Impact of learning analytics feedback on self-regulated learning: Triangulating behavioural logs with students' recall

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ABSTRACT

Learning analytics (LA) has been presented as a viable solution for scaling timely and personalised feedback to support students' self-regulated learning (SRL). Research is emerging that shows some positive associations between personalised feedback with students' learning tactics and strategies as well as time management strategies, both important aspects of SRL. However, the definitive role of feedback on students' SRL adaptations is under-researched; this requires an examination of students' recalled experiences with their personalised feedback. Furthermore, an important consideration in feedback impact is the course context, comprised of the learning design and delivery modality. This mixed-methods study triangulates learner trace data from two different course contexts, with students' qualitative data collected from focus group discussions, to more fully understand the impact of their personalised feedback and to explicate the role of this feedback on students' SRL adaptations. The quantitative analysis showed the contextualised impact of the feedback on students' learning and time management strategies in the different courses, while the qualitative analysis highlighted specific ways in which students used their feedback to adjust these and other SRL processes.

CCS CONCEPTS

• **Applied computing → Learning management systems**; **Education**.

KEYWORDS

learning analytics, personalised feedback, self-regulated learning, learning strategies, time management strategies, mixed methods

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1 INTRODUCTION

Students transitioning to higher education study are required to take more responsibility for their learning [3]. This responsibility extends to decisions regarding course selection and future goals as well as developing their proficiency for SRL. Yet, students often have poorly developed SRL skills that negatively impacts on academic performance and persistence in higher education [10]. Successful self-regulation involves a combination of cognitive and metacognitive skills and motivation [28, 40] and can be improved through the provision of feedback [4, 11]. However, the benefits of such feedback are not consistently uniform [11]. Effective feedback needs to be timely, personalised to students' progress, and targeted at developing students' SRL [11]. Given the context of contemporary higher education, the ability for educators to provide such timely and personalised feedback at scale is increasingly diminished due to workload constraints and the growing complexity of student needs and diversity [25].

LA can provide viable solutions to address the challenge of providing personalised feedback at scale [26]. While the use of LA dashboards and metrics are a commonly noted approach to provide personalised feedback [14] there remains scant evidence of the impact data-driven approaches to feedback on student learning and achievement [7]. Feedback is "a dialogic process, whereby learners make sense of information from various sources and use it to enhance their work or learning strategies" [5, pg. 190]. Provision of feedback via LA approaches has so far relied on aligned user interpretation and action. As such, sense-making is an inherent part of the process [33]. How students interpret their LA-based feedback to make learning-related decisions is a critical area of ongoing research [39]. This present study explores the impact of LA feedback through (a) the learning and time management tactics and strategies that can be detected from trace data, and (b) students' recall of their experiences with feedback.

The education context is an important consideration in feedback impact. The learning design alongside the course delivery method or modality strongly influences a student's level of engagement and

SRL strategies adopted [3, 21], and ultimately their academic performance [9, 21]. However, there remains limited research exploring the role of course context in the impact of LA feedback on students' SRL. An understanding of the different ways feedback is influenced by context is important for informing the design of analytics-based feedback that will foster students' active engagement. To address this research gap, the present study examines the impact of LA feedback on SRL in two contexts that differ in their learning design and modality.

2 BACKGROUND

2.1 SRL and feedback

SRL is a commonly referenced theoretical construct in LA and feedback research [34]. Broadly, it refers to the control that students have over their thoughts, feelings, and actions toward the attainment of learning goals. Although different models of SRL have been proposed (e.g., [28, 36, 40]), they share a common understanding that the learner is an active agent in their learning, and that SRL is a staged, iterative process. In this study, we emphasise the importance of two components of SRL namely, learning tactics and strategies; and time management, and how these components are influenced by feedback.

2.2 Learning tactics and strategies

Although used somewhat interchangeably in the literature, learning tactics and strategies are qualitatively different concepts. Learning tactics refer to specific techniques or cognitive operations during the performance of discrete tasks [18]. Examples of discrete learning tactics that students might undertake in a blended learning context are: (i) reading, (ii) doing practice exercises, or (iii) reviewing a lecture video. Learning strategies may be considered at a higher level, involving the coordination of various study tactics towards the achievement of goals [17]. An example of a learning strategy is reading a topic-related resource and then doing practice exercises. Learning strategies are amenable to the dynamics of learning contexts. External conditions play an influential role in students' adoption of learning tactics and strategies [36, 40]. For example, different learning modalities require students to employ different learning strategies to succeed academically [3]. However, it is often difficult for students to identify and employ the optimal learning strategies to achieve course goals [8]. In this context, feedback supports students in their adaptation and selection of learning strategies. While the importance of such rich and personalised feedback has long been known, the capacity to scale such feedback in contemporary education settings has been lagging. Developments in LA can provide a technological solution to scaling personalised feedback processes [25]. By drawing on students' learning traces in their interactions with online activities and reporting these in terms of engagement metrics, students may be prompted to reflect on their current use of tactics and strategies, and adapt their self-regulation in more optimal ways [32].

2.3 Time management strategies

As with learning tactics and strategies, time management sits within the wider concept of SRL. Time management is related to goal setting and refers to a student's ability to schedule, plan, and manage their personal study time [27]. Students are frequently challenged in being able to self-regulate their management of time to stay on task in their learning. A common problem is procrastination, where students delay working on requisite tasks until the last minute [12]. Procrastination is a failure of self-regulation leading to poor performance [3]. As such, time management is key to effective SRL especially in higher education settings. Students benefit from feedback interventions that support their time management strategies. Effective feedback highlights standards or goals by which students can evaluate their learning strategies or progress and then adjust their learning strategies in order to better meet those standards or goals [40]. As with learning tactics and strategies, LA can facilitate the provision of timely and personalised feedback to help students to know whether they are completing the course requisites in a timely way, and therefore to evaluate their strategies for time management.

