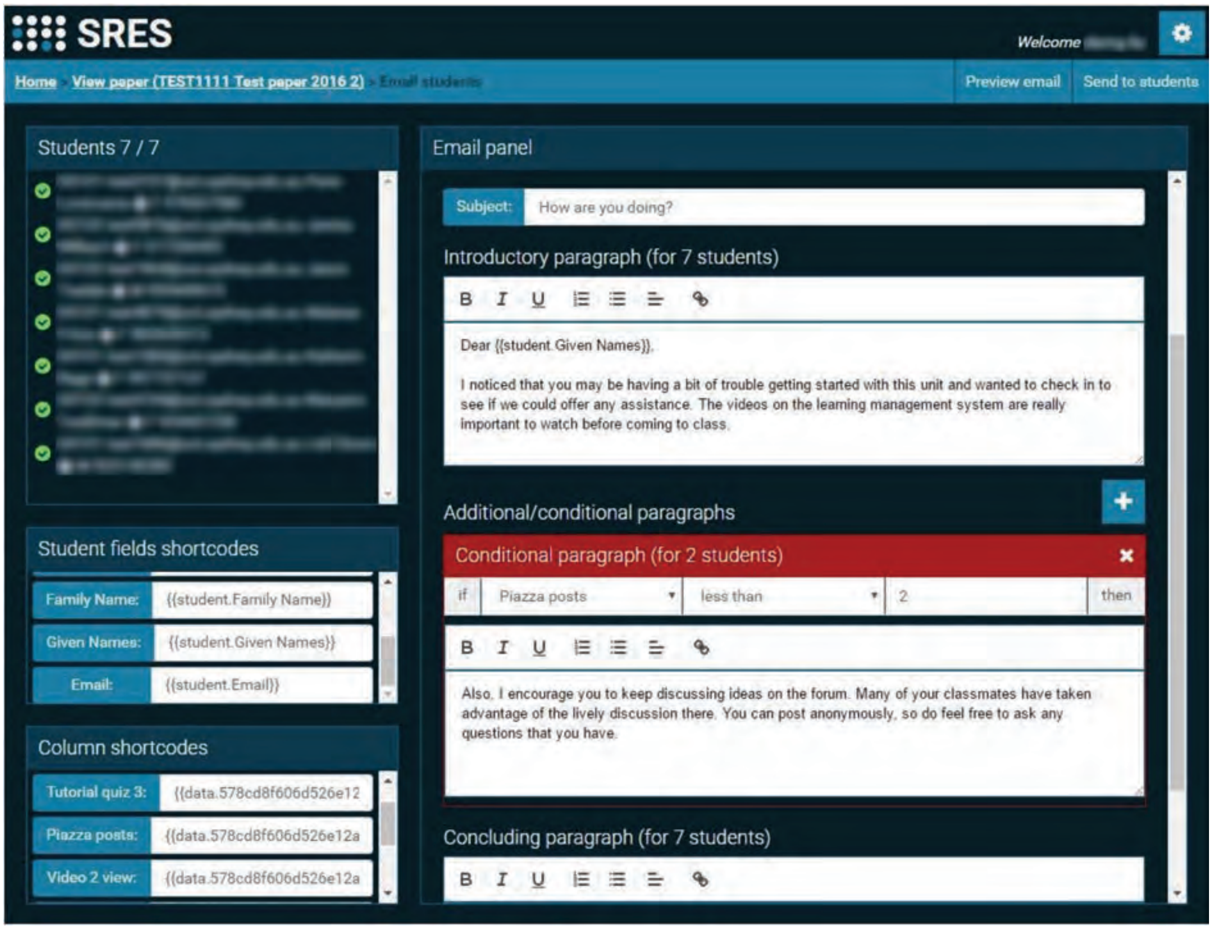

Figure 2: Email composition screen of SRES v2 showing conditional messaging for subsets of students

per student) and easily accommodated through use of delimited files or spread sheets (e.g. CSV, TSV, Excel etc.)

In semester 2 2016, SRES v2 was piloted for the first time at the University of Auckland in three large first year courses in engineering, science and business studies with student numbers ranging from 860 to over 1700. Teachers or course coordinators were already acquainted with the concepts of learning analytics and teaching and learning pedagogies through their previous involvement as teaching fellows in our central academic practice programs. In essence, pilot courses were chosen based on being able to rely on teaching champions who would feed back any experiences about usability and efficiency of the SRES to our learning designers and developers. For research purposes, beyond institutional evaluation of the SRES tool, ethical approval was obtained from students. Data sources drawn on are mainly student log activities collected by the LMS. It was important to meet with the entire teaching team, course coordinators and academic advisors (where applicable) to discuss the SRES trial some weeks before semester began. Teachers then identified several actionable indicators as proxies for student engagement or disengagement as discrete points during the course where they could introduce a personalised message to intervene.

The indicators can be broadly categorised into two areas, resource use (Figure 3) and student performance (Figure 4). All data compilation, data upload into the SRES, and email messaging was performed by the teachers themselves but in close collaboration with learning designers from our University's centralised academic development unit.

Intervention - Resource Use

A previous email intervention study in a large first year cohort at the University of Auckland showed a relationship between delayed engagement with the LMS and study success, i.e. students who log in to access course resources / learning materials more than 10 days after the course has started are on average performing lower compared to early engager (unpublished data). Therefore, learning analytics data on students' page views, particularly the time point when they first log in to the LMS, can be important indicators for engagement or disengagement. The email example from a lecturer below was aimed at a group of students who did not appear to be active two weeks into the new semester and course:

> *Dear XXXX,*
>
> *I'm the course coordinator for INFOSYS110 Business Systems and according to our system logs you have not yet visited our course page on CANVAS. This is somewhat concerning as we are at the end of week 02. Is there anything I can help with? Feel free to email me or pop in and see me. I have official office hours 9-10 on Tuesdays and Thursdays but I'm normally on campus during working hours and will be happy to see you at any time.*
>
> *Regards, ...*

In another course, quizzes were specifically designed to identify students early on who did not download a vital resource for their course work, statistics software program (iNZight). After uploading the combined student lists and student activity data (quiz results, page views etc) captured by the LMS into the SRES, the filter function identified a group of students who had not yet attempted the quiz (iNZight quiz)

Figure 3: Email composition screen of SRES v2 showing conditional messaging for subsets of students

that signalled to the teachers that the software had been installed and used. The teaching team then sent those students who apparently had not yet attempted to engage with the required software a personalised email:

Dear....

I am trying to ensure that my students stay on track with their assignments and have noticed that you haven't yet attempted the quiz to show me that you have engaged with the iNZight software that is used in this course. This quiz is required as part of your assignment. You can attempt it right now! It is due on ......Just by attempting this and submitting the assignment you will score full marks for question 1.

