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"I Feel Seen": What Higher Education Students Find Helpful in Learning Analytics-Informed Personalised Messaging from Teachers

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Abstract

There is a recognised disconnect between the learning analytics that are routinely collected by higher education institutions, and their application in improving learning and teaching. Often presented in standardised dashboards, either student or staff-facing, both learners and teachers struggle to connect learning analytics with improved outcomes. Also used in early-warning systems to identify at-risk students, algorithms employing them can often be overly reliant on demographic or past performance data, and not responsive to unit-specific learning conditions. An alternative approach to using learning analytics is to enable teachers to use data for tailoring messages to students in a fashion and rhythm that best suits the specific pattern of learning activities and assessments within a particular unit. Following an approach such as this, the Student Relationship Engagement System (SRES) has been in use at the University of Sydney since 2011. We analysed six years of students' feedback comments to uncover what students found most helpful when their teachers used learning analytics to design personalised communication. Our findings show that tailored feedback, direction to relevant unit resources, and timely reminders were most appreciated.

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Practitioner Notes

1. Universities struggle to make effective use of learning analytics to improve student learning.
2. Empowering teachers to use learning analytics to personalise communications with students in harmony with the learning design of their units is a promising approach.
3. Semi-automated platforms exist to enable teachers to email students personally, and tailor the message depending on each student's performance or behaviour.
4. Students most appreciated receiving tailored feedback on formative assessments.
5. Students also valued links to resources addressing identified weaknesses and receiving reminders.

Keywords

Learning analytics, personalised learning, assessment feedback, at-risk students.

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Introduction

Learning analytics are a rich source of information about students' individual learning journeys that universities collect in abundance but struggle to take full advantage of to improve student success. The standard definition of learning analytics is "the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimising learning and the environments in which it occurs" (Conole et al., 2011). Institutions attempt to make use of them in several ways. Dashboard representations of learning analytics data are common; some dashboards are staff-facing, intending to provide an overview of how a cohort is progressing, as well as help identify individual students or groups of students in need of support. Other dashboards are student-facing, providing tracking data of the student's progress, perhaps in combination with current or historic cohort data for comparative purposes. Student-facing dashboards are typically intended to encourage self-regulated study behaviour (Matcha et al., 2020). However, dashboards have often been criticised for being overly simplistic, providing data that are conveniently available rather than useful in addressing learning and teaching needs (He et al., 2015). Furthermore, student-facing dashboards are not always perceived positively by students, and "very few dashboards are adequately integrated into the learning environment or the learning design" (Jivet et al., 2018, p. 32).

Another common use of learning analytics is in predictive modelling, typically taking place at the institutional level, designed to identify at-risk students early as a means of developing and deploying targeted interventions. Some have questioned this approach because it typically relies almost exclusively on standardised demographic data and seldom takes into consideration what is occurring in the learning environment (Blumenstein et al., 2018). Even modelling which includes students' Learning Management System (LMS) activity can be overly generic, since a "lack of attention to instructional conditions can lead to an over or under estimation of the effects of LMS features on students' academic success" (Gašević et al., 2016, p. 68).

An alternative approach for deploying learning analytics in higher education involves the use of platforms that utilise learning analytics to personalise messaging to students, tailored to the unit, which have been termed "open automated feedback" tools (Buckingham Shum et al., 2023). One such platform is the Student Relationship Engagement System (SRES), in use at the University of Sydney since 2011. This study analyses a large corpus of student feedback comments gathered from across the institution concerning the helpfulness of the communication the students received via this platform. To our knowledge, this is one of the first large-corpus studies of the student experience of a learning analytics-informed, teacher-led messaging personalisation platform in higher education (see also Lim, Gentili et al., 2021). This serves to answer, in part, Buckingham Shum and colleagues' (2023) call for further research on how personalised messages from these tools may be perceived by students and how best to use these tools to develop students' ability to use teacher feedback appropriately. Our broad research question, formulated according to the advice of Purvis et al. (2024), is: What types of messages do students find most helpful, when teachers use learning analytics to design personalised communication?

Literature

Higher education institutions routinely collect a wide array of incidental student engagement data, such as LMS access, performance in assessments, discussion forum participation, results of self-check quizzes, and attendance at practicals, tutorials or other classes, in addition to demographic data provided upon enrolment.