2.4 Measuring the impact of LA feedback on SRL

Advances in the field of LA have resulted in the development of numerous LA feedback interventions that are noted to support student SRL [13, 26]. Yet, despite the volume of tools available, there remains limited work demonstrating the impact of these technological solutions on students' learning processes, outcomes or motivation [34]. The relative novelty of these LA feedback systems means there has been limited time to research the effects on student learning. To date, studies have found benefits of this novel approach to feedback on students' satisfaction with feedback [25] and course performance [15, 25]. Evidence is also emerging that shows some positive impact of this feedback on aspects of students' SRL. For example, Matcha et al. [20] employed an innovative approach to analyse students' learning strategies in a flipped classroom over three years. During this period, LA feedback was provided for two years in different extents. The authors found evidence of an association between feedback and students' learning strategies. Specifically, the proportion of students using intensive-high engagement strategies (akin to a deep approach to learning) was significantly higher when feedback was present. This was more acute when the provided feedback was further elaborated with information about recommended learning strategies. Furthermore, the intensive-high engagement strategy was associated with high course performance, implicating the impact of feedback on learning outcomes. In a similar study, Ahmad Uzir et al. [1] examined time management strategies in the same flipped classroom over three years. Using process mining procedures, they observed an association between feedback and students' time management strategies. When feedback was present, a greater proportion of students were found to use comprehensive time management strategies that involved revisiting and preparing for the weekly topics. This strategy was associated with high course performance, suggesting that students were prompted by feedback to optimise their time management strategies in the course. While these studies contribute to a growing evidence base of the impact of LA feedback, they are limited in their generalisability as they only take into account a singular instructional context: flipped learning. Further studies incorporating a diversity of instructional contexts are needed to evidence the extent to which LA feedback makes a difference to students' SRL behaviours. Accordingly, the first research question guiding this study is:

RQ1: Are there observable differences in students' SRL with and without feedback with reference to (a) learning tactics and strategies; and (b) time management strategies, across different course contexts?

The studies outlined above show that LA can detect meaningful tactics and strategies, and emphasise the potential for feedback to impact students' SRL in this way. However, SRL consists of a range of processes beyond observable behaviours. Theoretical notions of SRL describe it as a multifaceted concept comprising elements of metacognition, motivation, cognitions, and behaviours (e.g., [28, 36, 40]). Furthermore, SRL is generally understood as an iterative process involving a preparatory phase, performance phase, and appraisal phase [23]. For example, the cyclical phase model of SRL [41] posits a Forethought, Performance, and Reflection phase. Briefly, the Forethought phase involves processes of task analysis, setting goals, and selecting strategies to achieve those goals. Personal motivational beliefs drive these forethought processes. During the Performance phase, the learner executes self-control processes, involving volitional efforts and learning strategies. During this phase, self-observation processes provide an internal feedback loop for the Reflection phase, where the learner self-evaluates progress, with input from self-observation in the Performance phase and the set goal(s) during the Forethought phase. Self-judgment is an evaluation of progress, while self-reaction is an emotional response to the judgment, in the form of self-satisfaction, or adaptive/defensive reactions. Internal feedback arising from he self-reflection phase serves as input for the next iteration of SRL, by influencing motivation and task analysis processes.

Advanced data-mining processes have been used to detect associations between learning and time management strategies with feedback – processes that fall within the 'Performance' phase of SRL. Given that SRL comprises highly connected phases, research is needed to capture feedback's impact on these broader aspects of SRL, such as the Forethought and Reflection phases which, in the current state of knowledge, may not yet be robustly detectable through data-mining. Capturing this information necessitates a more qualitative approach. To date, few studies have been able to capture both trace data and students' recall of their experiences with LA feedback to understand the impact of this feedback on their SRL. Furthermore, the observed associations between students' tactics and strategies with LA feedback are yet to be aligned with students' subjective experiences of how they adapted their strategies. Importantly, the role of feedback in these adaptations has not been made clear. In effect, there is an overall lack of qualitative studies in LA research designed to unpack how LA feedback is perceived, experienced and interpreted [19]. LA feedback interventions are sociotechnical systems, where decision-making by students in response to the analytics is as important as the analytics provided [39]. Presently, evidence is limited regarding the role of feedback in students' decision making with respect to SRL [13]. As such, the second research question was defined as:

RQ2. What was the role of LA feedback in students' SRL adaptations, from the subjective experience of students in different course contexts?

3 METHOD

This mixed-method study was conducted in two different first year undergraduate courses at two Australian Universities. Ethics approval for the study was obtained from both institutions. Table S1 (in Supplementary material at http://tiny.cc/FBImpact) provides a summary overview of the two contexts.

The first course was a Biology course that used a blended learning pedagogy involving a mix of online and face-to-face activities. Students were required to attend the face-to-face learning sessions including three hours of weekly lectures, one hour tutorial session, three hours of laboratories and two hours of workshops. The online learning activities aimed to help students in their revision as well as to help them to prepare for the laboratory sessions. Hence, the design of the online activities included a number of reading materials; a set of pre-laboratory activities provided through an external tool called SCORM; and information about the objectives, syllabus and other general information. A discussion board was also available for students. External learning tools included an e-book, noted as an important revision tool. Assessment included two quizzes (20%), practical laboratories (25%) and final exam (55%). Data were collected over a two year period. In total 255 and 232 students were enrolled in the 2016 and 2017 offerings of the course, respectively. In 2017, personalised feedback messages were sent to students during weeks 4 and 9 by using a software tool called OnTask [24]. Feedback for the course was oriented around checkpoint analytics, drawing on metrics relating to whether students had completed certain learning prerequisites [16]. This included meeting attendance requirements and the extent to which they completed the noted learning tasks.

