Chapter 12

Data-informed nudges for student engagement and success

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Introduction

Higher education providers are increasingly being measured for the effectiveness of returns on students' investment (Bradley et al., 2008; 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, facilitating the transition to tertiary study of mature-age students, and enabling students from low socioeconomic backgrounds, minority groups, first-in-family, and international students (Briggs et al., 2012). It is well documented that, in order to succeed in their studies, students need to be well supported in both their academic and social learning (Hattie & Timperley, 2007; Tinto, 2009). Whilst many institutions pin their hopes on learning analytics (LA) to gain insight into and influence student learning, motivation, engagement, and performance (e.g. Clow, 2013; HEC, 2016), the vast field of LA research lacks practice-orientated approaches that are transferable into everyday teaching. Therefore, data-informed student engagement remains an unrealized buzzword for many practitioners. This presents a real need for tangible solutions that can provide insight into the 'whys' and 'hows' of student engagement and give teachers a way to act on this information. Our practical conceptualisation of 'data-informed' therefore encompasses both the use of data to indicate engagement and action based on these data to impact engagement.

In this chapter, we firstly discuss the conceptualisation of student engagement and how it might be measured. We then introduce the concept of nudges and choice architecture in the context of education, and use four case studies from three Australasian higher education institutions to illustrate practical applications of nudging for engagement. Three of these involve open source LA tools that focus on capturing and acting on timely and meaningful data about students'

engagement and success. While not the only approaches possible, the examples of real blended classroom scenarios presented here provide feasible examples of how data can be translated into action aimed at enhancing student engagement and success

Student engagement – what is it and can we measure it?

According to Astin (1985) student engagement refers to “...the amount of physical and psychological energy that the student devotes to the academic experience” (p. 518). Coates (2010) defines student engagement as “active and collaborative learning, participation in challenging academic activities, involvement in enriching educational experiences, and feeling legitimated and supported by university learning communities” (p. 122). This definition highlights the importance of positive and (pro)active teacher-student-university interactions. While numerous other definitions exist, there is general agreement in the literature that student engagement is a multifaceted construct, comprising affective, cognitive, and behavioural dimensions (Fredricks, Blumenfeld, & Paris, 2004).

Importantly, these dimensions or types of student engagement are influenced by structural (e.g., university, culture, assessment, policies) and psychosocial (e.g., teaching, staff, support, motivation) factors impacting on students’ academic success and social outcomes (Kahu, 2013). Kahu’s framework features an important bi-directional relationship between the affective, cognitive, and behavioural domains of students’ engagement and both immediate antecedents and proximal consequences. Factors such as the inextricable link between learning and teaching (Klem & Connell, 2004), the mix of cognitive and affective processes where interest impacts attention and level of effort invested in learning (Kim & Bonk, 2006), the sense of belonging and desire to attend classes (Willms, 2003), and the fine line between boredom and challenge (Skinner, Furrer, Marchand, & Kindermann, 2008) all contribute to this complexity. Moreover, a causal relationship has been shown to exist between learner engagement with educational activities and academic success and satisfaction (Bulger, Mayer, Almeroth, & Blau, 2008; Leach & Zepke, 2009). Increasingly, student engagement is influenced by the affordances of educational technologies; for example, online tools that foster collaboration, communication and provide timely feedback to students have been shown to positively correlate with improved engagement and performance (Macfadyen & Dawson, 2012)

Engagement research commonly focuses on students’ academic engagement within two distinct contexts encompassing the institution (campus engagement) and classroom (classroom engagement: Skinner & Pitzer, 2012). While Appleton et al. (2006) identify four dimensions of student engagement (with academic engagement referring to academic achievement or performance), the majority of the engagement literature breaks engagement into three components: affective-emotional or psychological-emotional, cognitive, and behavioural (Fredricks, Blumenfeld, & Paris, 2004; Kahu, 2013).

- **Affective/emotional** engagement describes students' social, emotional, and psychological responses toward their education and the educational institution. Examples include the value students attach to their education and the emotions (e.g. enjoyment, boredom, anxiety) elicited when they engage in academic activity (Ainley, 2012; guNuc, 2014; Pekrun & Linnenbrink-Garcia, 2012; Skinner et al., 2008). At the institutional level, emotional engagement concerns their sense of identification, pride, and belonging to the institution and with their learning community of peers and teachers (Daly, Shin, Thakral, Selders, & Vera, 2009; Finn & Zimmer, 2012; Van Ryzin, Gravely, & Roseth, 2009; Voelkl, 2012).
- **Cognitive engagement** is concerned with how students think about their learning and academic ability, experiences, and environment. Cognitive engagement has an important relationship with learning motivation, and influences students' level of persistence to overcome challenges and can be measured by the amount of effort that a student puts into setting learning goals, planning and self-monitoring (Fredricks & McColskey, 2012; guNuc, 2014).
- **Behavioural engagement** can be measured by classroom related actions such as attendance in class, on-time submission of assessments, level of participation in class and time spent on assessment activities (guNuc, 2014). Behavioural engagement also includes campus-related activities such as participation in student societies or faculty social events (Fredricks et al., 2004).

Methods for measuring student engagement have previously been classified into three important areas: self-report, observational checklist and rating scales, and automated measurements (Whitehill, Serpell, Lin, Foster, & Movellan, 2014). Student engagement measurements can more broadly be categorized according to subjective and objective methods (Bouvier, Sehaba, & Lavoué, 2014). Both subjective (e.g. self-report, observational checklist and rating scales) and objective (automated measurements) approaches have advantages and disadvantages, dependant upon the data collection method. Our four case studies will present approaches that demonstrate how various actions that are informed by student data may be constructed by teachers in order to optimise students' engagement. Throughout this, caution needs to be exercised when learning activity data are used as proxies for student engagement so as not to generalise a student as a member of a stereotyped, "homogenous mass" as Bryson and Hand warn (as cited in Kahu, 2013, p. 766).

