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What changes, and for whom? A study of the impact of learning analytics-based process feedback in a large course

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Abstract

Recent developments in educational technologies have provided a viable solution to the challenges associated with scaling personalized feedback to students. However, there is currently little empirical evidence about the impact such scaled feedback has on student learning progress and study behaviour. This paper presents the findings of a study that looked at the impact of a learning analytics (LA)-based feedback system on students' self-regulated learning and academic achievement in a large, first-year undergraduate course. Using the COPES model of self-regulated learning (SRL), we analysed the learning operations of students, by way of log data from the learning management system and e-book, as well as the products of SRL, namely, performance on course assessments, from three years of course offerings. The latest course offering involved an intervention condition that made use of an educational technology to provide LA-based process feedback. Propensity score matching was employed to match a control group to the 2017 cohort, creating two equal-sized groups of students who received the feedback (the experimental group) and those who did not (the control group). Growth mixture modelling and mixed between-within ANOVA were also employed to identify differences in the patterns of online self-regulated learning operations over the course of the semester. The results showed that the experimental group showed significantly different patterns in their learning operations and performed better in terms of final grades. Moreover, differential impact on final course marks was found, with all except the lowest quartile group (based on prior achievement), deriving the most benefit from the feedback.

Keywords: Feedback, Learning analytics, Self-regulated learning, Large enrolment courses, Higher education

What changes, and for whom? A study of the impact of learning analytics-based process feedback in a large course

A challenge for contemporary educators is how to provide feedback to all students in large courses in a personalised, timely and instructive manner. The implementation of various technologies has been shown to minimise workload demands for teachers and enable personalised feedback, e.g. the SAERS recommender system (Santos, Boticario, & Manjarrs-Riesco (2014), the *Metatutor* intelligent agent (Duffy & Azevedo, 2015), open learner models such as SMILI (Bull & Kay, 2016), and *OnTask* (Pardo, et al., in press). This is a significant innovation for education. These technologies essentially target learning operations of students by drawing on learner engagement data and individual progress to provide a basis for personalising student learning feedback. As Pardo, Poquet, Martinez-Maldonado, & Dawson (2017, p.168) noted, feedback is "one of the most influential aspects in the quality of the student learning experience". The inclusion of learning analytics to such feedback processes can further add insights into the student's learning progress to promote self-regulated learning.

Learning analytics can be used to define and establish identified learning metrics and benchmarks that can be communicated to all students as feedback via dashboards, recommender systems, personal emails, or even phone calls from the instructor (Bodily & Verbert, 2017; Ruipérez-Valiente et al., 2015). The goal of such automated personalised feedback systems is to foster self-regulated learning (Duval, 2011). The last five years have seen growing interest in LA applications to 'close the loop' for key stakeholders in education, that is, to provide actionable feedback back to instructors and/or students, in order to improve teaching and learning (Clow, 2012). Accordingly, an increasing number of higher education institutions have been exploring the potential for learning analytics to improve the student learning experience through the

provision of personalised feedback and support mechanisms (Colvin et al., 2015; Tsai et al., 2018). For key stakeholders, namely students, LA offers an approach to address the challenge of providing timely (real-time) insights and personalised feedback.

Although the number of student-facing LA applications is on the rise, there is limited research demonstrating whether these are effective in improving learning outcomes or increasing student motivation (Bodily & Verbert, 2017; Ferguson et al., 2016; Gašević, Dawson, & Siemens, 2015; Krumm, Waddington, Teasley, & Lonn, 2014). The research is not clear as to whether "closing the loop" for students in this way actually improves their self-regulated learning (SRL), or whether such feedback provisions work equally well for all students. The latter is an important issue, since in today's higher education environment, there is a growing and increasingly diverse, student population. This paper presents the findings from a first year University course that implemented a LA-based system of personalised feedback to improve student SRL proficiency and ultimately, academic performance.

Supporting learners with data-driven personalised feedback

Feedback is defined as information that students receive about how they have been engaging in their learning or the extent to which they have grasped a topic. Feedback affects achievement by providing information to effect SRL. In terms of Winne and Hadwin's (1998) COPES model, SRL involves four phases: task definition, planning and goal-setting, enactment through study tactics and strategies, and adaptation of study tactics based on the experience of the first three phases. 'COPES' refers to the cognitive architecture that is at work within the four phases—conditions, operations, products, evaluations, and standards—which are weakly recursive. Feedback affects SRL by affecting learners' *evaluation* of the products of their

learning and effectiveness of study tactics and strategies used. Such evaluation raises learners' awareness of how they are learning (i.e., monitoring) and whether they are on the right track. As well, evaluation helps them to know how to adjust their learning operations to reach learning goals, thereby leading to enhanced achievement.