The second course was a Computer Engineering course employing a flipped classroom pedagogy. In this context, students were required to complete a set of online learning activities prior to attending the three hours per week face-to-face lecture. Students were also required to participate in two hours of tutorial and three hours of laboratories per week. The online learning activities aimed to help students develop an understanding of the concept of each week's topic. Hence, a wide range of learning activities were available for students including video lectures, reading materials, quizzes embedded to the reading materials and video lectures as well as some practical exercises. Similar to the Biology course, students were able to access course information, and a discussion board. Students were assessed on their weekly online preparation (20%), mid-term exam (20%), project (20%), and final exam (40%). Overall, four years of course and student data were collected. In 2014, no personalised feedback was provided. In 2015, personalised feedback messages were sent on a weekly basis to students for five weeks (weeks 2-5). In 2016 and 2017, weekly feedback was sent to individual students throughout the semester. The personalised feedback messages were customised based on each student's engagement and performance by using OnTask. The feedback gave students knowledge about their results and provided advice on how to improve on that result.

3.1 Data Analysis

3.1.1 Detection of students' learning tactics and strategies. To address RQ1, we first extracted the type of learning tactics and strategies used in both courses. To do so, we used the method adopted from the work of Matcha et al. [20]. The method was developed by considering the learning tactic as a sequence of online learning actions performed by students to accomplish a learning task in each learning session [17]. The strategy was considered as an overall pattern of tactic application [20]. Hence, the proposed method consisted of two main steps, including:

- Tactics detection: This step included data preparation by partitioning the sequences of learning actions to the corresponding learning sessions. Each learning session was at least 30 minutes apart from one another [14]. The First-order Markov model (FOMM) provided by the pMineR R package was then used to formulate the learning process based on the timestamp of involved learning actions in each learning session. The Expectation-Maximization (EM) algorithm was used to detect similarity in patterns of learning actions. Hence, similar processes of learning actions were categorised in the same group of learning tactics. To interpret the detected learning tactics, several dimensions of learning tactics were explored, including state distribution, length of learning sequences, and overall pattern of learning sequences.
- Strategies detection: This step involved calculating how individual students used each detected tactic. Then, the frequency of each tactic used and total number of tactics applications were taken as an input for the strategies detection. The (dis)similarity of the input was calculated based on the euclidean method. The Agglomerative Hierarchical clustering was used to detect the regularity of tactics used based on the 'Ward' method.

To explore the relationship of feedback intervention on the application of learning strategy, the Chi-square test was used. For each academic year, different levels of feedback interventions were provided, hence, observing the application of strategies used in each year reflects how the feedback impacted on the adoption of the learning strategy.

3.1.2 Labelling the time management modes of study. Prior research has shown that students with the ability to plan study and retain a strong sense of control over their time (time management) is positively correlated with SRL skills and academic performance [1, 2, 22, 31]. Time management is related to the ability of learners to schedule, plan, and manage their study time. Research in LA examined time management based on the time-stamped records of actions that learners perform while studying through online platform or LMS, and validated against the course structure prepared by the course instructor. An algorithm was defined by associating learning actions with appropriate time management modes based on the timing with respect to the weekly topic, as suggested in [1]: (i) ***ahead*** – gaining early access to the course materials prior to the scheduled week, (ii) ***preparing*** – studying learning materials prior to face-to-face sessions, (iii) ***revisiting*** – returning to course materials to re-study after in-class sessions, (iv) ***catching-up*** – delaying task engagement till later in the course, and (v) ***other*** – if the learning action was not assigned to any specific topic (e.g., discussions). To observe the transition of learning tactics in each week and time management, sankey diagrams were plotted. That is, the corresponding time management mode (i.e., ahead, preparing, revisiting and catching-up) was computed for each learning action contained in each tactic. Then, the diagrams were plotted according to the use of tactics in each week.

3.1.3 Examining students' subjective experiences with feedback and their SRL adaptations. To complement the quantitative analysis of students' learning strategies, we conducted focus group discussions with students in the final two weeks of the courses. The focus group discussions were designed to explore the students' subjective experience with their personalised feedback in each context, especially, the role of feedback in their SRL adaptations. Students were invited to take part in the focus group discussions. A total of nine focus groups were conducted: three for the Biology course, and six for the Computer Engineering course. The size of the groups varied from two to 10, due to the voluntary participation and students' availability after classes. Each focus group session took between 30 to 60 minutes. The focus groups were anonymous. To allow for comparison across contexts, a semi-structured interview schedule was used. Students were informed that discussions were recorded. As this study was situated within a wider project, students were asked a range of questions designed to elicit their recall of their experience with the feedback. For the purposes of the present study, the relevant questions were as follows: (i) Did you follow the recommended actions in the feedback? Why or why not?, (ii) Did you find that the emails motivated you to study in the course, or did it not motivate you? Why?, and (iii) How did the emails affect the way you learn in this course?

The focus group sessions were transcribed verbatim and imported into NVIVO 12 for analysis. To examine students recall of their SRL adaptations in response to feedback (RQ2), deductive analysis was carried out. Students' comments were coded in alignment with the cyclical phase model of SRL [41], so as to allow for triangulation with the quantitative analysis of learning strategies. For reliability, an additional coder classified 40% of the meaning units in a first attempt, resulting in a moderate level of agreement (Cohen's kappa = .51). The codes were refined and a second attempt undertaken resulting in a high level of agreement (Cohen's kappa = .93). Disagreements were discussed in order to reach consensus. A list of the nine themes with illustrative quotes are provided in Table S2 (Supplementary material[1]).