How these data can be used to improve student outcomes and learning experience has been the focus of institutional initiatives and research for over 20 years. Since 2011, the Horizon Reports have included learning analytics amongst the most impactful emerging technologies for higher education (Pelletier et al., 2022); in the UK a JISC report contended that "the effective use of learning analytics … presents opportunities for positive, evidence-led interventions" (Code of practice for learning analytics, 2023, p. 3); and in Australia a National Centre for Student Equity in Higher Education report highlights "the potential of analytics to protect and advance student equity" (Stephenson et al., 2022, p. 1). Applications of learning analytics cited in the scholarly literature as having the potential to improve the student learning experience include personalising feedback (Lim et al., 2020), prompting reflection on feedback and developing self-regulation of learning and time management skills (Banihashem et al., 2022), enabling dialogic peer feedback (Er et al., 2021), sending reminders relating to learning activities (Ustun et al., 2023), and real-time feedback in collaborative learning discussion forums (Zheng et al., 2021).

Despite this recognised potential, higher education institutions have been slow to harness the potential of learning analytics to improve the learning experience. Learning analytics tools have tended to be exploratory in nature, implementation is rarely systemic, and evidence linking such tools to transformation of the student experience is generally lacking (Arthars et al., 2019; Blumenstein et al., 2018; Gasevic et al., 2019; Gray et al., 2022; Ifenthaler & Yau, 2020; Márquez et al., 2023; Tsai et al., 2020; Viberg et al., 2018). Issues include a lack of clarity about how to transform data into effective interventions (Gašević et al., 2016; Larrabee Sønderlund et al., 2019), and ethical concerns associated with possible breaches of students' privacy (Diakopoulos, 2015; Drachsler & Greller, 2012).

A common approach to learning analytics is to collate data in dashboards, tailored either for individual students or teachers. However, evidence of the effectiveness of student-facing dashboards has so far been equivocal (Jivet et al., 2020; Karaoglan Yilmaz & Yilmaz, 2020; Kim et al., 2016). Some research suggests that student-facing dashboards may even be counter-productive (Gašević et al., 2017); the usefulness of including a comparison of performance between the individual student and the broader cohort in student-facing dashboards is also disputed (Jivet et al., 2018). Criticism of teacher-facing dashboards includes the observation that they may not support teachers in acting based on the data provided (Kaliisa et al., 2022; van Leeuwen, 2019). Teacher-facing dashboards may also suffer from over-standardisation, whereas research has revealed the importance of institution, discipline, and unit-specific context (Gašević et al., 2015; Larrabee Sønderlund et al., 2019).

A further use of learning analytics is as an early warning system to identify at-risk students for targeted support interventions. These systems typically use algorithms that predict students' potential outcomes using available data. However, such modelling tends to be over-reliant on demographic data and past educational performance because of the need for institution-wide consistency of indicators, whereas it has been argued that unit-specific conditions can be more pertinent. In this vein one study (Gašević et al., 2016) concluded that:

> findings obtained by generalized models for academic success prediction pose a threat to the potential of learning analytics to improve the quality of teaching and learning practice. Conversely, findings derived from more granular course-specific models can provide instructors with better insight into the factors that affect the academic success of students, so that the findings can be i) interpreted with respect to instructional conditions, and ii) directly used to improve teaching practice. (p. 82)

Furthermore, some argue that this approach risks stereotyping groups of students as predestined to experience difficulties (Slade & Prinsloo, 2014; Tsai et al., 2020). The algorithms used to predict student performance have also been criticised as being impenetrable (Liu et al., 2017). A recent systematic review highlighted that much of the research on predictive systems is still in the conceptual phase, with comparatively few studies reporting on large-scale implementations (Schmidt et al., 2025). For these and other reasons a shift has been reported away from predictive early warning systems "towards a deeper understanding of students' learning experiences" (Viberg et al., 2018, p. 108).

As Gašević et al. (2016) foreshadowed, an alternative approach to learning analytics implementation is to empower teachers to make use of unit-specific learning analytics in ways that complement their teaching and learning design (Arthars et al., 2019; Blumenstein et al., 2018; Ifenthaler & Yau, 2020). This approach recognises that it is teachers and unit coordinators who are "most experienced with the particular stress points in their courses and able to intervene during semester" (Liu et al., 2017, p. 147), and that their involvement in the design of learning analytics applications can ensure that relevant questions are asked of the data, and that the results are interpreted and reflected upon meaningfully (Gray et al., 2022, summarizing other research). From a practical point of view, such an approach also allows individual academics to harmonise intervention activity with their personal academic workload (Liu et al., 2017; Macfadyen & Dawson, 2012).

Recent consideration of human-centred approaches to learning analytics (Buckingham Shum et al., 2024) has also highlighted the need for an approach which "empowers teachers to implement interventions tailored to specific learning needs" (p. 756) and for the "inclusion of educational stakeholders in the design process [which goes] beyond initial encounters or one-off usability evaluations/focus groups" (p. 761). Encouragingly for this approach, despite changing social media trends, personal email (as opposed to newsletters) is still the preferred format, according to students, for communications from their educational institutions (Gilani, 2024).