If you need help getting started, the tutors are available Mon to Fri from...to... at...

If there is any reason you are unable to get started, and you think I can help, then please do email me.

Kind regards.....

Figure 8 depicts the data flow for indicators of resource use. Data are drawn from the learning management system ('LMS activity') triggering a timely email intervention ('Email triggers'). Quiz results and discussion posts are considered active participation (students creating content) whereas passive page views are represented as the downloading of readings or course syllabus or materials on past assignments (students consuming information).

Intervention - Performance

Diagnostic quizzes and early assignments are particularly useful in large class settings to identify students in need of additional learning support to ensure study success. At times, teachers may use the conditional messaging function in SRES which is particularly useful for further personalizing a message based on second and third filter criteria. Only a subset of students will then receive the additional paragraph(s), for example, a message aimed at students from recognized equity groups informing them about specialized learning support programs. The following message snippet is an intervention example aimed at students who did not do so well in their quizzes and first assignment:

Hi.....,

Looking at the results of your quizzes and first assignment I thought I'd get in touch and see how you are going. I know that you must be disappointed with your results but these early tasks are designed to give you feedback on how to improve. If you need help getting started, learning advisors are available Mon – Fri at [location] from {time].

Let me know if you have any questions!

Kind regards,...

Vice versa, reaching out to students who are performing well early on can ensure ongoing engagement with the course materials and beyond, for example, alluding to optional resources that may be of interest to a group of students based

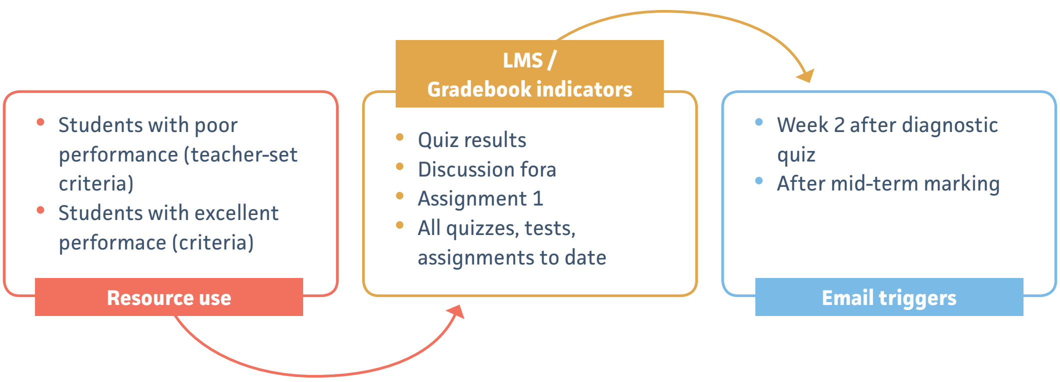

Figure 4: Flow diagram for indicators of "Performance." Note, data other than student activities drawn from the LMS or Gradebook may be considered, including (but not limited to) attendance, in class participation, student feedback, other learning support received etc.

on feedback received. A personalised message to encourage students to keep up the good work could be as follows:

> *Kia ora…,*
>
> *It seems that you are making good progress in this module. We hope that you are enjoying learning new things. Keep up the good work!*
>
> *All the best,…*

Actionable insights gained

Based on the very first experiences of teachers using the SRES three key areas emerged for further improvement: Firstly, the SRES tool itself is currently undergoing further development work to improve the user interface such as colour scheme, data input, data visualisation and full integration into the local IT architecture; secondly, ethics consent from students was very low and will require a more integrated approach to be able to contribute to the scholarship of teaching and learning in the area of student engagement (see for example Goh et al., 2012); thirdly, the tensions of student data access, handling and privacy require institutional governance and robust data policies. One important insight gained was that learning analytics and the implementation of learning analytics tools to be a success requires a collaborative approach involving learning designers, IT experts, teachers and management from the very beginning. Another insight gained was the importance of professional development and the sharing of knowledge in a community of practice. Feedback from attendees of learning analytics workshops where the SRES tool could be trialled and discussed, surfaced a multifaceted landscape of overlaps and also differences in teaching practice and issues at various levels of study: PETs, polytechnic and university.

SRES implementation

In order to pilot version 2 of the SRES, we enlisted the technical and infrastructural support of the University's Centre for eResearch and adopted a conservative security stance which restricted access to a small number of approved computer stations and users involved in this learning analytics project. Additional university funding helped to improve integration and security of the tool with the ultimate goal to fully integrate it as a web-based Single-Sign-On solution to improve overall security and thereby allowing us to extend the pilot work to more courses and users. In addition, digital design students were contracted to scope the SRES user experience and graphical user interface (GUI) to provide recommendations on how to improve usability.

True data integration between SRES and the rest of the University's key data repositories is a longterm aim for this project. This aim was also shared by our users whereby systems integration and automation are a minimum requirement of learning analytics tools to be implemented in practice. Teachers are commonly time-poor and for learning analytics tools to be usable they need to be simple in design without having to manually handle and manipulate large data sets.

Data governance

The move to implement Canvas as the core LMS at our university in 2016 highlighted a number of gaps in existing university policy around the ethical handling of student data, particularly in relation to leveraging the opportunities of learning analytics. Up to this point, the opportunity to access and analyse student data centrally was mainly considered from a top-down perspective to support the University's business intelligence and strategic planning needs and requirements. In addition, it was particularly difficult and time consuming for lecturers or student support services to access timely student engagement data from the University's previous in-house developed LMS. To consider the new opportunities afforded by Canvas, a working group of cross-institutional stakeholders was created to assist the DVCA's Office to outline and develop a set of guidelines and policies to ensure student data is managed, accessed and handled in an appropriate and ethical way (ensuring confidentiality and care). More importantly, the new guidelines/policies are expected to support both top-down (business intelligence) and bottom-up (learning analytics) needs for the improvement of the student experience and study success.

Action taken

The SRES tool is being further developed / improved at University of Auckland upon feedback by users and as new teaching needs arise. One of the major foci at time of writing are the plan to fully integrate the SRES into existing University of Auckland systems to enable automated data uploads from various sources into the SRES. This would greatly improve efficiency of data handling, a point made by several teachers who piloted the tool in S2 2016. Automation would do away with manually compiling large data sets drawn from various sources followed by a manual upload into the SRES. Furthermore, the multi-institution collaboration between the universities Auckland and Sydney and Otago Polytechnic has grown into a project to extend the capability of SRES to include dashboards not only for teachers on various aspects of teaching but also for students to provide feedback on their learning using learning analytics. Additionally, our experiences will feed into a larger project now underway at University of Sydney to develop a third iteration of the SRES tool which is financially supported by the Australian Office for Learning & Teaching and to which current collaborating institutions will have access to implement when the initial development work is completed.