Nudging students for engagement

Given the many facets of student engagement and its positive impact on student success, institutions are increasingly seeking to modify their approaches to optimise these. One group of strategies that has emerged more recently involves the use of 'nudge analytics' (Carmean & Mizzi, 2010). Nudge theory was popularised by Richard Thaler and Cass Sunstein in their 2008 book, *Nudge*, which intersected the key ideas of *choice architecture* and *nudges* in the context

of behavioural economics. Applying this construct to education, teachers can be understood as 'choice architects' who have "the responsibility for organising the context in which people [i.e. students] make decisions" (Thaler & Sunstein, 2008, p. 2). One way to influence these decisions is to provide nudges, which are characterised as "any aspect of the choice architecture that alters people's behaviour in a predictable way without forbidding any options or significantly changing their economic incentives. To count as a mere nudge, the intervention must be easy and cheap to avoid" (Thaler & Sunstein, 2008, p. 5).

The power of nudges lies in their ability to modify human behaviour without coercion. Examples include placing footprint stickers that lead up to garbage bins to reduce littering; setting a social norm by telling prospective voters about a high expected voter turnout (which was more impactful than messages about low expected turnout); and increasing savings deposits by involving people in peer groups where they voluntarily announced and monitored their savings goals (which was more effective than a much higher interest rate: (Ly, Mažar, Zhao, & Soman, 2013).

In the educational context, nudges have only been explored relatively recently. One experiment that sent personalised text messages to pre-enrolling students with reminders about registration, orientation, and placement found a marked increase in enrolments from students of lower socioeconomic background who often do not complete enrolment (Wildavsky, 2014). Another approach that used a mobile app to send students daily prompts with study advice and have them define goals and corresponding actions was associated with improved academic performance (Frankfort, Salim, Carmean, & Haynie, 2012). Others have shown a positive correlation between encouraging email or SMS nudges, either aimed at vulnerable first year students based on predicted performance drawn from log data behaviour (Corrigan, Smeaton., Glynn & Smyth., 2015) or at specific student groups offering targeted help (Goh, Seet & Chen, 2012).

In these cases, the nudges did not push students towards particular decisions, but subtly influenced decision-making processes. Importantly, the 'golden rule' of nudging involves actions or interventions "...that are most likely to help and least likely to inflict harm" (Thaler & Sunstein, 2008, p. 79). As nudges in education become more commonplace and data-driven (Desouza & Smith, 2016), it is critical to remember that beneficence/non-maleficence is also a key LA ethical principle (e.g. Prinsloo & Slade, 2013). In the context of student engagement, there are various aspects of students' choice architecture that teachers can alter to help promote student engagement and success. Thaler and Sunstein's framework suggests nudges are most needed for decisions that are difficult and rare, where there is no prompt feedback, and in situations where it is difficult to connect the choices made with impact on lived experiences. To benefit decision-makers in these situations, Thaler and Sunstein present six principles of choice architecture (pp. 89 - 108), which we contextualise here with educational examples (which our case studies will further illustrate):

1. **Incentives** - are the right incentives sufficiently salient to the right decision makers? For example, do students see the benefit for themselves in contributing to online or in-class discussions?

2. **Understanding mappings** - are decision makers able to connect their choice with their subsequent experience? For example, do students understand the downstream implications of particular approaches to study or decisions relating to enrolment?
3. **Defaults** - can a default choice be provided (which may represent a recommended course of action), especially if the choice is difficult? For example, can particular activities be designed so that disengagement will have minimal impact on students, whilst providing data for targeted follow-up?
4. **Giving feedback** - how can people be informed how they are performing? For example, are students provided an indication of their achievement relative to an established goal and provided suggestions on how they can work towards improvement?
5. **Expecting error** - how can the choice architecture be as forgiving to mistakes as possible? For example, reducing the summative (grade) impact of missed assessment opportunities wherever possible.
6. **Structuring complex choices** - especially for complex, multi-step decisions, can decision makers be guided through decisions, helped to learn about their choices, or provided comparative choices made by others? For example, do students understand the assessment structure, which aspects need more attention, and what characterises successful performance?

In this sense, an important distinction between nudges and the relatively well-established early warning messages (e.g. Jayaprakash, Moody, Lauría, Regan, & Baron, 2014) is that nudges seek to address all performance levels, not just those 'at risk'. What follows are a presentation of four case studies where teachers (as choice architects) design nudges to enhance engagement customised to available student data. These nudges are discussed in the context of large-scale personalisation of student learning, support, and mentoring to enhance student engagement. Dietz-Uhler and Hurn (2013) noted that "faculty have, for the most part, relied on their intuition and hunches to know when students are struggling, or to know when to suggest relevant learning resources...these hunches are not going to disappear with the advent of LA, nor are the actions derived from them" (p. 20). The case studies will show how translating LA for the classroom needs to leverage the deep contextual understanding that teachers have about their students and learning design.