4 RESULTS

4.1 RQ1: How feedback influence a) learning tactics and strategies; and (b) time management strategies

4.1.1 ***Computer Engineering Course.*** Five learning tactics were detected including (see Figure S1 – Supplementary material) :

- Diverse: 11.93 percent of all learning sessions were categorised as diverse tactics. This is considered as the lengthiest learning session consisting of (median (Q1, Q3) = 55 (31, 92) actions per session). There was a fair distribution of learning actions performed by students when interacting with the online learning resource including content access, interaction with the exercises, and videos.
- Reading and MCQ Oriented: This tactic consisted of 30.66 percent of all learning sessions. This tactic was relatively

[1] http://tiny.cc/FBImpact

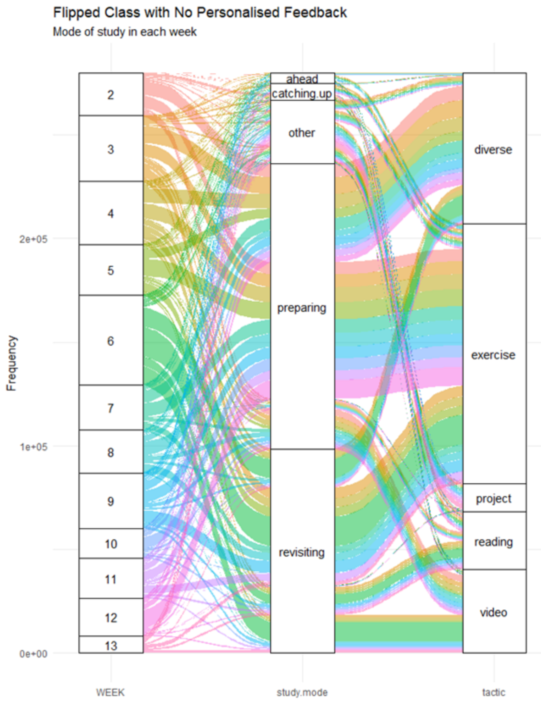
short (median (Q1, Q3) = 5, (3,10) actions). The most dominant learning actions were access to the learning content that contained the reading material and also interacted with the embedded MCQs.
- Planning and Monitoring Oriented: 18.48 percent of all learning sessions were categorised as this tactic. This tactic consisted of the very short learning sessions (median (Q1, Q3) = 3, (2,6) actions). The most dominant learning actions included access to the pages that provided information related to the project. The second most frequent actions were accessing the dashboard as well as the pages containing information about the course such as syllabus, course objectives.
- Video Oriented: 12.94 percent of all learning sessions were grouped as video-oriented tactics. The length of learning actions in each learning session were moderate (median (Q1, Q3) = 21, (10,43) actions). The most dominant learning actions were interaction with the video contents and answers to the embedded MCQs.
- Exercise Oriented: 25.99 percent of all learning sessions were categorised as the exercise oriented tactic. The length of learning actions in each learning session were moderate (median (Q1, Q3) = 24, (13,43) actions). The most observable learning actions were interaction with the exercises.

The dendrogram from the application of hierarchical clustering suggested three types of learning strategies. Figure S1 (Supplementary material) illustrates the pattern of learning tactics used in each learning week for this course. The three strategy groups include:

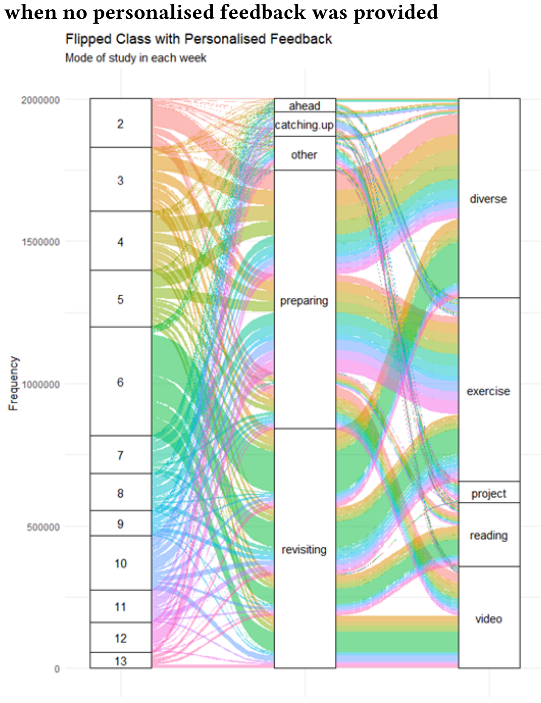
- Strategic-Moderate Engagement: The pattern of tactics application suggested a moderate level of engagement. During the first half of the semester (weeks 2-6), the reading oriented tactic was frequently used, but dropped as the course progressed. The exercise oriented tactic was used throughout the semester, indicating that students in this strategy group focused on the summative assessment. The use of Planning and Monitoring oriented tactics was visible during the beginning of the course (week 2) and during the second half of the semester. The overall performance of students who adopted the Strategic-Moderate Engagement strategy group was relatively high (median (Q1, Q3) = 35 (27.00, 46.00), out of a total score of 60). In 2014, when personalised feedback was not implemented, the overall score was lower compared to the years when personalised feedback was present (median (Q1, Q3) of 2014 = 33.00 (26.00,45.00); 2015 = 38.50(28.58,46.83); 2016 = 34(25.25,45.00) and, 2017 = 36.00(28.00,45.00)).
- Intensive-High Engagement: The level of engagement of students in this strategy group was much higher compared to the first strategy group. Similar to the Strategic-Moderate Engagement group, students applied a high level of reading oriented tactics at the beginning of the course. They also focused on summative assessment as reflected in their use of exercise oriented tactics through the semester. The students' use of video and planning oriented tactics were also visible at different levels of applications. The Planning and Monitoring oriented tactic was initially used during weeks 2 and 3, but dropped thereafter. From the second half of the semester (week 7), an increase in Planning and Monitoring oriented tactics use was observed. Students who adopted this strategy performed the highest as compared to the other two groups (median Q1, Q3) = 39.00 (29.33, 50.00)). The overall performance in each year was similar for the first three years (median (Q1, Q3): 2014 = 38.00(28.00,49.00); 2015 = 38.83(32.42,48.67); and 2016 = 38.00(25.00,49.00). In 2017, the median score of students in this strategy group was higher than the other years (42 (33,52)).
- Highly Selective-Low Engagement: The overall level of engagement in this group was much lower than the other two strategy groups. Students applied reading oriented tactics during the first half of the semester, consistent with the other strategy groups. The exercise oriented tactic was the only consistently applied tactic. This suggests that students in this strategy group aimed to pass the course with minimum effort. The use of Planning and Monitoring oriented tactics were observed twice – after the mid-semester exam and before the final exam. Students in this group showed poorer performance as compared to the other two groups (median (Q1, Q3) = 27.00 (20.00, 36.00)). The performance for each year was similar for 2014, 2016 and 2017 (median (Q1, Q3) of 2014 = 27.00(21.00,33.25); 2015 = 31.17(22.08,39.33); 2016 = 25.00(20.00,33.00); and in 2017 = 26.50(17.25,37.00)).