Context

The Student Relationship and Engagement System (SRES), developed by the University of Sydney, is a flexible platform allowing teachers to import available learning analytics data that they consider useful, and to create messaging for students that is personalised in two ways. The student's own data can be inserted into the message, and the message itself can also be structured or worded conditionally upon the individual student's data. Messaging delivered directly from the teacher via an email or embedded within the LMS is managed so that each student sees only the personalised message intended for them. Both modes provide data tracking, including delivery details, and whether the message was opened. Furthermore, SRES also allows students to upload input onto the platform, which can also be incorporated into subsequent message personalisation. The SRES platform thus allows for a rich array of communications with students, from simple mail-merge-type emails providing students with their grade and feedback on an assessment task, with messaging conditional upon how well they performed, to semi-automating assignment submission, marking and feedback processes, to automating class evaluation of student presentations, and peer and self-review of groupwork. The SRES platform "gives precedence to teacher intelligence and small (but meaningful) data over predictive algorithms and big data. It enables teachers to design a learning analytics approach that is contextualized to their unique learning and teaching situation" (Arthars et al. 2019, p. 229).

SRES also addresses privacy concerns in that it typically involves unit coordinators making use of data that are routinely collected in the course of their teaching. Experience has shown that the data used by teachers using SRES tend to be of three main types: resource use (participation in discussion forums, quizzes, etc.), student performance (including both low and high results on assessment items), and student perceptions (e.g. "Was this week's content helpful?") (Blumenstein, 2017; Dollinger et al., 2019). The learning analytics used for message personalisation in this study tended to be current, unit-specific data to which educators already had routine access, such as tutorial, workshop or practical attendance; non-submission of an assessment item close to the deadline; marks on practice or formative assessments; individual feedback on an assessment provided by a marker, or more generic feedback tailored according to performance in specific sections of an assessment; and LMS activity, such as accessing a specific module, completion of a series of modules, involvement in a discussion forum, or signing up to a team for a groupwork activity. Messages also often related these analytics to unit-specific information such as assessment deadlines or provided links to existing information or resources that were pertinent to the individual's situation. By scaling up personalised feedback provision, and delivering it directly to students' inboxes, message personalisation platforms like SRES increase the likelihood that students will act on the feedback provided, with the aim of nurturing the development of self-regulated learning strategies (Buckingham Shum et al., 2023; Liu et al., 2017).

The study detailed here provides a largely qualitative evaluation of a teacher-driven approach to employing learning analytics for the purposes of improving student learning, as an alternative to expert-driven dashboard or predictive approaches, by addressing our research question asking what kinds of messages students find helpful, when teachers are empowered to utilise learning analytics to personalise teacher-student communications.

At the end of each SRES email message, students were asked if the message was helpful. They were then given the opportunity to comment on their response. (If a student voted "no", the question was "Sorry it wasn't helpful. How can we improve?"; if a student selected "yes", the question was "Thanks for your feedback. How was it helpful?"). While typically only a small percentage of students voted yes or no, and even fewer chose to comment, the collated responses nevertheless provide a rich corpus to answer our research question. Comments from 6 years of SRES operation at the University of Sydney (2017-2022) provide the data for this study. The University of Sydney is a leading research-intensive university in Australia; comments analysed in this study were from students studying disciplines across the university, including in business, exercise science, humanities, pharmacy, psychology, STEM, postgraduate higher education, and work integrated learning units. Our corpus encompassed responses to 790 messages sent to a total of just over 300,000 (non-unique) recipients. Some 1,977 students responded to the question “Was this message helpful?”. Of these, 1,845 responded with “yes” (93%) and 132 with “no” (7%). Students went on to provide a comment in 1,562 instances.

Method

Given the volume and breadth of the teacher-student communication facilitated by SRES, an inductive approach to the coding of comments was taken, without a particular reference framework to determine coding categories. We followed a thematic analysis approach as described by Braun and Clarke, who noted that this methodology is “essentially independent of theory and epistemology, and can be applied across a range of theoretical and epistemological approaches” (Braun & Clarke, 2006, p. 78), and is particularly useful “when exploring new terrain” (Clarke & Brown, 2017, p. 298). Preliminary coding was first carried out on a subset of the full corpus by one author (CB), and a set of thematic categories was proposed based on key themes. The three authors then met to discuss these categories, and to determine a precise definition for each category’s inclusion and exclusion criteria (outlined in the results section). This protocol was then applied to the full corpus. Subsequently to this, the authors met again to clarify the definitions of subcategories of one of the categories (“Feedback”). This revised protocol was then re-applied to the full corpus.