Case study 1: University of Sydney - Empowering teachers with tools to nudge at scale

The University of Sydney is a metropolitan research-intensive university with over 60,000 students and 6,400 academic staff. As almost all of the university's unit of study offerings are face-to-face or blended, the learning design and pedagogical focus are heavily geared towards the on-campus or in-class experience, which are mostly invisible to electronic systems. Congruent with other reports, these teachers lacked capacity to address issues around student disengagement at scale due to heavy workloads and a lack of tangible approaches (Colvin et al., 2016; West et al., 2015). Student data that teachers needed either existed in database silos

or, in most cases, on pieces of paper or staff computers. In this environment, an organic, bottom-up approach to LA design and development was necessary, with the aim to provide teachers with the tools to collect, collate, and use data that they considered meaningful in their specific contexts. This meant that (i) the data a system collected (and how it was used) had to be flexible and customisable to suit varied teaching contexts, and (ii) the system had to possess key features that help to catalyse the adoption of innovations such as compatibility with (yet advantageous over) existing approaches (Rogers, 2003). The LA system that was adopted helped these teachers collect predominantly objective measures of behavioural and cognitive engagement and provide nudges that addressed psychosocial antecedents of engagement in order to enhance it.

This in-house LA system was the Student Relationship Engagement System (SRES; www.sres.io), intentionally called this to emphasise to teachers its purpose of engaging and building relationships with students. The SRES (Figure 12.1) is accessible via a web front-end, which guides users through adding enrolment lists, pre-existing data (such as from spreadsheets or the learning management system), and creating mobile-friendly interfaces for viewing and editing pertinent in-class data (such as attendance, grades, feedback, and comments). Data are stored centrally on a server, enabling live access for all staff. Teachers can easily create personalised and customised emails or text messages that nudge students by building rules to 'filter' students based on data in the SRES database. The uniqueness of the SRES approach was grounded in being closely tied to teachers' needs and focussing on the teacher-student relationship aspect of LA, as well as being eminently customisable and affording efficient avenues to act on data (further described in Liu, Bartimote-Aufflick, Pardo, & Bridgeman, 2017). The SRES is now supporting blended classrooms across the university in over 100 units of study, reaching over 20,000 students. Due to the variety of (noisy) contexts surrounding student success and the dangers of applying a one-size-fits-all model to understand engagement (Gašević, Dawson, Rogers, & Gasevic, 2016), our evaluation instead concentrated on qualitative analyses of data collection approaches, rules, messages, and interviews from teachers' perspectives to provide insight into the application and effectiveness of nudges for engagement. We present a representative selection here.

Interestingly, the most sought-after functionality in the SRES was its ability to efficiently collect attendance and other in-class indicators of engagement (Figure 12.1B). This was afforded through mobile-friendly web interfaces that, for example, allowed teaching assistants to mark an 'electronic roll' or use the camera on a mobile device to scan student cards. Data were immediately saved to the central SRES database, allowing real-time monitoring and action by teachers. This fixation on class attendance may seem superficial, but positive relationships between attendance and academic performance are widely reported (Credé, Roch, & Kieszczynka, 2010; Newman-Ford, Fitzgibbon, Lloyd, & Thomas, 2008). Our teachers supported this perspective by linking this behavioural indicator to cognitive engagement, including students' study strategies (which therefore can be nudged for improvement):

Figure 12.1: Overview of basic SRES functions. Data can be entered and made available via (A) existing spreadsheets or (B and C) customisable mobile-friendly screens. Student data are stored in a central database (D) and can be used by teachers to (E) personalise feedback and learning support. Note: Student names and ID numbers are fictitious.

"I use the SRES to mark attendance, not to control them, but for feedback purposes. For example, if I have an assignment due that week, during the class they should be asking questions... that's why I use the system to know who is in the class and who is not... during the prac class I'm there to help them out".

However as an indicator for engagement, attendance is often difficult to collect and commonly neglected in LA (HEC, 2016). In conversations with teachers, we observed that attendance has inherent meaning for many and can form an important part of LA data depending on local contexts. In addition to class attendance, in the blended learning institutional context, teachers were interested in using data on interim grades, assessment submission, online resource usage (including views of recorded lectures), and face-to-face interactions (such as quality of student class contributions) to personalise learning support. Having the ability to target feedback to individual students or groups based on data was a key aspect for all teachers. These quotes are instructive in understanding teachers' motivation for personalisation:

"The personalisation, definitely, the impression that you care individually is without question the thing that [students] say the most [in terms of impact]. In general they like that you care about their progress as well, which is separate to caring that you've personalised it."

"I think they start believing that I care about them... and they feel like I want to know who they are as people. Sometimes when you're in a class with 200 students it's very hard to believe that your unit coordinator... actually cares about who you are... That helps them; the emails, the scanning barcodes, it helps them remember that we genuinely care."

Because of the flexibility of the SRES, teachers could act on measures of engagement that were specifically meaningful for their teaching context. Through targeted feedback to students based on these engagement measures, teachers (perhaps unknowingly) invoked key aspects of nudges and choice architecture to influence antecedent engagement factors. In the example below, the teacher used an objective measure of behavioural engagement (posts to an online discussion board) to infer a lack of cognitive engagement (i.e. low value given to some aspects of the course). The corresponding message addressed all three of Kahu's antecedents (Kahu, 2013), such as reminding students of their self-efficacy in steering their own learning experiences and being part of the learning community. The nudge presented clear incentives and helped students better understand how their decisions mapped to consequent experiences:

Dear [preferred name],

The discussion board can sometimes seem superfluous to your learning. I understand there is already a lot going on and it seems like extra work to post a question. However, you may not know that the discussion board is really what drives the lecture material. I like to use the questions students have, and answer them in class. The rationale for this is to focus on the things you have not had [sic] answer for, rather than the things you understand.

This week, why don't you post any questions you have while watching the pre-class videos to the Piazza discussion board [link]

I will address these in class. It is an opportunity for you to direct what is taught. I think you will find it useful.