Influence of feedback. Figure 2a presents the proportion of strategies used by students enrolled in each year. In 2014, when personalised feedback was not applied, the use of Highly Selective-Low Engagement strategy was higher than in other years. The number of students exhibiting these behaviors reduced as the personalised feedback was introduced in the following three years (2015-2017). In contrast, use of the Intensive-High Engagement strategy in 2015-2017 was higher than 2014. This result showed the potential benefit of elaborated customised feedback. That is, the application of ineffective learning strategies (i.e., Highly selective-Low Engagement strategy group) reduced and the use of effective learning strategy (i.e., Intensive-High Engagement) increased. However, when exploring in terms of statistical significant association by using the chi-square test, we found no significant association between the year and proportion of strategies used (χ^2 (6, N=1727)= 5.6757,p-value = 0.4605). Nevertheless, the Strategic-Moderate Engagement strategy group steadily increased across the four years. The use of the Intensive-High Engagement strategy was higher for the years when students received personalised feedback than in the year they did not receive it (2014).

The sankey diagram (Figures 1a and 1b) illustrates the transition of learning tactics and corresponding time management strategies in each academic week. When feedback was present, the revisiting mode was more frequent. Students performed a range of tactics in this mode (i.e., diverse, exercise, reading and video tactics). When in preparing mode, activities focused on diverse tactics. In contrast, without feedback, students were more inclined to focus on exercise tactics while in revisiting mode. Exercise tactics were more frequently observed during the preparing mode. In terms of week-to-week activity, when feedback was present, the revisiting activities were more frequent during the midterm test week (week 6), while more preparing and revisiting modes using video and exercise tactics were observed in week 10. Without feedback, more revisiting modes using exercise tactics were observed in weeks 9

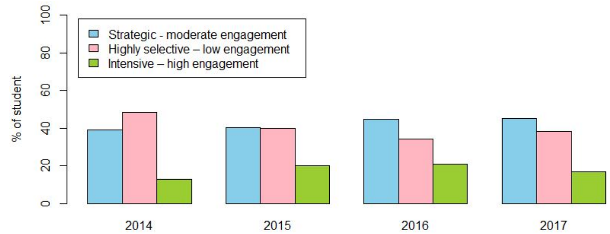


(a) Tactics used and the corresponding mode of study when no personalised feedback was provided

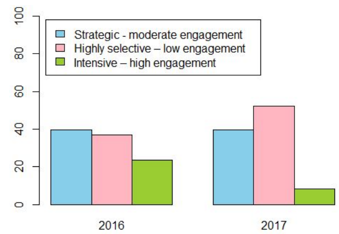


(b) Tactics used and the corresponding mode of study when the personalised feedback was provided

Figure 1: Tactics used and the corresponding mode of study for Computer Engineering course



(a) Computer Engineering course



(b) Biology Course

Figure 2: Proportion of students used each strategy group according to year

and 11. In week 9 especially, there were higher levels of preparing and revisiting activities. Overall, without feedback, more exercise tactics were observed.

4.1.2 ***Biology Course****.* Three learning tactics were detected based on the sequence of learning actions (see Figure S2, Supplementary material) including:

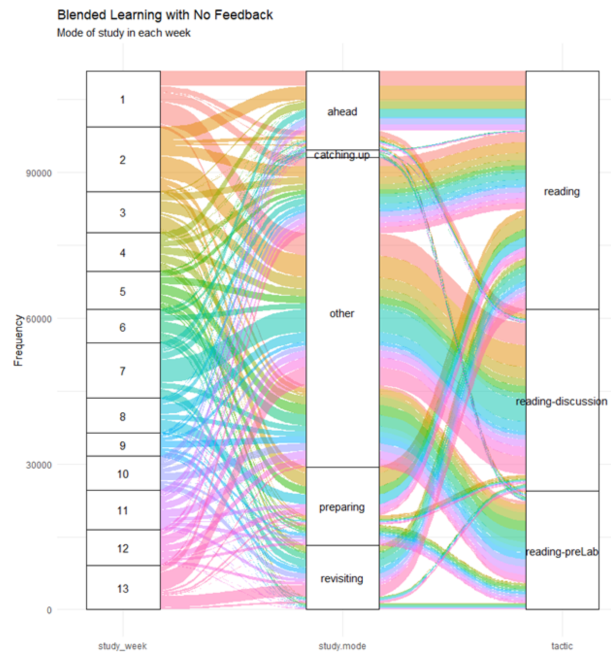
- Reading Oriented: 44.28 percent of all learning sessions were grouped as reading oriented. In general, this tactic consists of short learning sessions (median (Q1,Q3) = 5 (3,8) actions per session). Interaction with the reading material and navigation to the home page which provided general course information and announcements from the course instructors were the most frequently observed actions performed during the learning session.
- Reading and Pre-lab Oriented: This tactic comprised 16.71 percent of all learning sessions. This comprised the longest learning sessions among the three tactic groups (median (Q1,Q3) = 9 (4, 16) actions). The most dominant learning actions were interaction with the reading materials as well as navigation to the home page. Another type of action observed in this tactic was the interactions with the pre-laboratory activities.
- Reading and Discussion Oriented: This tactic comprised 39.00 percent of all learning sessions. This tactic contained short learning sessions (median (Q1, Q3) = 4 (2, 7) actions). Similar to the previous two tactics, the observable learning actions included interaction with the reading material and home page. Actions related to interaction with the forum and discussion board were also prominent.

