

# Feeling supported: Enabling students in diverse cohorts through personalised, data-informed feedback

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Students entering enabling programs as an alternative pathway to University tend to have higher rates of attrition than their peers admitted via more traditional pathways. Students in enabling programs require high levels of personalised feedback to support their transition to study. However, the size and diversity of the enabling student cohort presents formidable challenges for instructors. The field of learning analytics offers a viable solution for scaling the communication of personalised, data-informed feedback to support student learning. This study describes the use of a novel learning analytics-based feedback system called *OnTask*, to provide personalised feedback and support to students in an enabling course at one Australian higher education institution. An end-of-course student survey (N=41; 17% response rate) was employed to gain insights into their perceptions of personalised, data-informed feedback messages. Using importance-performance analysis (IPA), the survey results indicated that this technology-mediated form of feedback exceeded students' expectations of learning support, as well as the enhancement of their overall course experience. The implications for using learning analytics and data-informed feedback mechanisms in teaching and learning are discussed.

Keywords: higher education, learning analytics, personalised feedback, diverse cohorts

## Introduction

In response to the Australian government's push to widen access to university education, many universities have opened up alternative entry or pathway courses into degree programs. These pre-university enabling programs are designed to support students who cannot enter university due to inability to meet the academic program prerequisites. Compared to students in undergraduate courses, students in enabling programs are more likely to come from low SES backgrounds, have a more diverse range of ages (20 to mid-seventies), have more limited educational experiences, low to very low levels of educational attainment and academic skills (Hodges et al., 2013). Accordingly, these students require high levels of support in order to help them navigate a rigorous academic environment to prepare them for study in their future degree program. Although outcomes have been found to be mostly beneficial for students with regard to university acclimation, reports have also pointed to low levels of engagement and high levels of attrition in these programs. This is due in part, to a range of challenges faced by students, such as poor study skills, a feeling of lack of belonging in the university community, and time pressures - especially for mature-age students who are juggling study, work, and family.

These challenges are not isolated to students engaging in enabling programs – however they are often more acute. Personalised support and guidance is essential to promote engagement and success (Hellmundt & Baker, 2017; Lane & Sharp, 2014). However, large class sizes and diverse cohorts make it challenging for instructors to provide personalised support to all students. A promising solution to this challenge lies in the field of learning analytics (Pardo, Poquet, Martinez-Maldonado, & Dawson, 2017). This study examines the impact of data-informed feedback through the use of learning analytics, to support students in enabling programs.

## Background

### Enabling programs –supporting diverse students to develop skills for learning at university

Pre-university enabling programs are foundational programs that allow students who otherwise would not have been admitted into university gain entry into university. The programs aim to equip students with the academic skills to succeed in future undergraduate studies (Klinger & Murray, 2011). Students in these courses include many first-in-family applicants with little knowledge about the experience and expectations of university (Habel, Whitman, & Stokes, 2016). Given the target enrolment, enabling programs share the same goal of helping students to develop key skills for learning at university, by immersing them in the culture of higher level learning, and developing language proficiency as well as critical thinking, research and study skills (Agosti & Bernat, 2018). While the outcomes of enabling programs have been promising (Cullity, 2006; Habel et al., 2016; Klinger & Murray, 2011; Lisciandro & Gibbs, 2016), many students fail to meet the standards and level of academic

engagement required resulting in high attrition rates (Hodges et al., 2013). Tinto (2006) has discussed the challenges for first year students adapting to a new and demanding academic culture. These challenges are further exacerbated for those entering through alternative pathways, due to additional hurdles presented by language and cultural barriers, the juggling of family and work commitments, being first in family to attend university, all of which can result in heightened anxiety (Stokes, 2018).

Lane & Sharp (2014) argue that a key contributor to students' engagement and retention in enabling courses, is the quality of the student experience. In particular, an important part of the experience is the perception of instructor guidance and support (Hellmundt & Baker, 2017; Lane & Sharp, 2014). Stokes (2018) recommends the inclusion of a "supportive and informed enabling pedagogy" that "will assist students to gain knowledge, skills and confidence, and establish study practices for lifelong learning" (p.240). Ultimately, while universities may not have control over the student factors such as those described earlier, they do have control over the quality of instruction and support models.