[Teacher]

The next example comes from a set of distinct messages that another teacher targeted to different subsets of their cohort through the SRES. The cohort was divided into performance bands based on interim grades, and the following personalised message used this objective measure as a proxy for cognitive and behavioural engagement. In Kahu's framework (Kahu, 2013), the measurement used here (academic achievement) was actually a proximal *consequence* of engagement, which was applied to evaluate the outcome of engagement and initiate a feedback loop to positively influence its antecedents. To do so, the teacher here was unintentionally leveraging a number of nudge elements. Aside from providing directed feedback and clear incentives, the choice-maker (student) was presented with a clear breakdown of key upcoming steps (aspects to focus on, making the most of revision resources and sessions, and exam structure). Additionally, in mapping upcoming choices (relating to revision) to potential consequences, the teacher invoked the experience of other, similar students - an application of 'social nudges':

Dear [preferred name],

You have now finished the coursework assessments in [unit code and name]. You scored [grade] for the Excel online Course and the Worksheets (worth 20%), and [grade] for the Practical Skills exam (worth 20%). This gives you [grade] for the coursework assessments in this unit, which is the pass range.

It is really important that you start your revision early for the final exam, this is worth 60% and will test all aspects of the course - covering material from lectures AND tutorials AND practicals. Students often do not score as well in the final exam as they do in the coursework sections of this unit, and to be eligible to pass the unit, you must achieve more than 40% in the final exam. In week 13, the revision lecture will give you more practice questions and a chance to revisit the practice exam from week 7. Make sure you attend and ask for any clarification you may need.

It is still possible for you to do well in this unit [preferred name], but you must make sure you devote time to understanding the concepts and calculations. Good luck in the final Exam!

[Teacher]

The teacher who used the SRES to deliver these sets of email nudges personalised for different performance bands suggested a marked improvement in student feedback. However, as with most practitioners simultaneously implementing multiple innovations, the specific impact was difficult to parse: “...so we used [a new assessment feedback tool] and we had SRES emails [to provide feedback]: the [unit of study survey] scores were remarkable, the agree/strongly agree for the feedback score on the [survey] was 86%, which is huge... it's both”.

Others using the SRES for more traditional early-warning style nudges suggested improvements in retention and completions: “I think the SRES did help... it certainly got some students over the line who would have otherwise dropped out... it can initiate conversation and it looks personalised and obviously targeted, it can initiate the kind of conversation that wouldn't otherwise happen... the system helped a lot and it did boost completions. Sally Kift did a big project and she concluded that if you can reach students with difficulties early on in

their student career, about half the students you reach you can significantly help. I feel the halving of the [year on year] withdrawal date in our unit is some kind of evidence for it [impact of messages from the SRES].” Further evaluation is underway to establish a stronger evidence base for impact on student engagement.

Case study 2: The University of Auckland – Engaging teachers in nudging

The University of Auckland is the largest research-led university in New Zealand with around 5,000 staff and over 40,000 domestic and international students from diverse ethnic backgrounds, with a proportionally large cohort of undergraduate students (77%). The implementation of a new LMS at the university in 2016 allowed for a number of opportunities to leverage LA at scale in order to understand and optimise student learning behaviour and engagement (despite the gaps surrounding student data access and governance). To consider these new opportunities, cross-institutional efforts are currently underway to support both top-down (business intelligence) and bottom-up (LA) needs for the improvement of the student experience and study success. Specifically, one of the strategic objectives afforded by teaching technologies is to leverage LA for the optimisation of teaching and learning, enabling teachers to implement LA within their own contexts using local data and their own criteria.

The Sydney SRES offered all of the key features important for successful uptake by teachers (as described in the previous case study) and was collaboratively redeveloped into ‘version 2’ under an open source licence (for details see McDonald et al., 2016). Since its redevelopment, SRES v2 has been implemented at the University of Auckland in three large first year (face-to-face taught) classes in engineering, science and business studies where class sizes range from 860 to over 2400, as well as some first year courses at Massey University, New Zealand. The approach to piloting SRES v2 initially relied on networks of teaching champions who would feed back any experiences about usability and efficiency of the LA tool to learning designers and developers. What followed were meetings involving teachers, course-coordinators and academic advisors to identify actionable indicators as proxies for student engagement (or disengagement). Those teacher-determined criteria led to the determination of discrete time points where personalised messages would be seen as effective interventions to modify student learning behaviour (Table 1). The case study presented here aims to:

- Improve student-teacher connections at scale for personalised support and interaction using targeted nudges.
- Empower teachers to implement LA within their own teaching contexts
- Build LA capability across an education institution from the bottom-up

Proxies for engagement

Only some of the complexity behind the factors affecting student engagement can be explained, thereby limiting the ability to fully describe and impact it.. Frameworks - despite their limitations - are useful in designing interventions based on LA data to modify students’ learning and engagement. To demonstrate data-informed nudges in practice, we have operationalized student engagement as it is understood by teachers in their specific contexts in

a blended learning environment. These proxies are aligned with Kahu's cognitive and behavioural engagement measures eliciting proximal academic outcomes (2013). However, other teaching contexts may consider different proxies for engagement (or disengagement) resulting in different 'nudges' as described in our third case study about peer mentoring. The measures and interventions depicted in Table 12.1 are examples of real classroom occurrences (log data) and interventions (email nudges) triggered by pre-determined criteria and at pre-determined time points for a large first year class (over 2,000 students). In order to manage the administrative task of filtering the data and sending persuasive nudges according to these criteria, an academic advisor worked closely with the teaching team.