Discussion

Higher education providers are increasingly being measured for the effectiveness of returns on students' investment (Stefani, 2015). Over the years this has resulted in major efforts to increase student retention and success at many tertiary institutions globally. Commonly these are evidenced through initiatives such as the first-year experience, and facilitating the transition to tertiary study of mature students, students from low socioeconomic backgrounds, minority groups, first in family, and international students (Briggs et al., 2012). Many institutions pin their hopes on learning analytics to gain insight into, and influence, student learning, performance, motivation and engagement (e.g. Clow, 2013; HEC, 2016). Whilst it is well documented that students need to be well supported in their learning—academically and socially with clear expectations and feedback (Hattie & Timperley, 2007; Tinto, 2009)—to succeed in their studies, the vast field of learning analytics research lacks practice-orientated approaches that are transferable into everyday teaching. Therefore, data-informed student retention and engagement remain unrealized buzzwords for many practitioners. SRES v2 presents a tangible solution that can provide insight into the 'whys' and 'how' of student engagement or disengagement, and give teachers a way to act on this information.

Conclusions

Learning analytics in practice requires a team of experts, including IT specialists, learning designers, teachers, academic advisors and institutional teaching & learning managers. The SRES case study at the University of Auckland clearly shows that the implementation of a new educational technology has to grow from the bottom up. It requires careful planning and design to be adopted by a wide range of teachers. Each context is unique and thus triggers for actionable insights will vary depending on the teaching and learning requirements. Therefore, learning analytics tools such as the SRES v2 need to be designed to accommodate these variations. The focus has to be on what actually works in real-world teaching settings rather than having to rely on centrally compiled reports of learning analytics. In order to answer the third question posed at the beginning "At what points is that data most useful?" a larger data set on student performance is required. Hopefully this will be achieved by the end of S1 2017 with ten more large undergraduate courses trialling the SRES at the University of Auckland. Planned interviews with students as well as teachers will explore questions of timing and impact of the intervention more closely. In summary, we identified four main areas that require close attention when implementing learning analytics for the first time into a course or institution-wide initiatives:

- **Data & IT:** Access to data, data wrangling, technical hurdles.
- **Practice:** Understanding teaching and our learners is contextual.
- **Capability:** Professional development and training for learning analytics implementation.
- **Governance:** Influencing institutional agendas & policy, working together.

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Two postgraduate taught courses in science and engineering

Claire Donald, The University of Auckland

Purpose and scope of enquiry

This is a case study of two university educators' experiences with and expectations of learning analytics (LA) over a two-year period. Both are lecturers who co-ordinate and teach postgraduate courses, one in science and the other in engineering.

The purpose of the case study was to investigate the lecturers' desired, required and actual use of learning analytics in their course design and teaching practice, and to identify what gaps might be addressed by learning analytics. Both lecturers had invested substantial time developing innovative course designs. They had started exploring how student learning data might be used to help evaluate the effectiveness of their course designs, and provide clearer insights about student learning – both during and after the course. The expectation was that this learning analytics data might be used to help answer questions about the relationship between pedagogical intentions and outcomes of student learning (Lockyer, Heathcote and Dawson, 2013).

In particular, the lecturers were seeking ways of using passively collected system data that they had not used before to evaluate their courses. They wanted to see whether the "trail of digital breadcrumbs" (Dawson, 2011) could provide an additional data source to supplement the course evaluation data, student grades, course evaluation ratings, responses to questionnaires and focus group interviews that they were already using. Collectively, these data sources are called learning analytics data. Learning analytics is defined as "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (Ferguson, 2012).

Both lecturers were 'early adopters' of learning technologies, with several years' experience of innovation using educational technologies. Both courses were at similar stages of third or fourth iterations of course development. New course designs and related technologies had been implemented on a trial basis, and subsequent changes made, based on feedback to further improve and embed new teaching and learning technologies.

Each student cohort for both courses was very diverse in terms of age, professional experience and location (students might be local or overseas). Having made a significant investment in developing, teaching and maintaining these online courses, the lecturers were seeking more feedback and evidence on how well their course design and assessments addressed the students' learning needs, especially for those students whom they never met in person.

The case study monitored and recorded:

- what questions lecturers had about their course designs and student learning,
- their expectations what the system data could tell them,
- whether there were gaps between lecturers' expectations and what the different elearning systems offered in terms of learning analytics, and
- what was involved in translating the data so that it was meaningful to these teachers.

In addition, both lecturers agreed to participate as test users and educational consultants in a pilot software development project aimed at developing new LA components for an existing, bespoke teaching tool at the University of Auckland, called CourseBuilder (CB).

Background & context

The Centre for Learning and Research in Higher Education (CLeaR) at the University of Auckland supports leadership, research and professional development on teaching and learning in higher education, including technology supported teaching and learning. This is achieved by partnering with academics in the faculties in collaborative learning design projects. Two recent such collaborations were between CLeaR's elearning team, and the lecturers who participated in this case study. Their course information and the elearning tools used in their courses are summarised in Table 1.

Student usage data has been accumulated by the range of elearning systems and tools used in both courses for several years, some of which was available for analysis.

Engineering – Project Management *Postgraduate, blended course*

The classroom delivery of this course has been modified on a yearly basis since a new lecturer became the course co-ordinator in 2010. The course became progressively blended from being mainly a traditional classroom-based course. A variety of data was collected on the effectiveness of these changes, including Google analytics data, CourseBuilder (CB) usage data and questionnaire and focus group data on student learning.

The course had also been a focus of research on information flow patterns related to student decision-making, for the lecturer's postgraduate studies (Miller and Donald, 2014). This research traced what decisions students made in response to the course requirements (usually assignments), and then monitored the information channels and sources they

Table 1: Summary of courses, class sizes and technologies for the case study

Discipline	Subject, *course type*	Level + student numbers	eLearning tools and platforms
ENGINEERING	M.Eng. Studies Project management *Blended course*	Postgraduate taught Masters, semester course 80 students	CourseBuilder, Cecil, Canvas, Google Analytics, Turnitin, Socrativ, Piazza, TodaysMeet, Notable, LinkedIn, Edublogs, Lecture theatre recording
Population Health, SCIENCE	Population Health *Distance, fully online course*	Postgraduate taught Masters, semester course 100 students	CourseBuilder, Cecil, Canvas, Google Analytics, Turnitin, QuestionMark Perception, Articulate Presenter

use in relation to these decisions. The lecturer wanted to know what learning analytics data could add to this investigation.