Three groups of learning strategies were detected (see Figure S2):

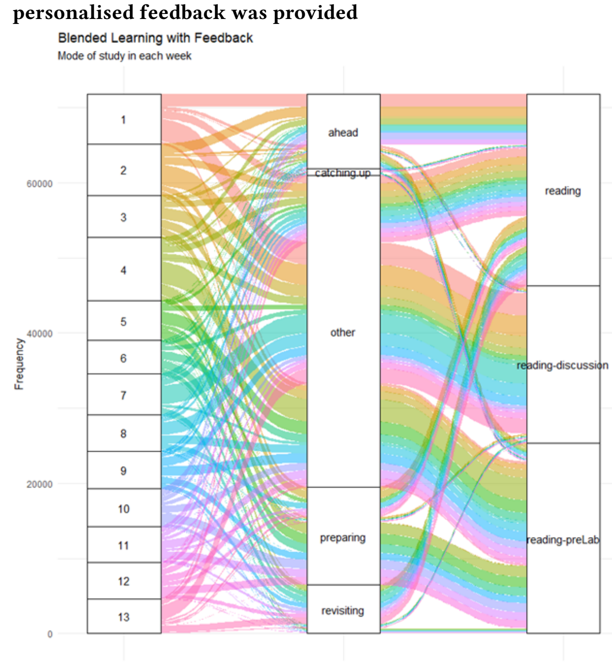
- Intensive-High Engagement: The overall level of engagement of students in this strategy group was high. At the beginning of the course, students highly applied the reading oriented as well as reading and discussion oriented tactics. However, the level of engagement dropped in the first half of the semester and increased again after the mid-semester exam. The use of reading and discussion oriented tactics reached its peak during week 13 when students prepared for the final exam. The reading and pre-lab oriented tactic was observed once a week. Students who adopted this strategy performed well in their learning and showed high academic performance (median (Q1, Q3) of total score = 71.37 (62.095, 81.20)). In 2016, the total score was lower than that in 2017 (median (Q1, Q3) in 2016 = 68.34 (56.14, 74.08); and in 2017 = 82.38 (75.58, 87.84)).

- Strategic-Moderate Engagement: Overall level of engagement of students in this strategy group was moderate as compared to the first strategy group. The use of reading oriented tactics was observable throughout the semester. The application of reading and discussion oriented tactics was highly used at the beginning of the course (weeks 1-5). The most frequent use of reading and discussion oriented tactics appeared during exam weeks (weeks 7 and 13). During weeks 4-6 and weeks 9-12, the physical laboratories were scheduled. Students in this strategy group selected and applied the reading and pre-lab oriented tactic during this particular week. This indicates the ability to strategically adopt the learning tactic according to the course requirement of the students. Overall academic performance of students who used this strategy was considered high (median (Q1, Q3) = 71.26 (58.95, 78.10). In 2016, the overall score was lower than that in 2017 (median (Q1, Q3): in 2016 = 59.99 (53.37, 69.65); and in 2017 = 77.46 (73.41, 82.18)).
- Highly Selective-Low Engagement: Students in this strategy group showed a shallow level of engagement. At the beginning of the course (weeks 1-3), the use of reading oriented and reading and discussion oriented tactics were observed. However, the level of tactic application dropped. During weeks 4-6, when students were scheduled to have physical laboratories, they were instructed to prepare by completing a set of online pre-lab activities. The use of the reading and pre-lab oriented tactic was visible once during week 4, however, this tactic did not have the prolonged use by students in this strategy group. The overall performance of students who used this strategy were much lower (median (Q1 and Q3) = 63.70 (47.96, 75.54)). Similar to other strategy groups, students who enrolled in 2016 showed lower performance than those who enrolled in 2017 (median (Q1 and Q3) in 2016 = 53.79 (36.64, 63.50) and in 2017 = 73.65 (59.25,81.67)).

Influence of feedback. Figure 2b shows the application of each strategy group according to year. In 2016 when no feedback was provided, the number of students who used the Intensive-High Engagement strategy was greater than in the 2017 cohort when feedback was provided. The number of Highly Selective-Low Engagement also increased in 2017 compared to 2016. One possible explanation can be traced back to the personalised feedback messages that were sent out during week 4 and week 9. The common advice offered in the personalised feedback was for students to



(a) Tactics used and the corresponding mode of study when no personalised feedback was provided



(b) Tactics used and the corresponding mode of study when the personalised feedback was provided

Figure 3: Tactics used and the corresponding mode of study for Biology course

revise the learning topics by using the external revision tool. The students' actual interactions with this external resource were not part of the dataset used in this study. Moreover, final marks of the students who enrolled in 2017 were higher than those enrolled in 2016; no significant differences between the groups were found with respect to the grade average points prior to the enrollments in the two course editions [15]. This suggests that there were hidden learning activities during offline sessions and untracked online learning activities (e.g., those completed in the external revision tool).

With regard to the management of time with learning tactics, both groups employed relatively similar learning tactics (e.g., ahead — reading and other — reading-discussion) during the first three weeks (refer to Figures 3a and 3b). However, from week 4, when feedback was introduced, the learning tactic orientation changed, with an increase of the reading-preLab tactics (e.g., other — reading-prelab and preparing – reading-prelab). The reading-preLab tactic was also observed in subsequent weeks (e.g., weeks 5-6 and 8-12). Meanwhile, the group without feedback maintained the same learning tactics (e.g., ahead — reading and other — reading-discussion) with low levels of the reading-prelab tactic. Likewise, both groups seem to have been highly active in the use of the reading-discussion tactic in week 7 and reading tactic in week 13. In terms of time management, students with feedback focused on preparing their learning with reading-prelab tactics (e.g., preparing – reading-prelab and other – reading-prelab), and were more likely to revisit their prior learning by performing the reading tactic. In contrast, students without feedback tended to prepare and revisit their learning by reading tactics (e.g., preparing – reading and revisiting — reading). Overall, students receiving feedback employed more active time and learning strategies.