### **Using learning analytics to scale up personalised feedback and support**

Feedback and communication are important aspects in supporting students. Despite changes in the educational landscape over the last two decades, feedback remains a crucial factor for improving student learning (Harks, Rakoczy, Hattie, Besser, & Klieme, 2014; Hattie & Timperley, 2007; Hounsell, 2003). We define feedback as "a process in which learners make sense of comments about the quality of their work in order to inform the development of future performance or learning strategies" (Carless, 2018, p.2). This definition reflects the shift in an understanding of 'feedback as product', to 'feedback as process' (Boud & Molloy, 2013; Carless & Boud, 2018), and highlights the importance of student engagement with feedback in order to close the feedback loop. Students need feedback, not only on their performance (outcome feedback), but also on their learning process (process feedback) and where to direct their future efforts (Hattie & Timperley, 2007). Feedback influences self-regulated learning by making students more aware of how they are learning (i.e., monitoring), whether they are on the right track, and helping them to know how to adjust their learning strategies to reach learning goals, thereby leading to enhanced achievement (Butler & Winne, 1995). Developing self-regulated learning through feedback and support is an essential process for students entering enabling programs with limited knowledge about how to learn in an environment that demands greater independence in learning. Feedback also heavily influences the quality of student experience and learning progress (Robinson, Pope, & Holyoak, 2013; Weaver, 2006).

The provision and quality of feedback is impacted as the cohort size and diversity increases (Pardo, Poquet, et al., 2017). A possible solution to this challenge lies in the field of learning analytics. Learning analytics is 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, 2013). With the broader use of learning technologies and growing awareness of how such technology mediated learning data can be used to bring new insights, it is possible to personalise feedback to students based on their learning data. Learning analytics can be used to automate the collection and analysis of student engagement data and transform these data into useful metrics that can be fed back in a personalised way to all students, either through visual dashboards, recommender systems, or personal emails from instructors or course coordinators (see Bodily & Verbert, 2017 for a review). These forms of feedback are considered personalised insofar as they are derived from an individual student's data, and facilitated at scale. For enabling students, such methods may serve as an external feedback loop to support their own monitoring of learning (Winne & Hadwin, 1998), facilitating an evaluative process about whether an adjustment of learning operations is needed. These learning operations could be learning tasks, specific learning strategies, or attendance at face-to-face sessions. Using feedback based on their own learning data, students who have been up-to-date with their assessments, consistent with tutorial attendance, or performing well on interim assessments would be informed about specific areas where they have done well, thereby boosting confidence and motivation for subsequent learning efforts. However, students who have fallen behind on assessments or attendance would receive data-informed feedback on where engagement could be improved, as well as specific recommendations for further action. The level of specificity is critical, so that students know how to act upon their feedback, thereby completing the feedback loop - this is key to feedback effectiveness (Jonsson & Panadero, 2018; Winstone, Nash, Parker, & Rowntree, 2017). Although student-facing learning analytics dashboards (LADs) have gained prominence as an approach to personalised, data-informed feedback, these highly visual systems have come under criticism (see reviews by Jivet, Scheffel, Drachsler, & Specht, 2018; Matcha, Ahmad Uzir, Gasevic, & Pardo, 2019). Ultimately, much research has pointed to LADs as falling short of the principles of effective feedback, namely, that feedback should be: specific or actionable; timely; clarifies expectations of performance; and conveyed in a supportive tone to foster positive motivational beliefs and self-esteem (Nicol & Macfarlane-Dick, 2006; Price, Handley, Millar, & O'Donovan, 2010; Shute, 2008). Essentially, effective feedback is sustainable, carried out in a regular cyclical process that encourages

independent learning by developing students' self-regulatory skills in the longer term (Boud & Molloy, 2013; Carless, 2018), which LADs have thus far been unable to afford.