The sources of student learning data were:

- Coursebuilder (CB) web logs
- Cecil (LMS) web logs
- Canvas web logs
- Quiz attempts and scores (CB)
- Student grades (LMS)
- Piazza usage and posted comments
- Lecture theatre recording access logs
- Participation data from Edublogs, LinkedIn
- Socrativ poll data

Population Health
Postgraduate fully online large class teaching

This postgraduate course in Population Health was developed over several years to be taught completely online to Masters students in diverse locations. The university Learning Management System (LMS) was used with various other enterprise etools to present course materials, facilitate and mark assessments, run quizzes and discussions, support reflection and invite student feedback.

The sources of student learning data were:

- Student log data for CourseBuilder (CB)
- Cecil (LMS) web logs
- Canvas logs
- Quiz attempts and scores (CB)
- Student grades

The lecturer wanted to know whether students were using the online materials as intended, and whether their online learning behaviour patterns correlated in any way with their grades. Initially, just the final grades were used. Future analyses were planned to be finer-grained, using student grades for each of the four assignments that made up the final grade, in relation to patterns of student usage. This course had no exam.

Development of the intervention

As noted above, both lecturers participated in piloting new LA features for one of the teaching tools they were using, CourseBuilder (CB).

Early development work on these LA features was focussed on what lecturers required that was not already provided, by other teaching tools, namely Google Analytics, Moodle, Cecil (in 2015) and Canvas (2016). Both lecturers found the Google Analytics (GA) dashboards confusing, difficult to use, and inaccessible. The CourseBuilder Learning Analytics features needed to complement GA and be more user-friendly.

Requirements for the LA features of CourseBuilder

The two lecturers in this case study wanted the learning analytics to show trends in students' use of their CB websites. This involved being able to monitor:

1. differences in usage between *staff* and *students*,
2. usage of CB *elements* and groups of elements,
3. *patterns* of use of CB pages over time, in relation to the overall website structure,

These trends and patterns had to displayed graphically, rather than supplied for exporting as data files that the lecturers then would have to analyse further independently.

Early plans, according to specifications of the UoA learning designers and web developers, were to represent the lecturers' CB website structures visually and then map student use of the pages of the site in relation to the website structure in two ways (see Figure 1):

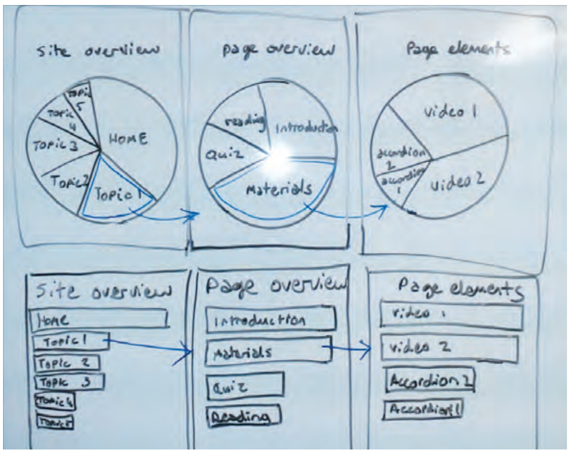

Figure 1: First draft visualisations proposed for CourseBuilder Learning Analytics

a. According to **number** of users: From individual students, to groups of students (defined by class data), cohorts of students for different years, and for all students for all years of the course.

b. According to **time** of use: Student uage patterns would be displayed for *completed* courses, i.e. *post course delivery*, and also dynamically while courses were running. The requirement was therefore for "snapshots over time" that showed patterns of usage of a course for different student groups and cohorts. This would be used by the lecturers to monitor student engagement in relation to course designs, and by students to monitor their own progress and completion of their CB course.

A first version of the data tables (see Appendix) was compiled and trialled by the lecturer of the Population Health course.

As noted above, the lecturer of the Engineering course wanted to explore student usage by monitoring the flow of information between student decision points in response to course assignment tasks. He was particularly interested in using Sankey charts, as demonstrated in an early version of a new open analytics toolkit, 'MOAT' that was being developed at Macquarie University (Figure 2).[8] The ability to customise the data collection points and flow diagrams to the specific assignments and learning activities in his own course were seen to be highly valuable. He anticipated that this approach would address his teaching questions about the effectiveness of his course design, and his research questions on information flow in relation to student assignments.

8 . . . Dr Danny Liu, University of Sydney. http://www.slideshare.net/DannyLiu8/codeveloping-bespoke-enterprisescale-analytics-systems-with-teaching-staff-57817212

Case study findings

The goal of this case study was to monitor and record:

- what questions lecturers had about their course designs and student learning,
- what their expectations were of what the system data could reveal,
- whether there were gaps between lecturers' expectations and what the different elearning systems actually offered as regards learning analytics, and
- what was involved in translating the data so that it was meaningful to these tertiary teachers.

Lecturers' questions and expectations about LA

As noted previously, both lecturers had invested many hours in designing and developing their course websites. Their questions of the LA data were therefore very detailed and specific to their own design decisions and intended learning outcomes for the courses they were co-ordinating:

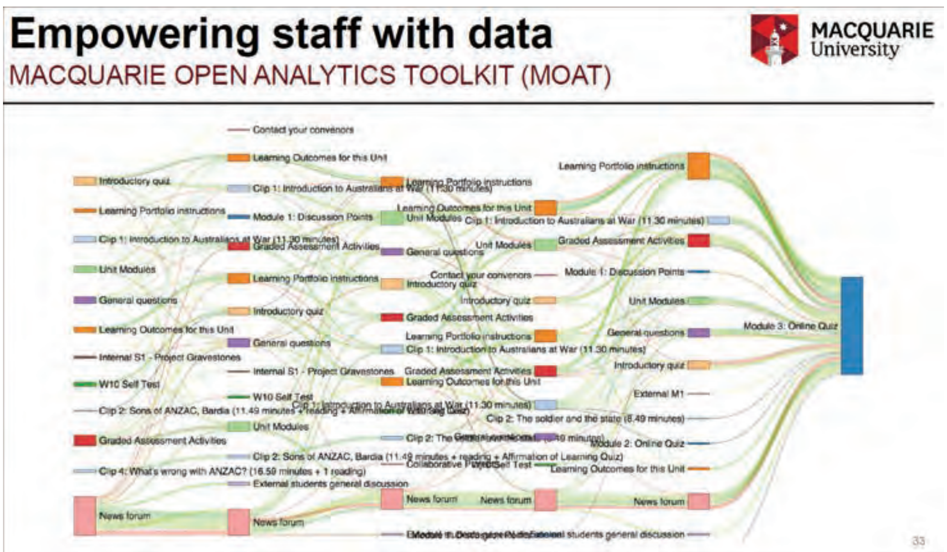

Figure 2: Sankey charts to visualise decision points and student usage as information flow

The lecturers wanted learning analytics to show:

1. Site usage over the semester e.g. day of week, time of day,
2. Individual, named student usage e.g. number of times they visit specific parts of the website,
3. Number of people who accessed the resources,
4. The number of students accessing discussion pages and when,
5. Frequency of posts to feedback/comment boxes at the end of each module,

Less interest was expressed in overviews of the extent of the whole class use of different parts of the course (e.g. videos, tutorials or resources). This was, in part, in order to provide background information on students so that when they asked questions, reliable and current information about their performance and activity in the class was available.