In keeping with the principles of thematic analysis (Braun & Clarke, 2006), the coding counts for each thematic category are intended as general indicators of prevalence, and not the basis for quantitative comparison or analysis. In the coding process we strove for an inductive derivation of thematic categories, however we recognised and strove to take into consideration the influence that previous work and research in higher education learning and teaching may have had on our thinking, in an effort to pursue what Braun and Clarke (2023, p. 1) refer to as a “knowing” application of thematic analysis. As our research question called for a descriptive rather than an interpretive analysis of the data, themes were largely identified at a semantic level, through the presence in the data of key descriptors and their synonyms (outlined in the results section). Some thematic categories did have a limited latent dimension, particularly those associated with affective responses, such as in the case of messages students found motivating, encouraging, or providing a sense of connectedness. In keeping with our largely descriptive research question, our epistemology was essentialist, in that we took students’ accounts of the usefulness (or otherwise) of the message they received at face value. We have endeavoured to be as transparent as possible in our coding decisions, as described in the results section of this paper. It is worth noting that our inductive application of thematic analysis to our corpus led to the derivation of themes which for the most part corresponded closely to the coding schema. The secondary, more subjective level of thematic analysis, in which themes are “generated, created or constructed” (Braun & Clarke, 2023, p. 3) was therefore not a strong influence on our analysis.

The focus of the first part of our study was on how students found the personalised messages helpful, rather than the intent of the message from the point of view of the message sender. However, familiarity with typical message construction will provide important context for the interpretation of our results concerning student reactions. To this end, in the second part of our analysis we present a description of the most appreciated messages, according to student voting. We first ranked messages according to the proportion of "yes" votes they had received in answer to the question "Was this message helpful?" relative to the total number of recipients of the message. Messages sent to fewer than 100 students were excluded. We then selected messages receiving a 10% (rounded) or greater "yes" vote as a proportion of the total number of recipients, resulting in 15 messages. The message receiving the highest "yes" vote, 82% of all recipients, was also excluded because it asked students to indicate their interest in participating in a practice exam by clicking the "yes" button. Of the remaining 14 messages, the "yes" vote ranged from 33% down to 10% (rounded) of total recipients. This study was approved by the Human Research Ethics Committee of the University of Sydney (Protocol Number 2017-2018).

Results

Student Comments

The categories resulting from the thematic analysis of the comments provided by students who found an SRES message helpful are presented in Table 1, along with the corresponding counts. In what follows, each category is defined and illustrated by one or two example comments. As our data do not include unique student identifiers, these comments are not attributed to any pseudonym or anonymised identifier. The category with the highest number of counts (462) corresponded to students identifying a message as helpful because it provided feedback. To further investigate this "Feedback" category, we broke it down into 5 subcategories. Many students expressed appreciation of the personalised nature of the feedback. In this category, labelled "Personalised feedback", we included comments containing descriptors such as "personal", "individual", "tailored", "detailed", "specific", "thorough" in relation to the feedback received, but also cases where it was clear from the context that the feedback was specific to an individual's assessment submission, such as a presentation. Comments in this category included:

> Personal feedback is always appreciated, it allows me to focus on specifics to improve.
>
> Very helpful to get this feedback on my presentation. Thank you

Some students made the connection between the feedback they received and hoped-for improved performance in future assessments in the unit, or in a future unit. In this subcategory, which we coded as "Feedforward", we also included references to finding the SRES message helpful for revision for a future assessment (not just performance in it). Typical comments included:

> Thank you very much for the in-depth feedback on quiz 2. It is very valuable and will assist with preparing for future quizzes.
>
> I am extremely appreciative for the feedback I receive for quizzes. In particular it is extremely helpful as I am aware of what I need to further revise as well as how I can further build on my knowledge.

Other students were less proactive in connecting feedback to a specific objective, but nonetheless referred to feedback allowing them to improve in a general sense:

> Thank you for the feedback ! It clearly justifies where my marks came from and things to improve.

> Its helpful. Because It tell me which question I did wrong, so that I can pay more attention on that part.

This subcategory of “Feedback” was labelled “Improvement”.

Table 1

Coding Categories for Comments Describing why the SRES Message Was Helpful.

Category	Subcategory	Counts	
Feedback			462
	Personalised feedback	156	
	Feedforward (to improved performance on a specific objective)	110	
	Improvement	87	
	Timely feedback	13	
	Feedback – other	133	
Reminder, time management advice			175
Encouragement, motivation			110
Unit or learning activity clarification			92
Direction to resources			71
Human connection			69
Information on progress, rank in cohort			64
Assessment clarification			24
Comment not providing further information			405
Other			64

A small number of students also expressed satisfaction with the timeliness of feedback enabled by SRES:

> It’s so nice to get such speedy any person [in-person] feedback despite the huge cohort, I really appreciate it!

> Thank you for giving me feedback. I feel surprised that I could gain my feedback immediately.

These were labelled “Timely feedback”.