4.2 RQ2: How students perceived the role of feedback in adapting SRL

4.2.1 The Computer Engineering course. Students in this course frequently commented that their feedback elicited reflective responses. A few comments described a longer term impact of the feedback on reflection. Comments described how students used their feedback as a reflection tool to prepare for the examination by attending to topics flagged in their feedback as requiring further reinforcement (see Table S2, Quotation 6, Supplementary material). Comments also described how students perceived their feedback as being ‘embedded’ in the course, meaning that it was a part of the curriculum structure emphasising the weekly activity cycles. This feature of the feedback was key to enhancing their reflection on learning (see Appendix, Quotation 10, Supplementary material).

Students commented on planned strategies for learning in relation to their feedback. Students who expressed this theme described the course as ‘content-heavy’, and therefore appreciated how their feedback equipped them with learning strategies to help them optimise their learning. As illustrated by Quotation 11 (Appendix, Supplementary material), the feedback helped them to ‘structure’ their learning with a clear strategy that involved: (i) reviewing topic resources (Reading tactic), followed by (ii) working on problems (Exercise tactic). As such, this comment aligns with the increase in use of strategic – moderate engagement strategies as observed in Section 4.1.

4.2.2 The Biology course. Students frequently commented that the feedback in this course helped them to gain more control over procrastination, describing the feedback as a “nudge and tell you just to work” (R17, Focus Group 1). Related to this point, students also described how feedback influenced their goal setting, by prompting them to set goals to complete learning tasks. Students frequently expressed how feedback had a positive impact on their motivation, especially because of the encouraging tone of the message.

The qualitative analysis provides some insight into the observation that a greater proportion of students in the feedback group employed less optimal learning strategies, as reported above in Section 4.1. This finding may suggest that students were disengaging from their learning as a result of the feedback. However, students’ comments indicate that some they were adapting SRL processes in other ways, such as control of procrastination and goal setting, likely fuelled by enhanced motivation upon receiving feedback. A closer examination of students’ comments found that some students held defensive self-reactions in response to feedback, which could illuminate students’ learning tactics and strategies. These students expressed that while the feedback drew their attention to their engagement with the online learning tasks, they felt that their own study strategies were more helpful for learning in the course, as illustrated by Quotation 12 (Appendix, Supplementary material). Students described their own strategies in the form of discussions with peers, reviewing their lecture notes, or doing their own research to strengthen their understanding (Quotation 13 in Appendix, Supplementary material). Such comments highlighted that students were engaged in other untracked and offline “embedded tasks” [35] in response to their feedback. This finding aligns with other research indicating that time spent in LMS activities does not fully represent the learning behaviours of students [9].

5 DISCUSSION

5.1 Impact of LA feedback on SRL: influence of course context

The results of this study illuminate students’ SRL adaptations in response to feedback in two different contexts.

The Computer Engineering course. An important finding for this course was how students perceived the integration of the instructional design and LA feedback implementation as supporting their SRL. The perceived embeddedness of feedback within the curriculum was instrumental for students’ reflection on learning, especially by helping them to identify topics that required stronger mastery. The prevalence of reflection themes in students’ recall of their feedback experience provide evidence that the course and feedback design facilitated ‘feedback loops’ [5] where students are made aware of the gap between current and desired performance, and given the opportunity or knowledge to act to close the gap. Since the metrics informing feedback were drawn from students’ performance on the tasks, the type of feedback communicated to students was to a large extent elaborated feedback with a knowledge of results [30]. Students’ comments indicate that they applied their feedback to subsequent cycles of activity, as well as to the final exam by leveraging the feedback messages for exam preparation. Research on feedback recipience has found that assessment and curriculum design influence students’ willingness to receive and enact their feedback [38]. In this course, students appreciated how personalised feedback was part of the weekly curricular activity cycles. This facilitated them to make use of the feedback to optimise their learning strategies, as evidenced by the higher frequency of high engagement strategies when feedback was present. Ultimately, the integration of course design and feedback implementation was designed for students' uptake of feedback.

The Biology course. A notable finding in this course concerned students' time management strategies: students were more active in their preparation of weekly topics when feedback was present. This result can be tied to feedback design. The instructor's feedback was intended to foster students' SRL through regular study instead of cramming behaviour. The higher use of studying before the weekly topic indicate that this intent was achieved through the feedback, as shown by the increase in preparing mode and more consistent activity levels over the weeks. Students' qualitative comments highlighted the role of LA feedback in this course as a reminder nudge, prompting them to manage external distractions and to return their attention to their studies. Reminder nudges support student attention and self-control [6], which relate to the performance phase of SRL [40]. This association between reminder nudges and attention and self-control explains the prevalence of the self-control theme in students' comments. As noted earlier, control of procrastination through effective time management strategies is critical for students' success in higher education [3]. The qualitative comments also indicated that, while the feedback was helpful for reminding students of their priorities, some students still preferred to use their own offline or untracked learning strategies, e.g., reviewing written notes, discussing with peers, or furthering their own research. The qualitative analysis in the present study provides evidence that students were enacting their feedback by adjusting their time management strategies to engage more consistently in study habits, whether online or offline.

5.2 Implications for measuring feedback impact: triangulating trace data with students' self-reports

The present study also contributes to a central issue in LA, that is, the measurement of key learning constructs, such as SRL [9, 29]. At the heart of this issue are two questions. Firstly, are the data that are used in LA sufficiently robust to depict such theoretical constructs? Secondly, are students' self-reports accurate representations of their SRL? In this study we attempted to seek alignment between measures of SRL obtained from trace data and qualitative focus group data. Thematic analysis of qualitative data helped to provide a fuller understanding of the impact of LA feedback, by allowing deeper insights into how students made SRL-related decisions in response to feedback. Especially noteworthy is the finding of increased revisiting study mode in the flipped course through learning trace analysis. Students' qualitative comments explicitly linked this adaptation of time management strategies to the feedback, by illuminating the role of feedback in supporting their reflection on learning.