Table 12.1: Proxies for engagement and timely intervention

Behavioural engagement proxies	Measures (LMS log data)	Persuasive email nudges at time point
Course syllabus	Viewed	End of week 2
Reading lists	Viewed	2 days before assignment due
Discussion fora	Participation	Before mid-semester break
Diagnostic quiz	Submission	End of week 2
Cognitive engagement proxies		
Poor academic performance	Quiz scores	<div style="display: flex; align-items: center;"> <div style="font-size: 3em; margin-right: 10px;">}</div> <div> <p>Week 2 after quiz marking</p> <p>After first test</p> <p>After mid-semester marking</p> <p>(all results to date combined)</p> </div> </div>
Excellent academic performance	Test results	
	Assignment marks	
	Discussion posts content	

Note. Academic performance is used here as a proximal measure of cognitive engagement. Data other than student activities drawn from various sources may be considered including (but not limited to) attendance, in class participation, student feedback, other learning support received etc.

An example of an email sent by the teacher to students who had not logged into the course at the end of week 2 illustrates how the teacher attempts to alter students' learning behaviour to help promote student engagement, applying the nudge principle of giving feedback on one's own performance (Thaler & Sunstein, 2008). Students may not connect their choice made (disengagement) with the impact on lived experiences, which in this case could have a potential negative impact on academic performance later during the course of study.

Dear [student],

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 2. 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, [teacher]

In another example, a teacher sent an email to students encouraging them to seek assistance from learning advisors to help with their learning in the situation where students are not performing as well as they could:

Hi [student],

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, [teacher].

Reaching out to students who are performing well early on can encourage ongoing engagement with course materials and beyond- for example, by pointing to optional resources that may be of interest to a group of students. The following nudge presents clear incentives for students, helping them to recognise how their decisions map to outcomes if they 'keep up the good work':

Kia ora [student],

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, [teacher]

From the bottom up, through professional development and initiatives such as hands-on workshops and communities of interest, there has been a steady increase in the uptake of the SRES at the University of Auckland. More importantly, an initial reluctance to leverage LA to inform course design by some was often alleviated as the benefits (for students as well as teachers) became more obvious in practice. Although some teachers interviewed did not find that it supported their teaching practice *per se*, it did allow them to connect with specific student groups. For example, teachers commented: “As a lecturer, I was perceived by the students to be more approachable because I take an interest in them,” and, “The email responses from our repeat students provided valuable insight into how they prioritise their studies.”

We are currently working towards conducting a more comprehensive study about the effectiveness of the SRES, focussing on student perceptions.

Case study 3: The University of Auckland - Improving retention through mentoring

The SEALLS Project was established at the University of Auckland with the goal of enhancing Student Engagement and Achievement in Large Lecture Settings (hence, the acronym). While the project now includes courses from several faculties across the university, the case presented in this chapter is based on a first semester course for first year students in the Faculty of Education and Social Work. Beyond the typical challenges associated with first year students in their maiden semester, this course possessed several characteristics that may impact student engagement and achievement: it is a requirement (a compulsory course for all Bachelor of Education teacher candidates), it is large (300+ students), it is a multi-campus offering (serving students at three different campuses, one via video-feed), and it is diverse (a multicultural student cohort with a wide range of academic motivation and skills).

For these (and other) reasons, in the years preceding 2013, the course had a stable and relatively high failure rate of 15%. From 2013, changes in course leadership and design resulted in a dramatic change from a traditional large lecture structure to a 'blended learning' approach. By 2015, fewer than 5% of students failed the course. However, this reduction was not the effect of a single change, but rather a number of changes working in tandem. In addition to a change of teaching staff, moving to a blended delivery approach, incorporating in-class feedback tools, and swapping from a bespoke content management system to Moodle LMS (in order to support the blended delivery style), instructors leveraged and integrated with an existing peer mentoring programme to serve as a 'human face' for several 'nudge' strategies. This peer mentoring programme began in 2012 as a means to monitor and support the transition of first year students into the University and was based on the Queensland University of Technology FYE programme (Heirdsfield, Walker, Walsh & Wilss, 2008).

As the course re-design began in 2013, one major goal was to utilise LA derived from student engagement in the course to inform and add nuance to the mentoring programme. Previous research into the efficacy of peer mentoring programmes has highlighted the importance of sustained and targeted intervention (Tinto, 2006). However, to date, research in the field of LA has primarily focused on understanding and leveraging student interactions in online learning environments (Gašević, Dawson, & Siemens, 2015) without connection to the importance of student feedback (Hattie & Timperley, 2007). Within the Faculty, every first year student is assigned to a mentor group containing no more than 15 students. An academically successful, third year student volunteer is provided as the group's mentor. A range of mentoring strategies was implemented throughout the academic year with mentors providing pastoral support for their cohort of 15 students. Peer mentors also work collaboratively with teaching staff to pre-empt potential academic challenges which may arise for their students.

LA as a risk indicator

Like many university courses today, the course in this case study used an LMS to facilitate a myriad of course-related purposes, such as basic administrative tasks, communicating with students, facilitating student discussions, archiving of lecture notes and recordings, student submission of assignments, marking, grade distribution, and providing feedback to students. As with most online services, modern LMS systems automatically log and archive a record of students' movements and actions while on that site. This log data can provide a rich source of information about differing types of student engagement, both passive and active (Lust, Elen, & Clarebout, 2013). However, it is important to remember that these datasets only capture online activity and thus are only proxy measures of learning in a blended delivery course. Engagement and learning that occurs "offline," including in the classroom, is not included in considerations of 'at-risk'. That said, the positive correlation between online engagement with course content, activities and study success is well documented (Macfadyen & Dawson, 2010).