> *"I'd want that (pie charts or bar charts) per student so that I can see they were late with an assignment or they bummed out with an assignment and I can see that one of the things causing their problem is they're not accessing the materials on the website.... And a snapshot of that student's usage per week... So I could see if nothing was accessed until Week 3 and then suddenly - bam... So allowing me to use a report function that allows me to look at "Sophie" for "Week 1 to Week 5". So being able to tailor it.*

The lecturers wanted quick, easy access to how individual students were tracking with the various course requirements on a daily and weekly basis.

> *"What I want to know is how often did they look at the actual content, are they attempting the (weekly) quiz and if so how often? Might find that only high performing students are using them and the poor performing students aren't going near them. Want to get some sense of whether the learning activities we're providing are benefiting the people that have the most need."*

Similarities in what both lecturers wanted were:

- graphs of (particularly but not restricted to CB) usage data for total views/attempts by all students in a particular cohort, that one could then drill down to identify individual student activity (views and attempts),
- finer-grained analysis of student engagement with course components and assessments,
- analysis of the discussion forum participation (e.g. do a few students access the forums often, or do lots of students access the forums but seldom?) and
- answers about possible relationships, such as correlations, between usage patterns and performance.

However they did qualify this, as one said:

> *".. there's a big assumption there. ... The assumption is that students will go to resources they find most helpful, relevant and accessible, when it comes to assignments. Frequency of use is a part of what we need. We still need to know - is it the right information? ... what's the quality of what's provided. You see some sites that have a quick exit poll – asking 'did this provide the information you needed?' You get an opportunity to rate it or give a little feedback. I really want intelligent, informed feedback from the system."*

Furthermore, each lecturer had additional interests in:

(for Population Health):

- data on student use of additional readings.
- to work in collaboration with data experts on learning analytics
- using student data to coach and correspond with students during the course, using an email tagging and early warning system to support student retention.

(for Engineering):

- usage data from lecture theatre recording system to inform future practice in class and online,
- Information flow diagrams (Sankey charts) and data that could be interrogated and linked to student performance and demographics to inform his educational research as well as course design.

> *"What I would like to see from something like Google Analytics or a simplified form, is the intelligence behind it. What is good about what you're providing? Where are students going mostly for the information?"*

Gaps between lecturers' expectations and what LA provides

The lecturers' perceptions of current affordances of learning analytics were insightful:

"Questions I'd like to know are questions you can't answer, like 'what do you find difficult about the course?'. They're the kind of questions you'd have to ask the people. 'What do you find as being useful? What is it about the teaching which is effective? What are the things that are annoying or frustrating? What are the things that inspire you to go the extra mile? What inspires you to get interested in the topic?' If the data could help you improve somehow. If it can pinpoint areas where you can do something differently and improve. But I don't know whether any data would be that sophisticated."

However, they both noted that that student usage data from their online courses could be used to:

a. assess which parts of the course the students used when, and how much,

b. view student patterns of usage and engagement to see whether students were using the learning opportunities and resources as intended (comparing design intent with actual student use),

c. correlate student engagement with performance.

Both lecturers hoped that in the near future LA could be used reliably and easily to

1. shed light on relationships between finer-grained elements of student engagement and performance,
2. reveal the timing of student engagement and patterns of user behaviour (ie early in semester, consistent throughout a semester, 'cramming' at the end), and
3. be used as a motivational tool for students, both by students themselves and by staff.

Talking more about this motivational use of LA for students, one lecturer offered:

> *"It would be great if there are shared visualisations so that students could gain feedback on themselves as well. Would be quite beautiful actually, … and the educator also had access. (So) … formative assessment that's IT labelled. That's the key really, close the loop on that reflective cycle for the teacher and the student to draw from. … The other thing for the educator is 'have you got the right design?' While students are getting feedback you are monitoring how they are using this – it tells how you design your teaching approach – how it's working….. Pathways would be useful, and patterns of use. Not just hits. Particularly when you come to redesign the site, or do the next one."*

Providing this kind of information at a course level about individual students, was echoed by other lecturers at this university at the time of this case study. A common concern was whether, from an ethical point of view, it was permissible to use student data in this way.

Translating learning analytics data for lecturers' use

The lecturer in Population Health used the vast (raw) CB data tables that were prepared for the early prototype of the learning analytics intervention, and compared the overall usage data for individual students in one year's cohort, with their final grades. Upon inspection, usage scores did not correspond to either high or low performance (using only the final grades). While the top performing student did have the highest usage score, the student with the second highest grade had used the course website very little. Average and lower performing students had a mixture of very high, average and low usage scores. This lack of correspondence between performance and usage supports similar research findings reported recently (Gašević, Dawson, Rogers & Gasevic, 2016; Agudo-Peregrina, Iglesias-Pradas, Conde-González & Hernández-García, 2014).

Initial work was done to develop LA features in CB that would address the lecturers' questions recorded in this case study. The student data base architecture was designed and built, ready to be populated with CB student usage data. Paper versions of reports and visualisations were trialled with both lecturers, and adapted based on their feedback. Plans were in place to test the LA functionality with a wider group of university lecturers using sample reports and visualisations.

However, the project was then put on hold. On-going development required significant work from a small technical team with conflicting priorities. With the parallel change in the university LMS taking place, changes in related enterprise systems led to heavy workloads that coincided with this research.

Both lecturers were disappointed but not surprised that the prototype development of learning analytics features for CourseBuilder was not completed, particularly since it was too early to make a meaningful assessment of the work done thus far. However, much was learned from this early work, by the developers, researchers and the lecturers. Being "early adopters" of elearning innovations in their teaching, the lecturers were well aware that this was an institutional reality, as well as a familiar phenomenon when working in an emerging field where projects are subject to the challenges of working in unfamiliar territory, on the edges of institutional policy and infrastructure. The response of both lecturers, true to their pioneering spirit, was undaunted: they expressed interest in collaborating with teams of data scientists and learning designers to pursue alternative avenues with other software tools to answer their learning analytics questions.