Finally, comments indicating satisfaction with receiving feedback that could not be categorised in the above 4 sub-categories were coded as “Feedback – other”. This included comments indicating appreciation of learning “where I went wrong”, or receiving a mark breakdown, or a summary of the correct answers only.

> The feedback is very useful and helpful.

> I can know clarely [sic] which answers I was wrong.

> clear outline of marks.

Note that some comments were coded into more than one of the first four (non-other) subcategories of “Feedback”, for example the following comment was categorised as both “Personalised feedback” and “Feedforward”:

> extremely detailed feedback. i have so much information now to go on about with my future reports not just for this unit but for any unit i undertake.

After feedback, the second largest coding category captured the student’s appreciation at receiving a reminder, for example of an impending assessment deadline, or time management advice more generally, or both. Examples of comments coded in the “Reminder, time management advice” category include:

> Good to have a reminder.

> Thank you [instructor’s name] for reminding me what to do for Design Thinking. I’m a bit overwhelmed with the load of all three units I’m having so I’m grateful to receive emails like this which gives me a direction of what to prepare ahead.

Comments coded as “Encouragement, motivation” contained references to finding the message “encouraging”, “motivating”, “inspiring”, or “giving confidence” in relation to engagement with study. This category is distinguished from the “Human connection” category described below, in that the latter captures a positive emotional response to being contacted, rather than references to increased application to study. Comments coded as “Encouragement, motivation” include:

> Yes, the feedback is quite helpful and also a way to motivate me to engage more with this unit.

> Thanks for encouragement!

The next largest category captured appreciation of “Unit or learning activity clarification”, which included comments such as:

> gave me all the info i need to start the course

> Provided us with a good idea of what was going to be discussed in the tutorial and helps us to better prepare ourselves.

Comments categorised under “Direction to resources” indicated an appreciation of “links”, “resources”, “materials”, “guides” or “more information” referred to in the email:

> I didn’t know where to find it and totally forgot about it. Until our tutor mentioned it in class. Thanks for the directions.

> It’s nice to get recommended links to help me improve.

Comments categorised under “Human connection” contained an explicit positive emotional response to being contacted, such as an indication that the message was “welcoming”, “friendly”, “caring” or “kind”, through statements such as:

> Very supportive, made me feel better.

> Thank you for checking in i’m doing fine :)

The category “Information on progress, rank in cohort” captured non-evaluative feedback on progress, such as information about attendance, LMS presence, a summary of assessment items completed to date, and performance of the cohort as a whole for comparative purposes. Comments coded into this category include:

> it updates me of my current progress on my time and participation on this course.
>
> The statistics [the instructor] provided about fail rates also adds a sense of reality and further pushes me to not fall into that fail category.

Finally, the category “Assessment clarification” was a separate category to the more general “Unit or learning activity clarification”, and included comments such as:

> It provided the info I needed about my exam, and it was clear and concise.
>
> Yes it was helpful, some useful reminders and tips for the quiz which will be 15% of the end grade.

Additionally, there were also 405 comments simply reaffirming that the message was helpful, without providing any further information, and a further 64 “Other” comments which did not fall into any of the categories listed in Table 1. Comments frequently contained multiple components, and as such were coded into more than one category.

As noted, the proportion of students voting that the SRES message was not useful was small (7% of those voting). Their comments typically indicated that these students believed the information received was insufficient, wrong or unclear (n=34); that they felt they had been wrongly identified (n = 20); that the student had a grievance that was possibly unrelated to the SRES message (n = 10); and 22 responses related to a case in which a teacher had accidentally sent a blank email. These results are summarised in Table 2. Because of the small number of dissatisfied students, and the clarity of the reasons for their dissatisfaction, the discussion of our results will focus on positive student feedback.

Table 2

Coding Categories for Comments Describing how The SRES Message Could Be Improved if the Student Indicated it Was Not Helpful