With this in mind, we come to the first rule in using LA as a risk indicator: the more one uses an LMS as a hub of course resources and activities, the more plentiful and useful the log data will be as an indicator of student engagement and achievement. In this case, the LMS was employed in the ways outlined above, such that the average student amassed over 100 interactions ('clicks') three weeks into the semester. While much of this interaction is 'passive' (e.g., viewing a page or resource), a relatively small but very important portion is 'active' (e.g., completing an activity or submitting an assignment). Active interaction is critical in terms of student achievement, and thus the specific data utilized to assess risk indicators. For example, in the first three weeks of the course, students are required to use the course LMS to complete two short participation activities and a quiz. These assignments are purposefully 'low stakes', intended to serve as proxies for student engagement and an early warning system in the case of no- or low engagement. Failure to complete these assignments does not mean the student will fail the course, but it does indicate the potential risk of doing so.

When the LA data for the first few weeks of the course is analyzed, close attention is paid to this 'active' interaction. The students of most concern typically have not completed any of the assignments or worse, not visited the course website.. This group of 'no engagement' students is at risk of failing the course without a change in learning behaviour. Also at risk is a 'low engagement' group whose online engagement is largely passive; they have viewed several pages and even downloaded lecture notes, but they have not completed one or more of the assignments. Many of these students are active during the first week of the course and complete the first assignment, but then drop offline. Together, these two at risk groups of students comprise approximately 20% of the first year cohort.

Nudging 'at risk' students with a message

In keeping with Thaler and Sunstein's (2008) conceptualization, the 'nudge' employed in this course did not change students 'economic incentives' but rather put the 'fruit at eye level'. In other words, students were not offered the promise of a greater reward (e.g., additional points)

or a threat of punishment (e.g., loss of privileges). Rather, the nudge, delivered via an email message, simply reminded students of the stakes at play. For example:

Dear [student],

I am your Course Director and Lecturer for [course code]. I'm writing to let you know that I have noticed that you have not yet completed the first two Participation Activities that I assigned for this course. Thankfully, these are only worth one point each so you have not missed much by way of marks.

Our first Quiz, due a week from Saturday, is worth 10 marks. You won't want to miss it. If it would be helpful to you, I'd be pleased to meet with you to discuss the course and strategies for being successful in it. Your tutor is another great resource to reach out if you're in need of support.

In the meantime, I've attached a copy of the Course Booklet that provides all the course details. Below is a link to the course web site. All lecture notes, recordings and assignments are located on this site: [link]

Best, [teacher]

The engagement indicators gleaned from the LMS were shared with staff managing the Faculty's First Year Experience (FYE) programme. This group also had access to additional datasets including student demographics, English language proficiency, and tutorial (but not lecture) attendance data. In addition to personalised messages from the teacher, identified students could be contacted directly (face-to-face) by FYE staff or by student mentors via generalised and de-identified messaging within a mentor group meeting. The LA information provided to the leaders of the FYE programme gave them the ability to focus their resources based on data trends, and they indicated that it improved their capacity to intervene directly with the students in a more timely and nuanced way than had previously been possible. In short, through blending course delivery, instructors were not only able to increase opportunities for student engagement, but also to use the LA data to identify and support—through a nudge and a mentor—students at risk of course failure.

Case study 4: Macquarie University - Establishing a teacher-focussed LA solution to target 'at risk' students

Macquarie University is a large public university based in Sydney, Australia. It currently has over 40,000 domestic and international students and 3000 staff. It was established as a university in 1964 with a mission to be innovative, adaptive and community focussed in ways that the more established universities could not. A bottom-up LA project sought to evaluate and extend the MEAP (Moodle Engagement Analytics Plugin: Dawson & Apperley, 2012) so that teachers could use data from the institutional Moodle-based LMS to send timely nudges to 'at risk' students. Early detection of 'at risk' students has been recognized as an important strategy in addressing issues around student success and retention (Lynch-Holmes, Troy &

Ramos, 2012). Using MEAP, students were sent concrete and actionable nudges at time-of-need based on their behavioural and academic data in the LMS. Through this process, the aim was to ascertain student preferences for and attitudes towards receiving early alerts, as well as teachers' perceived barriers or benefits of sending these nudges.

Design and implementation of MEAP

MEAP provides a means to measure behavioural engagement through evaluation of: 1) login activity (frequency and duration); 2) forum activity (posts written and read); 3) assessment activity (on-time assignment submission). Following confirmation that MEAP was able to use historical data to predict the students' final grade (Liu, Froissard, Richards, & Atif, 2015a), a design-based research approach used student and teacher feedback to refine MEAP. We recruited unit convenors and support staff through evangelising the idea of early alerts across the institution, particularly seeking to identify units with high failure rates, large enrolments, and use of online learning and assessment activities. Feedback was also provided via a reference group representing all faculties and their Learning and Teaching Associate Deans and staff associated with other LA projects.

New user interfaces were identified and designed, and new features were added, including the ability to use gradebook data (a proximal consequence of engagement). Functionality was also extended so that once the unit convenor had identified at risk students, they could be contacted directly via email from MEAP. We recognised that the timing and wording of these nudges would be crucial to changing student behaviour. As a form of teacher nudge and motivator, we sent emails to convenors of approaching special dates in the academic calendar and periodic phone or face-to-face catch-ups to see how things were going. We found that this positive support often prompted teacher activity in MEAP. To reduce the cognitive effort involved in getting the wording just right and to help with consistency, we added a message bank categorised by type of message content (e.g. late assessment, lack of forum participation, support service details) and the ability to save and retrieve past messages. This new version was called MEAP+ (Liu et al. 2015b).

Teachers' and students' perceptions

In semester 1 of 2015, MEAP was trialled across 12 units with 4800 students and extended to MEAP+. In semester 2 of 2015, MEAP+ was trialled across 13 units with over 6000 students.. By the end of these trials, over 2000 emails had been sent. Student surveys and unit convenor and student support officer interviews were used in both trials to identify needs, barriers, and usefulness of an early alert system and to examine the impact of receiving emails on student motivations and experiences and their learning behaviours and outcomes. Unit convenors reported that using MEAP+ allowed them to perform tasks that they would otherwise be unable to perform. It efficiently allowed them to strategically identify and contact specific students in large units. They reported that in response to their emails, students contacted them to make

appointments and acknowledged their lack of engagement and intention to re-engage with the course.