Conclusions

This case study aimed to provide insights in two discipline areas of science and engineering, of how tertiary educators use learning analytics data during and after teaching their courses, when course materials are revised and updated. We observed the similarities and differences in how the lecturers viewed and worked with the student usage data in its current form, and documented the steps required to turn this data into meaningful information.

The case study was also intended help researchers define criteria for a) the use of learning analytics by lecturers (such as criteria for accessibility, ease of use and data translation literacies) and b) the design of learning analytics features for educators (data base structure and dashboards).

Both lecturers, quite independently, and once introduced to what the field of 'learning analytics' was, expected that learning analytics data could help address long-standing questions they had had about student learning in their courses. The comparison between usage and student grades done by the lecturer in Population Health revealed that collecting and analysing such data was not useful if it did not reveal anything about students' learning experiences.

When the lecturers' feedback was sought on the early sketches for visualising their students' use of CourseBuilder data in particular, they were quick to point out that they needed information and tracking about individual students in relation to a specific learning goal. They wanted learning analytics to help them test specific teaching techniques, or course design intentions.

Limited learning analytics capabilities for teachers in elearning tools leaves teachers to fall back on their own skills, or lack thereof, using spreadsheets, simple scatter plots or histograms. Some who are able, use modelling techniques (e.g. regression analysis). For others, simply extracting the data from the LMS can be a challenge, and further investigations are beyond their reach.

It is only a short next step for the lecturers in this case study to want to create new learning tasks and activities that record data about learner behaviour, such as responses to an early quiz with automated analysis of results. These learning design features may provide insights into students' learning experiences, provided the data is reported in a way that is easy for teachers to access and interpret. This is in contrast to the retrospective data analyses, which are designed to find or predict patterns of behaviour, and currently dominate the learning analytics field. As the lecturers pointed out, educators, students and data specialists need to collaborate on future developments for learning analytics to inform student learning.

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Appendix

Suggested structure of CourseBuilder data tables for Learning Analytics

1. Student access log – table format

Page name	Student id (+ name)	All students in the cohort →		
All page names in the course	Time and date stamp (per student per course page)	Time and date stamp (per student per course page)	Time and date stamp (per student per course page)	Time and date stamp (per student per course page)
↓	Time and date stamp (per student per course page)	Time and date stamp (per student per course page)	Time and date stamp (per student per course page)	Time and date stamp (per student per course page)
	etc	etc	etc	etc

2. Page list

Page code	Page title
(e.g. menu0_8.html)	AP_Random (this is a link to that course page)
menu0_9.html	AP10Apply
menu_00.html	Glossary
etc	etc

3. Student list

Student UPI/code	Student first and last name
e.g. cdon021	Claire Donald
etc	etc

4. Page views

Page code / page description	Student UPI/code	Viewed Datetime
e.g. index.html (Welcome to the course) this is a course page link)	e.g. cdon021	e.g. 2015-03-08 23:05:51
etc	etc	etc
etc	etc	etc

Learning analytics scenarios for professional development

Scenarios present real-world problems most teachers can relate to and prompt them to consider ways that solutions developed by others might work in their own professional practice. The scenarios outlined in this document describe ways that teachers can:

- Use learning analytics data as a form of feedback on learning design decisions;
- Identify and provide support for students who are not active in their courses;
- Deepen their understanding of student learning and behaviour.

The scenarios are based on interviews with early adopters and case studies of emergent learning analytics practice in higher education. They are mapped to a Learning Analytics – Learning Design Framework (Figure 1) to show how actionable insights can be generated and aligned to a 'Rhythms of Teaching' cycle.

The scenarios cover three broad areas where learning analytics data, viewed through appropriate lenses, can provide insights that prompt action by teachers to enhance student engagement, student achievement, and student retention. They are designed to be adapted for different institutional elearning environments and teaching contexts.

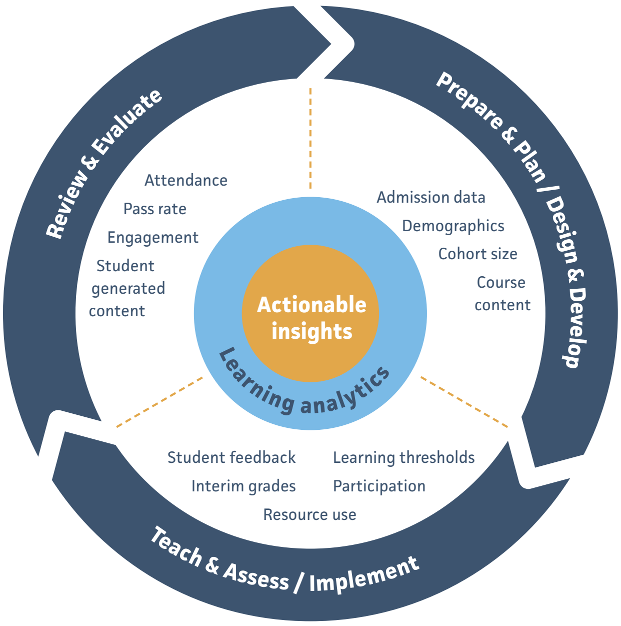

Figure 1: Learning analytics and learning design cycles

Scenario 1

Support students to avoid drop out in the first year

Problem

Learners struggle early on to find pathways to successful study

High drop out rates in the first year are a problem for many institutions. With the right tools and background information, insights can be drawn from usage data for online learning systems to help teachers identify and take action to support struggling students.

Strategy

Monitor student progress to keep learning on track

The ability to monitor students' progress and performance throughout a course has become more feasible with the routine collection of activity logs from online learning systems and tools. Checking progress at milestones set during a course can reveal common challenges and identify individuals or groups of students who may require guidance or additional support.

Data sources

Data presented in standard LMS analytics reports shows who has logged in, when, for how long and what resources they have accessed. This 'course grained' data gives a broad picture of student presence and performance in online course activities. It does not identify reasons, but it can trigger further investigations.

Evaluate and take action

If students don't log in, access essential resources or engage in required activities in the early weeks of a course, this may be a sign they are struggling. Making contact will determine if this is the case, and if further action isrequired. Capable students may be fine, while less experienced learners may need guidance to stay on track, or to transfer to a more suitable course. In this case, the course lecturer made contact with a mentor for students judged as potentially at risk, based on English language ability score, physical attendance at tutorials, submission and performance on assignments, and online behaviour or presence: Mentors discussed learning and attendance issues with groups of students they were responsible for. If an 'at risk' rating persisted, the lecturer reviewed student background information to determine the appropriate action for each individual.