Perhaps most importantly, the qualitative analysis provided insights into conflicting or unexpected results from the analysis of trace data. For example, the finding from the analysis of learning strategies in the Biology course: a greater proportion of students were observed to be using low engagement strategies when feedback was present. As shown in Table S1 (Appendix, Supplementary material), the trace data collected in this course was much lesser: data were collected from five activities in this course. In this blended course, students could engage in other strategies that were untracked or offline; this was verified in students' comments. The role of the feedback was mainly to nudge students to use self-control processes in order to maintain consistency in their study. The qualitative self-reports provided some evidence of how students were self-regulating apart from the online tracked activities. Overall therefore, the benefit of triangulating the trace data with students' self-reports in this study was to gain insights into the reasons behind students' observed behaviours, as well as a deeper understanding of how they engaged in those behaviours when prompted by feedback.

As noted in our review, researchers are critical of students' self-reports of SRL, particularly self-report surveys [37]. However, self-report surveys continue to be a mainstay in SRL research [29]. Our triangulation study offers a way to study the effects of feedback on SRL, by capturing self-reports of SRL through focus group discussions and analysing responses thematically using the framework of SRL. Importantly, the discussions explicitly probed for the (subjective) effects of feedback on students' learning. This enabled a more direct link between feedback and its impact on students' SRL that would not have been as well afforded from either trace data or qualitative data alone.

Finally, recent research (e.g., [2, 29, 31]) found that the analysis of trace data was aligned with SRL to some extent, notably in relation to time management. However, Quick et al. [29] also noted that behavioural data could not capture the breadth of SRL processes that were addressed in self-report surveys. This highlights the point that self-reports still play a role in obtaining insights into feedback impact on SRL, for example, to tap into students' beliefs about learning, or their reflections upon receiving their feedback.

5.3 Implications for personalising feedback in course contexts

The results of this study bear implications for instructors exploring personalised feedback in their courses. LA feedback interventions should be tied closely to learning design, in order to communicate meaningful and actionable feedback for students' SRL. This alignment is an issue which has gained importance in the field [19]. Most critically, metrics used for feedback should be aligned with the instructor's pedagogical intent [16]. This alignment is demonstrated through the courses in this study. For example, the pedagogical intent of the flipped course was for students to firstly grasp each week's topic through watching lecture videos and completing various formative assessments, and then to apply their learning through experiential activities in face-to-face sessions. Accordingly, the analytics were derived from data pertaining to students' activities with the tasks, as well as their performance on the assessments, so that students could reflect on and use the recommended strategies for future cycles of learning. When LA and learning design are well-aligned, personalised feedback becomes meaningful for students, fostering uptake and helping them to adapt SRL in more optimal ways.

A reliance on the use of checkpoint analytics is insufficient to elicit students' reflection on their learning. As noted by Lockyer et al. [16], checkpoint analytics provide information about whether the student has accessed a resource or completed a task, and therefore serves as a good indicator about whether they have met the basic requisites of the course. However, these forms of analytics give limited insights into the processes that students engage in while completing set learning tasks. In this study, students in the flipped classroom course received feedback on their performance on the formative assessments in addition to feedback based on checkpoint analytics. A prevalent theme that emerged in student comments in this course, was how feedback elicited self-evaluation on learning. The personalised feedback in this course provided students with knowledge about their own understanding, so that they could undertake targeted reviews of weaker topics. In short, including information about students' ongoing performance in formative assessments could foster greater reflection about their developing mastery of topics.

Thirdly, personalised feedback could be further enhanced by directly offering students feedback on their time management and learning strategies. The present study illuminated students' attitudes regarding the recommended strategies provided in their feedback. Students' attitudes or beliefs about learning play a role in their uptake of feedback [4]. This was clearly showed in students' comments regarding their preferred strategies. Consequently, they did not take up the strategies recommended in their feedback. This is concerning if students' preferred strategies are not optimal for the course. In this paper as well as in very recent research (e.g., [2, 8, 20]), data mining approaches have now advanced to being able to detect students' dynamic learning strategies from trace data. Currently, these processes take place after the intervention. If these advanced data analytic processes could be built into the pipeline of LA interventions, then this information could be reported to students as well. This is in line with Lockyer et al. [16] idea of process analytics, that provide insights into how students complete a learning task. Such an enhancement could also make the feedback more dialogic, facilitating students' reflection on the effectiveness of their current learning strategies.

5.4 Limitations and future directions

This study adds further evidence on the impact LA feedback interventions can have on students' SRL. The study also reinforces the link between LA and learning design. The adoption of a mixed methodology demonstrates how qualitative data from students' experience with personalised feedback can be triangulated with trace data analysis to gain insights into the contextual impact of this feedback. To date, few studies have been able to draw on both quantitative and qualitative data to examine the impact of LA feedback. Notwithstanding, we acknowledge that the study is not without limitations. First, the study did not consider students' demographics and other individual learning characteristics that may have also influenced responses to feedback [38]. Future research could address this by including learner characteristics and contextual factors. Second, the qualitative analysis relied on students' accounts of their experiences with personalised feedback. It is possible that students had difficulty articulating or recalling how they acted in response to their feedback. However, these accounts were necessary for obtaining greater insights into feedback from a student perspective. While retrospective recall may be subject to biased or fragmented memories of actual events, we argue that this limitation was ameliorated by the analysis of trace data, as shown by the triangulation of results. Nevertheless, further studies should be conducted to ensure generalizability of the findings.

6 CONCLUSION

The results contribute empirical evidence that LA based feedback from the instructor benefits students' SRL. Importantly, this study shows that the affordances of LA to enhance student learning and performance are tangible, but, these effects must be understood in relation to the cognition and metacognition of students. That is, how they make sense of feedback to inform their SRL decisions. Failing this, LA approaches to feedback might only be appreciated from the perspective of facilitating feedback provision at scale, instead of promoting a more sustained, dialogic support for scaffolding students' SRL.

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