Recent developments in student-facing feedback systems have seen the emergence of more contextualised feedback informed by analytics – two of these systems which have received attention in the literature are the Student Relationship Engagement System, SRES (Liu, Bartimote-Aufflick, Pardo, & Bridgeman, 2017) and OnTask (Pardo et al., 2018). These systems differ from LADs in that students' learning data is further augmented by personal messages by the instructor to enhance the actionable takeaways of the feedback. As the collection of learner data is automated, and feedback is pushed to students' inboxes, a regular feedback process is facilitated, whereby students can receive timely feedback regarding their ongoing progress, act on the recommendations of the feedback to improve their engagement, and begin another cycle of the feedback process, ultimately optimising their engagement. In this sense, instructor-augmented, personalised feedback to students based on learning analytics may be better able to provide the kind of support to help students engage optimally in the specific learning context. Thus far, evaluations of the deployment of these systems have been positive – with qualitative student comments pointing to students' enhanced motivation and better knowledge of course expectations (Arthars et al., 2019), and quantitative results showing effectiveness in helping students to adapt their learning strategies (Lim et al., 2019), improving students' satisfaction with feedback, and enhancing academic performance (Pardo, Jovanović, Gašević, & Dawson, 2017).

The development of personalised feedback to students based on the automated collection of learner data is a significant innovation for education, positioning “one of the most influential aspects in the quality of the student learning experience, feedback, within the current research space of the EDM [educational data mining] and LA [learning analytics] communities” (Pardo, Poquet, et al., 2017). However, what is less known about this approach to feedback, is the extent to which students actually engage with it, as well as how well this approach meets students' expectations of feedback.

## **Aim and research questions**

The present study aims to investigate the student perspective of personalised, data-informed feedback using OnTask. In particular, we use Importance-Performance Analysis, IPA (Martilla & James, 1977) to understand the strengths and weaknesses of this approach to feedback in the context of an enabling course. The study was guided by the following research questions:

RQ1. To what extent do students read their personalised, data-informed feedback?

RQ2. What are students' perceptions of the importance and performance with respect to the attributes of their personalised, data-informed feedback?

RQ3. How might students' action on their personalised, data-informed feedback be related to their perceptions of usefulness and impact on subsequent motivation?

## **Methodology**

### **Context**

This pilot study was carried out in an enabling course at an Australian University. Students seeking alternative entry into the University's degree programs are required to complete the 13-week course. In 2018, OnTask was piloted in the mid-year iteration (235 students) to then roll-out to the larger (600+ students) cohort in subsequent years. This system was implemented to support students to transition with their studies in their first semester as a university student. The course introduces students to the context of tertiary learning and develops a range of academic reading, writing and key research skills as the basis for future study. The course includes information on: organisation of resources and time, note-taking, student university systems (including course sites and discussion boards), and exposes students to university policies, services, teacher-student communication and career guidance. The course was conducted in blended format, with a weekly lecture (1 hour) and tutorial (2 hours). Students were expected to prepare for weekly tutorials by doing weekly readings which were available in the course site. An important aspect of the course design involved explicit scaffolding of students through this course so that they may apply the skills and knowledge learnt to future courses. Assessment comprised four summative assignments. To help students perform well in these assignments, they were strongly encouraged to access the relevant assessment information from the course site.

## OnTask - personalised, data-informed feedback at scale

OnTask (Pardo et al., 2018) is a learning analytics-based application that facilitates the collation of information about students and their learning from various sources, such as activity data from the learning management system, records of lesson attendance, and course performance. The platform allows instructors to develop “if-then” rules to generate personalised messages to all students in their course, and to deliver these as emails. An important feature of OnTask is that, unlike more generic student-facing reporting systems, instructors can choose the specific rules and metrics to provide more contextualised feedback (Pardo et al., 2018).

OnTask is open-source software (see <https://www.ontasklearning.org/tool/>). This tool was integrated into the institution’s Moodle learning management system (LMS), to create a seamless link with the Moodle course database and store all students’ interactions with the LMS. Instructors access the application within their course site and decide on the relevant metrics for feedback to students. A full description of the workings of OnTask can be found on the OnTask website<sup>4</sup>. In the current study the course coordinator used OnTask to support students’ out-of-class (online) engagement. Based on previous cohorts, specific trigger points in the course were identified, for which feedback messages could be sent to students to promote engagement with course content and activities. Trigger points included engagement with the course site, assignment submissions, and ongoing assessment performance. Individual student data from these trigger points were used as the basis for creating personalised messages to each student. Over the course of the semester, students received 11 personalised, data-informed feedback messages (referred to as ‘check-in’s for students) in their student inboxes (see Figure 1).