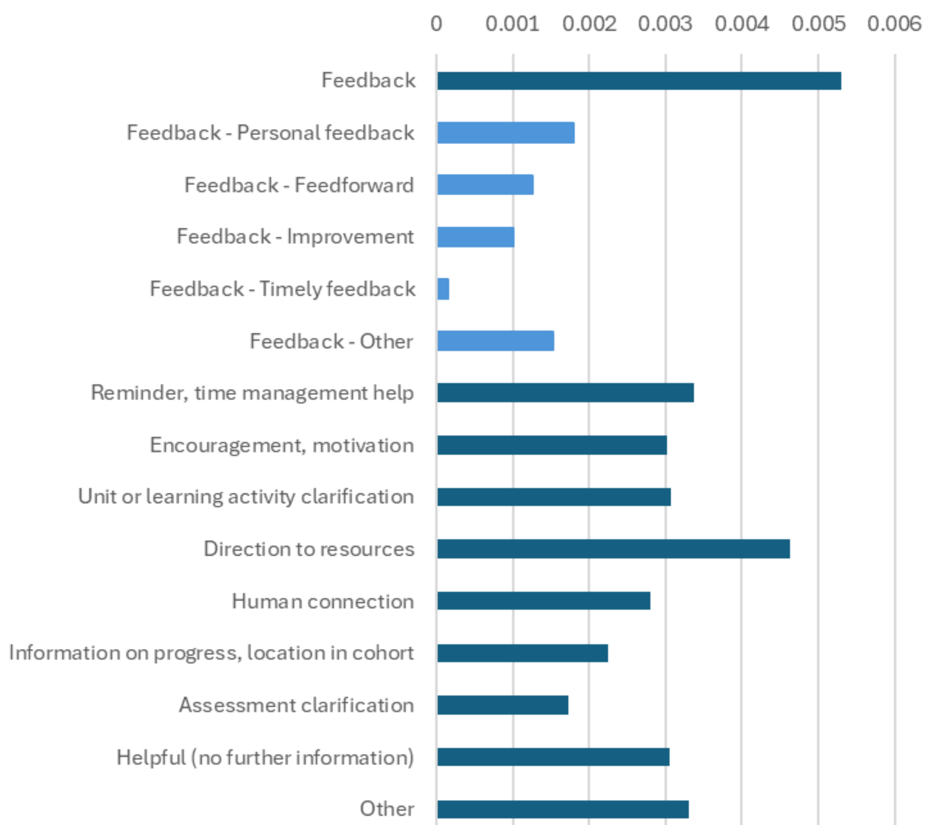
Category	Counts
Not enough, wrong, or unclear information	34
SRES user (teacher) error	22
Student wrongly identified	20
Student had grievance	10
Other	28

We have so far presented simple coding counts, which are not necessarily comparable with each other, since they do not consider how many students received a given message, nor how many students in other units and over the years received messages in the same category. Figure 1 presents the counts in Table 1 divided by the total number of students receiving a message on which any student commented in a way that was coded into the same category.

While this approach is only approximate, as due to personalisation different students may perceive the same message in different ways, it nevertheless provides a useful degree of comparability to our results. Significantly, it affirms our non-normalized counts indicating that messages providing feedback were the most likely to attract positive comments. The order of prevalence of our subcategories of feedback remains unchanged, as the same denominator was used for them as for overall feedback (precisely because they are subcategories). In descending order of perceived helpfulness, the remaining categories encompass messages that directed students to specific resources, messages providing reminders or time management tips, those giving clarifications of unit or learning activity requirements, messages of encouragement or motivation, messages conveying a human connection, information on the student's rank in the cohort or progress through LMS materials, and finally messages providing clarifications of assessment requirements.

Figure 1

The Coding Categories of Table 1 Normalised by the Total Number of Students Receiving a Message Coded in the Same Way



Most Helpful Messages

The following section provides a brief description of the 14 messages that were voted as helpful by 10% (rounded) or more of the recipients, and which were sent to 100 or more students, and identifies the coding of any comments the students made (Table 3). One message (labelled message 1 in Table 3) was a reminder for students who had missed the first lab class to attend the next one. Despite being sent to 291 recipients and receiving a 32.7% “yes” vote there was only one comment, expressing appreciation at “being asked if things are okay”. This had been coded as “Human connection”, as indicated in Table 3. Two messages (nos. 2 & 11) provided results for a quiz with feedback comments tailored according to how well each student had performed.

Table 3

Presence of Coding Categories in Messages Receiving 10% or Higher “Yes” Votes (to 100 or More Recipients).

			Coding of associated comments							
Message	% ‘yes’ vote	Number of recipients	Feedback	Reminder, time management advice	Encouragement, motivation	Unit or learning activity clarification	Direction to resources	Human connection	Information on progress, rank in cohort	Assessment clarification
1	32.7%	291						1		
2	28.9%	291		2	1				1	
3	20.2%	401	25		1	1	3	1	2	
4	17.1%	557	24	8	1	2	8			3
5	15.8%	171				2		2		
6	14.9%	101			1					
7	14.0%	751	23		5	1	8	2	2	
8	13.6%	220	5		1		5			
9	12.6%	159	2		3				1	
10	12.2%	221						2		
11	11.0%	264		1		2		1		
12	11.0%	283	1							
13	10.5%	172				2		1		
14	9.7%	751	14		2	3	5		3	
		Total counts:	**94**	**11**	**15**	**13**	**29**	**10**	**9**	**3**