Design implications

Set milestones to monitor learner presence and progress. Simple checks can be powerful indicators. LMS activity reports identified students who had not logged in by the second week of the course. Direct communication was made to find out why, so students could be directed to appropriate sources of support if required.

A formative assessment task (in this case a quiz) scheduled early in a course provided a simple measure of both presence and performance. A system-generated report showed both individual and aggregated data on the number of attempts taken to produce a final answer, time on task, quality of answers and overall results [check this is accurate]. This can also help to identify common misconceptions, and in conjunction with other data such as grades or demographics, show how particular groups of students (e.g. low or high achievers, priority groups) perform.

Caveats

Passively collected data from online systems such as an LMS shows what is happening without offering reasons or explanations. Further information is required to support reliable interpretation. Access logs alone can lead to wrong assumptions and misdirected messages.

Scenario 2

Reveal student (mis)conceptions and knowledge

Problem

Students arrive at university with high school passes in subjects they will continue to study. This early success can build false confidence, where experience shows that common misconceptions and rote learning habits lead to failure later on.

Strategy

Use analytics data to find out what students actually know, expose common misconceptions, and influence students' learning strategies. A purpose built pre-course test or quiz can offer useful insights for both teachers and students. It can also create an opportunity to give students constructive feedback and point them to further learning opportunities. In this case, tutorials were designed to promote deep learning and knowledge development in the subject.

Data sources

An analytics report showed quiz scores with a breakdown of correct and incorrect answers, time on task, number of attempts for each question and frequency of use of hints or feedback. This can provide useful insights, particularly where questions are designed to reveal common misconceptions. If quiz scores are linked to individual information such as GPA or grades in relevant subjects, patterns may emerge.

Evaluate and take action

Knowing what students bring to a course can help to sharpen the focus of teaching and learning design. Discussing quiz results with students helped them to understand common misconceptions and the reasons they arise. This discussion also guided students to pathways to successful study in the subject. Provision of online tutorials as unassessed practice opportunities, monitoring their use and inviting student feedback on perceived usefulness all helped to build understanding of learner knowledge and motivation. Cause and effect relationships are difficult to establish. However, higher mean grades for students who use tutorials over those who do not may be indicative.

Design implications

A pre-course or early weeks quiz with constructive feedback and pointers to self-access tutorials to introduce or revisit subjects previously covered required the investment of time to set up and administer. However, that investment was small compared to the benefits of increased awareness of areas that teachers and students need to focus on. A further benefit was that course activities and learning design could be based on the evidence of what learners actually need.

Caveats

Misconceptions may be deeply rooted and hard to shift. Identifying them is an important first step, but addressing them may be a longer-term initiative requiring frequent reinforcement. Strategies for reinforcement can include e.g. peer review, periodic quizzes or tests, and student designed questions or study resources.

Scenario 3

Track student presence throughout a course

Problem

Learning can be like a 'black box' with few visible progress indicators between course planning, delivery and assessment. Growing awareness that students do not access, read or otherwise engage with course resources is driving, among other things, policies to restrict the volume of required material. Many of today's students are busy and prioritize their use of time in strategic ways. Others are less independent and require guidance. The challenge for teachers is to identify students who fall into each group.

Strategy

Analytics data can be used to track students' presence throughout a course. With the right tools and learning tasks, data can show who accesses resources and when; who asks questions, what issues they raise and the level of ensuing discussion; how students perform on quizzes and whether they access feedback; and how long it takes to complete a task. Being aware of the choices students made about which resources to use and the issues they engaged or struggled with allowed the lecturer to steer the learning design towards achievement of objectives.

Data sources

LMS and elearning tool reports presented a record of log ins, resource access and quiz performance as well as topics raised in discussion. All of these helped to reveal the choices students that made and the learning pathways they followed.

Asking students to explain the choices they made helped to illuminate the data represented in statistical reports.

Evaluate and take action

The analytics reports backed up by qualitative data to explain learner choices and learning pathways prompted context dependent actions. This included a review of the required versus optional nature of course materials in order engage but not overload students while ensuring that key content was covered; shift of focus to issues raised in student discussions; and revision of material already covered where challenges were observed.

Design implications

The design of learning activities and the choice of elearning tools can facilitate the collection of meaningful data. Online discussion provided a record of learner questions, knowledge and understanding, and a means to provide feedback to the group rather than individual students. Quiz scores were a useful performance indicator with further feedback options. Where data shows students do not access resources, it may be worth considering alternative ways to engage them with essential material. Assessment is a powerful incentive with many options such as peer review, and student generated content or questions. Asking students to produce learning resources such as multichoice questions or video presentations requires them to focus on content and how to present it.

Caveats

Data reports show log ins and resource use but rarely, if ever, produce reliable correlations of resource use and grades or frequency of log in and successful outcomes.

Scenario 4

Use standard SMS data to improve student support and retention

Problem

Open Polytechnic services over 30,000 part-time learners (~5,000 FTE) across high-enrolment courses, sometimes in overlapping cohorts. Identifying and supporting potentially at-risk learners across various support services is a complex exercise.

Strategy

Make student engagement data available to all Academic Staff and support staff through an online interface (the Engagement Tool, or ET). Record actions taken by staff where students may be at risk. The ET provides class lists and context data (study history, demographic data, contact details), along with the ability to read and add contact notes. The ET improves the identification of students likely needing support, and helps coordinate the staff response.

Data sources

The ET draws on regular Student Management System (SMS) data, collected as a business-as-usual activity across the enrolment period. The course's starting date and student assessment performance (including non-submission) provide an early indication of risk. New students and students belonging to priority groups are also easily identified. The Polytechnic is ethically entitled to use student information in the SMS for the purposes of assisting students in their studies as a condition of enrolment.

Evaluate and take action

The ET is in use across teaching and support staff at the Polytechnic. Identifying at-risk students and providing ready access to their contact details, context data and a record of action taken by staff ensures that support is both targeted and coordinated. The benefits of the ET are well understood across Open Polytechnic staff. The ET provides user-friendly access to the Student Management System, and is flexible enough to allow staff in different support roles to customize its use. The student data available in the ET give staff the confidence to contact multiple distance students mindful of each students' contact history and circumstances.

Design implications

The ET was cost-effective to develop, and did not require the generation of any new data fields. Staff training was the biggest challenge, though the user interface is simple. The main discipline was that of remembering to update the contact records for each student, which are made available through the ET. Staff activity changed as a result of implementing the ET, although access to ET data made student contact significantly easier. The key benefits are ready access to student contact details, and the contact history (student notes).