Figure 1. Supporting students with personalised, data-informed feedback via OnTask

Thus, a student who had not accessed Assessment 4 resources would have received this message in Week 11:

Hi [Student name],

Please be sure to use the helpful resources online for the final A4 essay. There is an Assessment 4 resources folder under the Assessments tab online [URL] that has the important template, student examples and other helpful information in it. A study tip: set some goals or make a plan for how you are going to tackle the final A4 assessment so you are not rushing it at the end. Next week (week 12) also be sure to have drafts of your intro and conclusions ready to show in class! Only two weeks of classes left! Nearly at the end - be sure to keep up attendance for these last two weeks to help you finish strongly.

Kind regards, [Instructor]

<sup>4</sup> <https://www.ontasklearning.org/wp-content/uploads/OnTask-Brief-Description-v1.pdf>

## Data collection

Ethical approval for this study was obtained from the institution's human research ethics committee. A self-report instrument was designed to gather information about students' perceptions of their personalised, data-informed feedback which was received via email. The 21-item survey comprised two parts. The first asked students about their reactions to their feedback emails: how many feedback emails (referred to as "check-in's" by the instructor who sent the emails) they received over the course, and how many they read. Items were included to know the extent to which students acted on their feedback (1 item), the impact on their motivation (1 item), and the helpfulness of the feedback (1 item). The second part of the survey assessed students' perceptions of the importance and performance of the quality attributes of their received feedback, using a 5-point Likert scale (1 = Strongly disagree, 5 = Strongly agree). These items were informed by Nicol and Macfarlane-Dick's (2006) principles of effective feedback for self-regulated learning, such as timing, feeling of support, and helping students to improve their work. Examples of the items are:

10a. It is important for me to receive timely feedback about my progress.

10b. The feedback emails provided timely feedback about my progress.

The survey was administered in-class at the end of semester. Students were informed that completion of the survey was voluntary. Although the survey asked students to provide their student IDs, this was not mandatory. A total of 41 usable surveys were returned, yielding a 17% response rate. Of these, 34 respondents provided their student IDs which were able to be matched with demographic, program, and course performance data.

## Data analysis

Data were analysed using IBM Statistics SPSS 25. To answer RQ 1, simple frequency analysis was conducted on responses to the question "Of the feedback emails you received, how many did you read?". To answer RQ 2, paired samples t-tests and importance-performance analysis (IPA) were conducted, to identify the strengths and weaknesses of this implementation of personalised, data-informed feedback. Originally used in marketing research, the IPA technique (Martilla & James, 1977) solicits customers' perceptions of the importance and performance of defined attributes of service quality, identifying specific quality areas that are performing well, and areas in need of improvement. The model positions the assessed attributes within a 2x2 grid, where the vertical axis represents the level of perceived importance, while the horizontal axis represents perceived performance, of the attribute. The graphical space is divided into four quadrants by lines demarcating the mean importance and performance ratings of all the assessed attributes (see Patiar, Ma, Kensbock, & Cox, 2017). Finally, to answer RQ 3, correlational analysis was performed on the three items pertaining to student action on feedback, perceived helpfulness of the feedback, and subsequent motivation to learn.

## Results

### Sample characteristics

Survey respondents ranged in age from 18 to 51, with a mean age of 24 (SD = 8.00). Slightly above half of the respondents (55%) were female. These demographics were reflective of the course cohort for the semester. Although information regarding other demographics for the cohort for the semester under study were not available, we rely on the student profile for the preceding semester in order to understand the current sample characteristics. A large proportion of students in the program were recent high school graduates (53%), and a sizeable proportion entered with work and life experience (35%). A small proportion of students had gone through trades education (8%). As more than 80% of the present sample were from this fee-free, open-access program, all these characteristics point to a cohort of students with very diverse backgrounds and a range of educational experiences.