Message 2 also included two reminders (to join a team, and to submit the next quiz), while message 11 provided additional advice, encouraging students to submit part A of each week’s non-assessed quiz before the weekly lecture, so that difficult points could be addressed by the lecturer. These two messages also only prompted a small number of comments, the coding of which is presented in Table 3. Five messages (nos. 3, 4, 7, 8 & 14) were all from different instances of the same unit, and provided a breakdown of students’ results from an assessment quiz, with tailored feedback and direction to resources, depending on how well the student had performed in each section. These messages received a larger number of comments, ranging from 11 to 43. Two messages (nos. 5 & 13) were introductory emails reaching out to students very early in semester, describing how the first tutorial would be structured, and how students should prepare for it. One message (no. 6) confirmed details of the team the student had joined, and provided an update on how many formative quizzes the student had completed, with tailored messaging depending on the student's degree of participation in both the quizzes and the discussion forum. Note this would only have been coded as "Information on progress" if the student had commented that this feature was useful. Message 9 passed on workshop facilitator comments about students' participation in a class discussion. Message 10 was only sent to students who did well in a quiz, providing their result and a congratulatory message. And finally, one message (no. 12) simply provided students with the answer key for a set of multiple-choice questions, along with the responses they had given for comparison. These results are summarised in Table 3, which shows that all coding categories were present in the top 14 messages to large student cohorts, and that similarly to the normalised distribution for the full cohort, "Feedback" was the most frequent code, and "Direction to resources" the second most frequent.

Discussion

Our results demonstrate that unit coordinators used teacher-controlled, learning analytics-informed, personalised messaging to students for a wide range of purposes. Many single messages addressed multiple purposes, for example at the same time providing feedback and directing students to study resources, and their exact structure and content reflected highly individualistic design schemes. The learning analytics employed were typically unit data which coordinators had routine access to, but which the platform permitted them to use in time-efficient ways to address learning and teaching goals that were unit-specific, and in line with the cadence of formative and summative assessments, and possibly also variations in their own workloads. In answer to our research question asking what kinds of messages students found helpful in learning analytics-driven personalised messaging from their teachers, we draw the following conclusions.

Firstly, students appreciated messages that provided personalised feedback on assessment directly. This is supported both by the full corpus data, as well as by the strong representation of the "Feedback" category in the subset of the messages considered most helpful. The pedagogical value of personalised feedback is well-established in the literature (Karaoglan Yilmaz & Yilmaz, 2020; Leppänen et al., 2022; Lim et al., 2020), and our finding that students appear to recognise its value provides encouragement for emerging work on the application of learning analytics in formative assessment (Zhang et al., 2023). This result is also in alignment with scholarship on student expectations of learning analytics (Gray et al., 2022; Viberg et al., 2022), which reports that learning analytics-driven feedback on progress is a major desire. In many cases students also recognised the connection between feedback and improvement in future assessments, a major element of self-regulated learning (Boud & Molloy, 2013; Terzi Müftüoğlu et al., 2024). While improving feedback literacy is recognized as a key challenge when providing students with learning analytics-informed feedback (Tegpec et al., 2025), this finding indicates that personalised communications is worth investigating as a means for doing so. Though reflected in relatively few comments, it is also likely that semi-automation led to greater timeliness in feedback provision to students, increasing the likelihood of its use to improve performance in later assessment items (Dawson et al. 2019; Sadler et al., 2023). The usefulness of learning analytics-driven feedback provision is also a significant finding from the point of view of staff academic workload, given the time required to provide meaningful feedback on the one hand, and the efficiency facilitated by semi-automation on the other (Irons & Elkington, 2021; Pardo et al., 2017).

Secondly, students appreciated being directed to resources based on an individually identified need, such as poor performance in an evaluative exercise, or in one part of an exercise, that may or may not have been a formally assessed task. These resources had presumably already been provided in the LMS but connecting them to a student's particular learning need based on their recent performance is an example of just-enough, just-in-time, just-for-me support provision, which, it has been argued, promotes student engagement (Kift, 2015). This finding also provides backing for existing scholarship advocating the use of learning analytics to tailor recommendations for actions aimed at improving performance (Afzaal et al., 2021; Ustun et al., 2023).

Thirdly, students appreciated reminders supporting better time management, and progress updates concerning assessment completions or performance to-date compared with the current or previous cohorts. This is in alignment with other recent findings by learning analytics scholars on the value of reminders (Iraj et al., 2020; Lim, Gašević et al., 2021), and also with the notion of nudging from the general learning and teaching literature, according to which timely, appropriately phrased communications to students concerning deadlines and positive study behaviour can increase student engagement and performance (Blumenstein et al., 2018; Lawrence et al., 2021).

Fourthly, it appeared that the personal nature of teacher-student emails was effective in providing clarification of unit aims and learning outcomes, as well as learning activity and assessment information. Once again it is likely this information had already been provided in the LMS or unit learning guide, perhaps in a more formal register. Providing this information in a personalised teacher-student email, perhaps written with a degree of informality with which students could more readily engage, is another example of the just-enough, just-in-time, just-for-me philosophy in action (Kift, 2015). To our knowledge this function has not been addressed explicitly elsewhere in the learning analytics literature but may be an example of using learning analytics to reduce the learner-teacher transactional distance, as discussed by Karaoglan Yilmaz and Yilmaz (2021).