Caveats

The ET gives access to a very high-level view of student progress, based on a cohort's start date and assessment results. Further, given the multiple student support interventions adopted by Open Polytechnic over the last few years, it is not possible to isolate the effectiveness of the ET on completion outcomes.

Scenario 5

Analyse student answers to explore disciplinary knowledge

Problem

In large class settings options for individualised interaction with teachers are limited. However, teaching interactions, such as formative feedback on student written responses to questions, are central to encouraging deep approaches to learning and academic success.

Strategy

Analysis of student written responses has the potential to provide insights into student conceptions and thus directly inform teacher actions. While the provision of individualised, automated feedback to students is still a work in progress, the automated analysis of student responses to provide feedback directly to the teacher is achievable given the current state-of-the-art in natural language processing.

Data sources

Data were collected from a first-year undergraduate course, which is a prerequisite for competitive entry into professional health science courses (such as Medicine, Dentistry etc.). Enrolment typically averages 1600-2000 students each year. The course provides an introduction to human anatomy and physiology. Student participation was voluntary and informed consent was obtained from all students who participated. The dataset comprised student responses to questions posed in the context of the cardiovascular section of the course along with all course materials for that part of the course and lecture transcripts.

Evaluate and take action

Data analysis was conducted using a combination of manual and semi-automated text analysis techniques. Our analysis revealed two key findings: First, that evidence of the source of student understanding or interpretation of the question is often found in course materials. Second, grouping student responses allowed us to identify situations where students had interpreted questions in ways we had not anticipated. Sometimes, the source of student confusion only became clear after reading several similar responses.

Design implications

There are at least three design implications from our findings: First, if you can identify a source of confusion in the course materials it is possible to remedy this. Second, awareness of the range of ways in which students may interpret questions promotes teachers' skill in framing appropriate questions. Third, automated grouping of student written responses to short-answer questions creates possibilities for seeing the impact of course design on student understanding both within and between multiple cohorts. That is, teachers can check the impact of introducing new materials, or revising existing ones, on student understanding.

Caveats

This scenario used a combination of automated and manual analysis techniques. Nevertheless, simple semi-automated methods alone can take teachers some way towards analysing student responses in large-class settings. The ideal is to build text analysis dashboards, based on these methods, into existing LMS and systems used to collect student responses and present course materials.

Scenario 6

Focus teaching on student perceptions and knowledge

Strategy

The use of frequent formative assessment provides feedback to students and allows the lecturer to monitor their performance. This lecturer uses online dialogue to communicate and keep students on track, and structures LMS content to make it easy for students to work through a course, which provides optional resources for self-directed learning, practice opportunities and guidance on how to use feedback.

Data sources

LMS reports and online assessment analytics allow the lecturer to monitor learner engagement with course activities and performance on assessment tasks. It allows her to view individual student progress if questions about their performance arise (rather than for reflecting on the whole class, which is useful afterwards but too time consuming while the course is running).

Evaluate and take action

The data allows the lecturer to predict which students are at risk and likely to succeed based on use patterns, though she believes that this only works with large numbers.

More generally, the kind of questions raised in online communication and performance on assessments give a sense of what students know and where they struggle.

Design implications

Designing the course to include formative assessment, learning milestones and communication is a deliberate strategy. The lecturer would be keen to find a way to turn analytics back to learners so they know how they are doing as individuals without the teacher needing to intervene or mediate.

Caveats

It is important to use more than one data source to gain insights, and to gather qualitative data to supplement the numbers. The use of learning analytics is limited by systems as well as skills.

Scenario 7

Nudge students to improve engagement for study success

Problem

Students new to tertiary study often feel disconnected and overwhelmed in the first year. Moreover, large class sizes and fully online delivery are now relatively common in higher education. This presents obvious challenges not only for students new to tertiary study but also to teachers such as capturing and holding students' attention and creating opportunities for genuine engagement between teacher and student as well as fostering student-student interactions. Digital footprints obtained from students' usage of an online learning management system (LMS) and the resources provided within can help teachers identify students that are disengaged with either the course in general or certain content and personalise a response to modify students' actions.

Strategy

Monitor student engagement and devise personal messages at scale to keep students on task in large lecture settings.

The ability to monitor students' engagement with learning resources and their performance throughout a course has become more feasible with the routine collection of activity logs from online learning systems and tools, particularly in very large class settings. Checking engagement and progress based on teacher criteria set during a course can reveal whether students are using the resources provided and are achieving at set milestones. Individual students or groups of students who appear disengaged will receive a personalised message with the aim to encourage students seeking guidance or additional support.

Data sources

Data presented in standard LMS analytics reports show who has logged in, when, for how long and what resources they have accessed. This 'course grained' data gives a broad picture of student presence and performance in online course activities. It does not identify reasons, but it can trigger further investigations.

Evaluate and take action

If students don't log in, access essential resources or engage in required activities in the early weeks of a course, this may be a sign they are struggling and at risk of completing. Making contact with those students identified at risk early on and ending targeted, personalised messages can modify learning behaviours leading to study success. Teacher actions should never be just about students at risk, and encouragement to learn can be sent to all students based on criteria set at the beginning of a course. For example, capable students doing fine may receive a message to acknowledge this whereas students who appear disengaged (e.g., non-participation in discussion fora, very few page views) or perform poorly (e.g., diagnostic quizzes) may need more persuasive messages to stay on track, or to seek out support in tutorials that address specific pre-knowledge and skills, additional resources, lecture notes, exam preparations, mentoring schemes etc.

Design implications

Set milestones to monitor learner presence and progress. Simple checks can be powerful indicators. LMS activity reports identified students who had not logged in by the second week of the course. Email messages were sent to find out why, so students could be directed to appropriate sources of support if required (e.g., student centre, course tutors available at certain times during the week, Pacific and Māori student support initiatives, support for international students).

Formative assessment tasks (in this case two quizzes) scheduled early in a course provided a simple measure of presence, engagement, and performance. A system-generated report showed both individual and aggregated data on when the first attempt was made and the overall quiz score. The two quizzes had two different purposes: one, to gauge whether students had downloaded and engaged with specialised software necessary for the course work, and two, to test students' knowledge and identify common misconceptions. Personalised messages were sent to those who had not submitted one or both of the quizzes to keep students on track very early on in the course.

Caveats

Passively collected data from online systems such as an LMS shows what is happening without offering reasons or explanations. Another problem is that certain, externally linked applications (for example reading lists in Talis, Turnitin, Piazza etc.) may over- or under-report student usage which can lead to wrong conclusions. In addition, access to an LMS via a mobile device may not appear in LMS usage data reports. Further information is required to support reliable interpretation and data need to be checked carefully and cleaned before filter criteria as indicators for engagement and disengagement are applied.

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