An independent samples t-test was carried out on final course grades between completers and non-completers, to examine for self-selection bias. This analysis was based on the 34 respondents who provided valid student IDs, which meant that 7 respondents could not be matched for grades information. The analysis found that survey completers scored significantly higher in their final course grades ( $M = 71.1$ ,  $SD = 15.1$ ), compared to non-completers ( $M = 38.8$ ,  $SD = 26.4$ ),  $t(72.704) = 10.13$ ,  $p < .001$ . The mean final course grade for the whole cohort was 43.5 ( $SD = 27.5$ ,  $Md = 40.0$ ). This implies that the survey tended to be completed by higher performers, a point to consider when interpreting the results of this study.

**RQ 1. To what extent do students read their personalised, data-informed feedback?**

The majority of respondents (n = 25, 61%) read all their received feedback. Approximately 37% (n = 15) read less than half their feedback emails and 1 respondent (<1%) reported not having read any of the feedback emails. This result indicates that students were reading the vast majority of feedback provided.

**RQ 2. What are students' perceptions of the importance and performance with respect to the attributes of their personalised, data-informed feedback?**

Table 1 provides a summary of the relative perceived importance and performance of each quality attribute of the feedback. The three most important attributes of personalised, data-informed feedback were: *Instructor support* (M = 4.51, SD = .75), *Improved work* (M = 4.34, SD = .99), and *Improved overall course experience* (M = 4.29, SD = .90). The top three performing attributes of the feedback were: *Instructor support* (M = 4.39, SD = .80), *Improved overall course experience* (M = 4.12, SD = .95), and *Timely feedback about progress* (M = 3.95, SD = 1.00). Notably, *Instructor support* and *Improved overall course experience* were ranked highest on both importance and performance. From the paired t-test analyses, it was observed that three out of the seven attributes were significantly rated lower in performance than importance: *Fostering independence* (t(41) = 3.59, p = .001), *Improved work* (t(41) = 3.48), and *Fostering efficient study* (t(41) = 3.39, p = .002). These were all small effect sizes (all eta-squared values were between .22 to .24).

**Table 1: The difference between importance and performance of students' personalised, data-informed feedback attributes (n = 41)**

Survey item	M (SD)		t	p	eta <sup>2</sup>
	Importance	Performance			
Q6a. It is important for me to receive feedback that will help me improve my work.	3.90 (1.00)		3.48	.001	.23
Q6b. The feedback emails helped me improve my work.		4.34 (.99)			
Q7a. It is important for me to receive feedback that will help me to be more independent in my studies.	3.73 (1.05)		3.59	.001	.24
Q7b. The feedback emails helped me to be more independent in my studies.		4.22 (.94)			
Q8a. It is important for me to receive feedback that will allow me to complete my study more efficiently.	3.76 (1.04)		3.39	.002	.22
Q8b. The feedback emails allowed me to complete my study more efficiently.		4.15 (.96)			
Q9a. It is important for me to receive feedback that will allow me to complete my study more effectively.	3.88 (1.10)		1.60	.118	.06
Q9b. The feedback emails allowed me to complete my study more effectively.		4.10 (1.00)			
Q10a. It is important for me to receive timely feedback about my progress.	3.95 (1.00)		1.92	.06	.08
Q10b. The feedback emails provided timely feedback about my progress.		4.22 (.94)			
Q11a. It is important for me to receive support from my instructor.	4.39 (.80)		1.04	.30	.03
Q11b. The feedback emails made me feel supported by my instructor.		4.51 (.75)			
Q12a. I believe that communication regarding reminders and support will improve my overall course experience.	4.12 (.95)		1.42	.16	
Q12b. The feedback emails improved my overall course experience.		4.29 (.90)			
Grand means	3.96	4.26			

### Importance-performance analysis (IPA)

Figure 2 shows the position of the feedback attributes as perceived by students, in the four quadrants. Two attributes fell into the quadrant “Keep up the good work”, with *Instructor support* (Q11) as the highest, followed by *Improved overall course experience* (Q12). Three attributes fell into the quadrant “Low priority”: *Fostering effective study* (Q9), *Fostering efficient study* (Q8), and *Fostering independence* (Q7). *Timely feedback about progress* (Q10) sat at the borderline between “Concentrate here” and “Low priority”, suggesting that students’ expectations of this attribute of feedback were not quite met, but at the same time, it was relatively less important for students compared to other attributes. Only the attribute *Improved student work* (Q6) was in the “Possible overkill” quadrant. Overall, the result of this analysis indicate that students had positive experiences of nearly all their personalised, data-informed feedback attributes, and that, to a lesser extent, they were not expecting feedback to foster independence, and to foster efficient and effective study.