Finally, students found messages that encouraged, motivated or inspired them beneficial, along with communications that they felt established greater human connection with their teachers. Enhanced motivation has also been found in studies of other learning analytics-informed message personalisation platforms (Lim et al., 2020). It has been argued in the general learning and teaching literature that students benefit from or even expect some form of personal relationship with their instructors (Kahu & Picton, 2019; Stone & Springer, 2019), and this study shows that learning analytics-informed personalised messaging can contribute towards building this relationship – despite students potentially being aware that the messaging system is at least partially automated. As one student commented:

> I rly appreciate the recognition that I didn't attend. I don't know why. I feel seen and I appreciate being asked if things are okay even if it's an automated message.

The significance of these results, while tentative, lies in suggesting that supporting teacher-led, unit-specific applications of learning analytics may be a viable way of using student data to improve learning. Learning analytics in ever increasing quantity and granularity have been available to higher education institutions for decades now, and yet it is widely acknowledged that they are underutilized, as discussed in the literature section. In the preceding paragraphs links have been made between what can be achieved with personalised messaging, at least according to student perception, and recommendations arising from the general learning and teaching literature for improving the student experience. The possibility that empowering educators to act at the micro level may be more effective than providing generic, centralized solutions deserves further exploration. Moreover, placing teachers at the heart of decision-making goes some way to ensuring co-design of learning analytics interventions, which has been put forward as a promising approach to more effective use of learning analytics in improving learning and teaching (Buckingham Shum et al., 2024; Dollinger et al., 2019). Teacher direction also ensures that interventions are in tune with the unit-specific context, which has been identified as essential for improving the student experience (Gašević et al., 2016; Larrabee Sønderlund et al., 2019). This approach at least partly addresses ethical and privacy concerns about the use of student data, as users have been shown to use unit learning analytics that are routinely available to them as teacher or unit coordinator (Blumenstein, 2017).

Our study suggests, given access to a message personalisation platform such as the one described in this article, and training in its operation, the kinds of messages students are likely to appreciate most. Educators are likely to find that providing personalised feedback that students can apply to improve their performance on a subsequent assessment will be perceived as helpful by students. Similarly, directing students to specific learning resources that aim to support their personal learning, is likely to be perceived positively as just-in-time, just-for-me learning support. Reminders, time management advice, and timely clarification of unit, learning activity, or assessment requirements, in a personal, informal register, are also likely to be perceived as helpful. Finally, messages of motivation, encouragement, or simply establishing a human connection can conceivably help students to “feel seen”. Interestingly, while still evaluated positively, it appears that information on progress through the LMS, or comparisons with peers in the cohort – functions commonly included in student-facing dashboards of learning analytics – were among the least valued by students in our study.

Our study has several limitations. Firstly, we acknowledge that while our data derived from a wide range of disciplines, this study was confined to a single university, in a specific Australian geographical context, with the accompanying limitations on generalisability. Secondly, our data did not include any student information, so we were unable to ascertain whether students providing comments were a representative sample or otherwise. It is possible that more engaged students were more likely to proffer an opinion concerning why a message was helpful. Thirdly, our study is limited by the structuring effect of the design choices of individual educators on the responses of their students. Our results therefore need to be interpreted with caution, due to the lack of parity across messages and the consequent contingency of student reactions. We nevertheless contend that it is possible to draw tentative general conclusions from many messages sent and a very large sample of feedback comments from a 6-year period of institution-wide implementation of a learning analytics application. This study has also identified areas for further study, such as investigating what forms of sustainable, learning analytics-informed feedback may be most effective in developing self-regulated learning skills.

Conclusion

In answering our research question, asking what kinds of messages students found helpful arising from teacher-controlled, learning analytics-informed personalised messaging, a range of features were identified. These included messages that provided personalised feedback, directed students to specific resources based on identified need, gave reminders of impending deadlines or good study habits, provided clarification of unit requirements at the most relevant times, or simply offered words of encouragement or human connection. Many of these functions have been identified as good learning and teaching practice in the scholarly literature. These practices often remain aspirational, however, when large class sizes and limited teaching workload make personal communications and feedback provision challenging. Semi-automation brought about by technology-enabled platforms such as SRES provide a promising pathway for overcoming such challenges. While this evaluation was based only on student feedback comments, it nevertheless suggests that a teacher-led, unit-specific approach is worthy of further investigation as an avenue for closing the gap between the plethora of learning analytics gathered by institutions, and improvements in the student learning experience.

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