To investigate student preferences and responses to early alerts, between 2013 and 2015, we conducted a total of four online student surveys plus a pilot. The final survey represented units from all faculties and surveyed 7035 students with 588 responses. We found that 80% of responding students wanted to be contacted by their convenor if their performance was unsatisfactory. Also 91% of students wanted to be contacted by university email and 67% wanted to be contacted as soon as the behaviour occurred. It seems that most students are happy to be nudged.

In a follow-up study, with 84 respondents who were contacted by convenors about their performance, regarding student motivation, 55% said it made them feel better and 54% said it made them feel they could improve, while 12% reported feeling worse. While many responded with increased cognitive engagement (evidenced through behavioural engagement, such as meeting with teaching staff, putting in more effort and/or visiting student services), the increase in *emotional* engagement was noteworthy, with comments by nearly 75% of students relating to appreciating the care and interest of the teacher in their wellbeing.

The outcomes and findings of this project have nudged the institution to commit to ongoing support for MEAP+. Funding allowed for the integration of the tool into the LMS for wider use. MEAP+ is now available across the institution and being supported with training and advice from the learning and teaching team. Nevertheless, widespread use of MEAP+ to support student (and teacher) engagement is still a work in progress.

In the classroom

Nudging for engagement

Intriguingly, from these case studies, it appears that teachers apply elements of choice architecture (perhaps unknowingly). Leveraging fairly simple engagement measures, they design nudges that map choices to consequences, help structure decisions, increase the salience of incentives and disincentives, and provide feedback. Notably, this is in stark contrast to the 'nudge analytics' proposed by Carmean and Mizzi (2010), which was characterised as "gathering and pattern-matching data with the intention of suggesting better actions and influencing decisions" (p. 7), and that "the knowledge embedded in our machines makes it possible to do so without the guesswork of human design and intervention" (p. 2). Notwithstanding the value of complex analytics approaches in educational data mining, our contention is that blind machine mining based on mathematical algorithms can lead to nudges that just drive behaviourism (Lodge & Lewis, 2012), and fail to address the antecedents of engagement. The case studies also provide insight into how having the right data and affordances for acting on those data can practically transform teaching at the 'chalk face'. In

particular, by examining teachers' perceptions of data and their actual usage of those tools, we have seen that their appetite for data is specific and contextualised. Far from desiring algorithms to predict students at risk based on 'big data' with dubious value and ethics (such as library usage, WiFi access, and support service status), our teachers would rather have systems that simply helped them collect and collate data that were meaningful in their own context and allowed them to use these data to better interact with and support their students. In these cases, translating LA into classroom practice necessitated design thinking approaches where users' (teachers and students) actual felt needs (namely students' increasingly depersonalised learning experiences and teachers' desire to engage their students) were kept at the centre of development. By providing LA tools that were sufficiently flexible to meet the demands of a range of 'small data' (but meaningful data), teachers could see the merit of those tools and make their own decisions on how to nudge their students based on local data using teacher-determined criteria rather than centralised academic intelligence.

By using data about student engagement, teachers may manipulate students' choice architecture, nudging them into enhanced engagement. In a parallel conceptualisation, Pardo (2017) presented a model for feedback that could be targeted by applying evidence of students' learning processes, suggesting that these could be a "formal production of deliverables for review, a multimodal set of observed magnitudes (engagement with resources, performance, quality indicators, etc), or informal evidence such as verbal comments provided by the learner to [the teacher]" (p. 7). Synthesising Kahu's engagement framework and Pardo's data-rich feedback model, we propose a framework that includes 'measurable manifestations' of engagement and their consequent factors (Table 12.2). Furthermore, we suggest how these could be measured and acted upon using our approaches. These measurements may then be selected and applied by teachers to further enhance engagement by influencing (nudging) antecedent conditions to engagement.

Table 12.2: Synthesised framework for nudges to enhance engagement based on data.

Proximal consequences	Student engagement	Psychosocial influences
<p>Academic</p> <ul style="list-style-type: none"> • <i>Achievement</i> (interim grades) • <i>Learning</i> (capture teacher feedback) <p>Social</p> <ul style="list-style-type: none"> • Wellbeing • Satisfaction 	<p>Behaviour</p> <ul style="list-style-type: none"> • <i>Time and effort</i> (submissions, LMS activity) • <i>Interactions</i> (online discussions; class participation) • <i>Participation</i> (class attendance) <p>Cognition</p> <ul style="list-style-type: none"> • Deep learning 	<p>University</p> <ul style="list-style-type: none"> • Teachers and teaching practice • <i>Support</i> (structure complex choices, clarify consequences) • <i>Workload</i> (suggest management approaches) <p>Relationships</p> <ul style="list-style-type: none"> • <i>Student-teacher</i> (personalisation; build connections) • <i>Learning community</i> (build belonging; invoke social influences e.g. what others are doing)

	<ul style="list-style-type: none"> • <i>Self-regulation</i> (accessing grades; setting goals) <p>Affect</p> <ul style="list-style-type: none"> • <i>Enthusiasm</i> (class participation) • Belonging • Interest 	<p>Student</p> <ul style="list-style-type: none"> • <i>Motivation</i> (increase salience of (dis)incentives) • Skills • Identity • <i>Self-efficacy</i> (encourage self-regulation)
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Note. Kahu's engagement framework is purposively reversed to demonstrate the directionality of data to nudges (left to right). Readily measurable manifestations (italics) are suggested for proximal consequences and student engagement, along with examples (in parentheses). Influences of engagement that could be nudged (italics) also include examples summarised from the case studies (in parentheses).