### RQ 3. How might students’ action on their personalised, data-informed feedback be related to their perceptions of usefulness and impact on subsequent motivation?

This analysis focused on the three items in the survey which sought to know students’ action on their feedback, how helpful they found it to be, and the extent to which it enhanced their motivation in the course. While students felt positively about the helpfulness of their personalised, data-informed feedback (M = 4.02, SD = .96), and were somewhat more motivated as a result of the feedback (M = 3.88, SD = 1.1), they were less likely to act on the information provided in the feedback (M = 3.7, SD = 1.03).

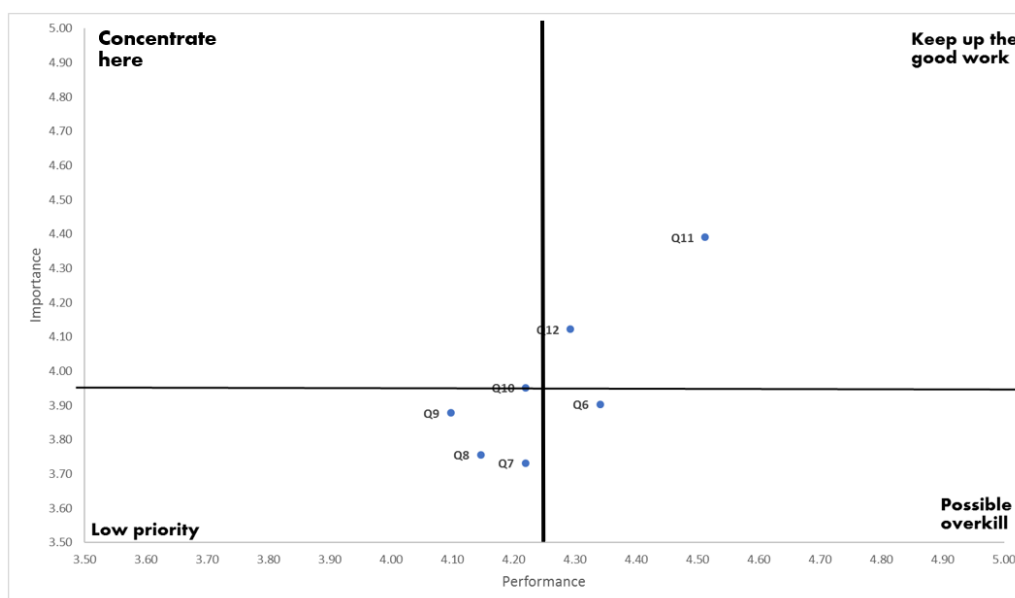


Figure 2. IPA grid showing students’ perceptions of their personalised, data-informed feedback

The correlational analysis (Table 2) shows a strong relationship between students’ self-reported action on their data-informed feedback and subsequent motivation to learn ( $r = .71$ ), as well as perceived helpfulness of their feedback ( $r = .81$ ), all  $p < .05$ . As well, there was a strong relationship between perceived helpfulness of feedback and subsequent motivation to learn ( $r = .90$ ). These were all large effects (Cohen, 1992, pp. 79-81).

Table 2: Correlations between students’ action on feedback, perceived helpfulness of their data-informed feedback, and subsequent motivation

Survey item	Q3	Q4	Q5
Q3. I acted on the information provided in the feedback emails.	.	.707**	.813**
Q4. The feedback emails made me more motivated to learn in the course.	.	.	.901**
Q5. The feedback emails were helpful for my learning.	.	.	.

\*\* $p < .01$

## Discussion and conclusions

### Students' reception and perceptions of personalised, data-informed feedback

It is important to identify if feedback mediated by technology is read by the intended audience. The survey analysis found that more than 60% of respondents had reportedly read all their personalised feedback, and more than 95% of respondents reported that they had read at least one feedback email. Thus, this mode of delivery can be considered a viable channel to communicate personalised, data-informed feedback to students. At the same time, the finding that a proportion of students read fewer than half of their emailed feedback messages should also be considered. It is possible that students actively read their feedback messages in the first few weeks of the semester, but as workload and other pressures increased, they may have stopped attending to it. Future studies will aim to examine how students interact with their feedback emails, in order to further optimise student engagement with technology-mediated feedback.