Sending sensitive nudges that move students forward is almost an art form. It requires not only technical skills to use appropriate software and understand what the data is saying, but careful consideration of what to say and how to say it. In the era of big data, data literacy training for teachers to measure behavioural engagement and instruction in how to nudge students to improve their cognitive and emotional engagement may be worth considering for the institutional agenda – so long as these are carried out in a way that is not overwhelming or forced.

Overarching principles

The four case studies presented here have illustrated several overarching principles that we believe can contribute to successfully translating and applying LA for the classroom:

- **Context.** Not only is context critical in determining the power of predictive LA systems (Gašević et al., 2016), but it is a key driver for more bricolage approaches to LA that are gaining traction in higher education (Colvin et al., 2016). Here, context is focussed more locally and refers to elements such as instructional design and pedagogical intent, disciplinary approaches, technology usage in courses, felt needs of teachers and students, workload pressures, and the everyday activities of learning and teaching. Being context-sensitive at this level ensures maximum relevance and meaning for teachers who, being at the confluence of students and learning and teaching design, are arguably the most important stakeholder in making LA impactful (Beer, Tickner, & Jones, 2014; Lodge & Corrin, 2017).
- **Small data.** The vast majority of LA literature reports on the analysis of big datasets to understand or predict student academic outcomes. These data usually include students' activity within an LMS and their socioeconomic and academic backgrounds, and sometimes include library usage, access to buildings, and WiFi access. These datasets are often made 'big' by aggregating data across multiple courses and

disciplines (Jayaprakash et al., 2014). However, a risk of this is often a loss of context, meaning, and value and a blurring of appropriate ways to interpret the data (Boyd & Crawford, 2011). In contrast, our case studies have exemplified the significance of small and specific data to teachers, which differ depending on their contexts.

- **Data literacy.** A lack of specialist data and analytics expertise is often touted as a key barrier for LA adoption (Arnold et al., 2014). Additionally, teachers may not be able to appreciate full LA workflows and feel that making meaning from data for personalising student support is out of reach (Dawson, Jovanovic, Gašević, & Pardo, 2017). While our experience implementing LA with teachers has necessitated some professional development and support in using specialised software, by and large we have observed that given the right (contextualised and small) data, teachers have been able to effectively put the data into action.
- **Personalisation.** This has recently become a buzzword in education, especially as various forms of data are collected and used to adapt learning resources and pathways (Reimann, Bull, Kickmeier-Rust, Vatrpu, & Wasson, 2015). Our case studies exemplify the importance of such targeted, personalised support. However, a nuance of personalised learning that is often missed is that of ‘person’-alisation; that is, the human aspect of learning and teaching. Our case studies illustrate that the human element is vital (such as establishing and strengthening relationships between teachers and students) as this forms a powerful antecedent to student engagement (Kahu, 2013). Specifically, teachers noted that all communications to students at scale should be crafted in such a way as though they have come from them personally (rather than from a generic or automated ‘no-reply’ email address) and that the wording needs to be “upbeat & positive”. This resonates with the ‘personalisation principle’ which suggests the positive effect of first- and second-person language along with friendly or polite feedback (Clark & Mayer, 2016). While this personalisation principle specifically addresses learning and not engagement, the underlying principle is the importance of human (or at least human-like) communication.
- **Empowering teachers.** The culmination of these principles appears to be the context-sensitive application of small data so that teachers can make sense of and act upon data to personalise student learning. Beer et al. (2014) characterise this as an “evolutionary approach” that ensures teachers’ practical needs for supporting their students are truly met (pp. 246). Indeed, empowering those involved in learning is one of the hallmarks of LA (Siemens & Baker, 2012).

Conclusions

Based on user experience, three key themes have emerged. First, for LA to be useful to teachers in the classroom, LA tools need to be simple to use and adaptable not only across various

systems but also teaching contexts and modes. Second, in order to share findings and contribute to the literature on LA (particularly in the area of optimising student engagement, see for example Goh et al., 2012; Corrigan, Smeaton, Glynn & Smyth, 2015), ethical issues need to be considered regarding data access and governance. Third, ongoing consultation with all stakeholders is needed to overcome the challenges of data access from complex systems, and data manipulation needs to feed into LA tools (such as the SRES).

For these reasons, the implementation of LA tools requires a collaborative approach across learning designers, IT experts, teachers, managers, DVCAs, faculty teaching, learning education boards, and especially faculty. Furthermore, we cannot stress enough the importance of professional development and the sharing of knowledge in a community of practice and inquirers. Across our case study institutions, we received invaluable feedback from trialling and discussing tools with colleagues which revealed a multifaceted landscape of similarities and differences in teaching practices and concerns. It is possible that some of those insights are transferable to high schools, as more and more schools are teaching in a blended environment. For example, many high schools use an LMS to support face-to-face learning and have many touchpoints with students where engagement may be measured. Targeted nudges based on usage, participation, or submission data may provide these high school students with insights on their learning, fostering self-regulation in preparation for life-long learning.

LA is canonically defined as “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs” (Siemens & Baker, 2012). Our case studies illustrate that an approach that seems to be favoured across institutions is for teachers to be at the centre of the LA workflow, controlling the collection and use of contextually meaningful data. Moreover, these data were used to inform actions in the form of targeted nudges that sought to modulate student behaviour and engagement. This lifecycle was enabled by simple to use LA tools that were designed to accommodate idiosyncrasies of unique educational contexts, affording the application of student data to support learners’ engagement and, ultimately, learning.

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