While students read the majority of their personalised, data-informed feedback and found it to be helpful for their learning and motivational for sustained engagement, the extent to which they reportedly acted on their feedback was much less. A reason for this conflicting result is that students may not have enacted their feedback immediately but may have made a mental note to review the recommendation at a later point. The strong positive correlations between students' reported enactment and perceptions of their feedback may support this hypothesis. Given that the majority of students in the course were from the open-access Foundation Studies program, they may not have had much opportunity to gain strong academic skills, due to the diversity of their backgrounds or other life circumstances. In terms of impact on self-regulated learning (Butler & Winne, 1995), the information in students' personalised feedback—for example, that they had not yet accessed assessment resources—may have prompted students to set more specific goals for themselves; these goals are critical to informing study strategies, in this case, to access the assessment resources within the week, in order to find out the next steps to complete the assignment on time. This then set in motion a process of monitoring, to ensure that these new goals are being met. Armed with greater control over their learning, they were subsequently more motivated to learn, signifying an increase in affective-emotional engagement (Fredricks, Blumenfeld, & Paris, 2004; Kahu & Nelson, 2018). This engagement is a psychological response which is elicited when students engage in academic activities (Blumenstein, Liu, Richards, Leichtweis, & Stephens, 2019).

The IPA highlighted the strengths of this form of technology-mediated feedback, particularly for enabling students. Foremost, instructor support emerged both as a highly valued as well as a high-performing attribute in this context. Also highly valued and high-performing was the quality of feedback being able to improve the overall course experience. These results provide further empirical evidence of the importance of instructor support as a critical enabling pedagogy (Lane & Sharp, 2014; Stokes 2018). As shown from the demographic data, enabling students enter the pathway program with limited educational experiences, as well as little knowledge of what to expect in terms of learning at university. The regular emailed feedback and support messages sent personally by the instructor were intentionally crafted to equip students with knowledge of how to engage optimally in this new academic environment. For example, to support students' preparation of their second assessment, the annotated bibliography, feedback was given to students based on activity data in the LMS relating to this assessment, such as the information page, template, and examples. Students received a personalised message tailored according to whether they had accessed the resources: those who had done so were acknowledged and provided further recommended actions to ensure a timely submission, while those who had not, were pointed to the resource and encouraged not to delay reviewing the documents.

### Implications for using learning analytics to support student learning

Overall, this study has found that students in the enabling course valued their personalised, data-informed feedback, and in particular, they perceived it as adding significantly to supporting their engagement in the course, as well as improved their overall course experience. Although the attribute "timely feedback about my progress" (Q10) was sitting at the border of the quadrant "Concentrate here", this attribute still performed rather highly. These positive perceptions of students toward their personalised, data-informed feedback in the form of instructor emails demonstrate Blumenstein et al's (2019) principle of translating and applying learning analytics for the classroom, namely, to ensure the presence of the 'human element', as the student-instructor relationship is an important precursor to student engagement. Thus, personalised, data-informed feedback should emphasise the care of the instructor toward the student, and written in such a way that shows it was a personal communication from the instructor herself.



## Limitations

We acknowledge that this pilot study is not without its limitations. As noted in the results, there was a self-selection bias, with higher-performing students responding to the survey, and a low response rate. In order to capture the perceptions of students from a variety of abilities, and to obtain a more in-depth understanding into how students engaged with the emails and how they enacted the feedback, focus groups will be conducted.

## Conclusion

Overall, students noted the feedback and support emails delivered through OnTask was a positive and effective process for supporting their learning. Given that this approach to feedback did significantly impact on students' perceived support and overall course experience, and the system facilitates instructors to scale up feedback, it is well considered as a worthwhile approach to personalised feedback provision in enabling courses. The technology-mediated approach allows instructors to easily scale personalised feedback and support to each and every student in a diverse cohort. The results of this study provide preliminary evidence that personalised, data-informed feedback enabled by technology can enhance support as an enabling pedagogy.

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