Although much of the research points to the benefits of feedback for learning, the effects are not uniform. As noted by Hattie and Timperley (2007), the power of feedback to improve learning is moderated by the type and timing of the feedback provided. Butler and Winne (1995) already pointed this out when making the distinction between process and outcome feedback. Butler and Winne suggest that process feedback adds more value for student learning than outcome feedback. In terms of self-regulation, this is because outcome feedback focuses on the result of the task and does not consider the specific actions a student can take to improve their learning approach and progress. Outcome feedback could be expressed as the correctness of a response, or a grade resulting from an assignment or exam. Conversely, process feedback is more explicit about what the student needs to do in order to bridge a learning gap. Process feedback could take the form of recommended actions, such as reading a specific article to strengthen understanding of a topic or pointing out how certain adopted learning strategies need to change (e.g. adopting more regular study in lieu of cramming behaviour). This broad distinction between the types of feedback has similarly been captured in other like-terms. For example, Harks, Rakoczy, Hattie, Besser, & Klieme (2014) define these as process-oriented or elaborated feedback as opposed to grade-oriented or non-elaborated feedback, with the former being found to be perceived as more useful by students.

Yet challenges remain for academic staff to manage and provide such personal and timely feedback on individual student learning progress. As education further incorporates online or blended learning models there is an associated increase in learner trace data that is captured and available for analysis. While the number of LA tools has grown, capitalising on the availability of such data, there has been criticism that they have been too reliant on generic learner log data in LMSs and student demographic and educational background information from institutional student information systems to generate early-warning systems (Gašević, Dawson, Rogers, & Gašević, 2016; Liu et al., 2017). Although these models are data-driven and empirically based, the generic approach has been shown to lack sufficient detail and insights to aid an individual student's learning needs (Wise 2014; Gašević et al 2016). More contextualised LA-based approaches to feedback and support is required (Dawson, Jovanović, Gašević, & Pardo, 2017; Liu et al., 2017). As shown by Gašević et al (2016), the instructional conditions in a course cannot be neglected when developing LA-based support interventions. In response to this, more contextualised systems have been developed, such as the Student Relationship Engagement System, SRES (Liu, Bartimote-Aufflick, Pardo, & Bridgeman, 2017) and OnTask (Pardo et al., in press). Systems such as these are situated within courses and designed to allow course instructors to prepare more personalised process feedback, to support students self-regulated learning.

To reflect the emergence of LA and the possibility of technology-mediated, data-driven feedback, Pardo (2017) proposed an extension of current feedback models to incorporate the role of technology in the dissemination of feedback. Pardo's model also explicates internal and external feedback loops in the process. While some of the basic tenets—translation of the task into goals which affect the choice of learning operations—identified by Winne and Hadwin

(1998) remain, what is new is the introduction of multimodal data in the process. This multimodal data serves as evidence that is processed by an agent (either technological or human) for contextualisation into the instructional design, thereby generating feedback. Feedback is theorised to prompt reappraisal of the task goals or learners' existing knowledge, beliefs and attitudes, and correspondingly, a calibration of learning strategies. Although parsimonious in that the model is able to account for newer measures of data collection, analysis and prediction while retaining the key tenets of traditional feedback models, this model needs to be evaluated through empirical and theoretical work. To date, the first steps in the validation of the model were described by Pardo, Jovanović, Gašević, & Dawson (2017), in their study of process feedback based on LA. Their study found significant increase with medium effect sizes on student satisfaction and small effect sizes on academic performance. However, the study did not investigate the effects of LA-based feedback specifically on SRL (Winne & Hadwin, 1998), as exemplified through existing research on the ways in which students used technology (e.g., Gašević, Mirriahi, Dawson, & Joksimović, 2017; Lust, Elen, & Clarebout, 2013; Winne, 2006).

The effects of feedback have also been found to be moderated by individual differences (Butler & Winne, 1995; Hattie & Timperley, 2007; Hermsen, Frost, Renes, & Kerkhof, 2016; Nicol & Macfarlane-Dick, 2006; Winstone, Nash, Parker, & Rowntree, 2017). In particular, prior academic achievement may influence the effectiveness of the feedback. In an experimental study (Teasley, 2017) where students were presented with hypothetical Blackboard dashboards providing mostly outcome feedback, students with higher GPA reported that they would engage less with the dashboard, as compared to their lower-performing peers. On the other hand, students with lower GPA reported that they would find the recommended follow-up actions more helpful, implying an effect on self-regulated learning: that they would adjust their learning

operations in view of the standards provided by the feedback. While Teasley's (2017) study was presented in a hypothetical setting, few studies have been carried out in live courses, investigating how prior academic achievement might affect the way students engage with LA-based feedback systems. In a real academic setting, would higher-performing students value the feedback and adapt their operations, or would they ignore the feedback since they are already satisfied with the product of their learning (i.e., academic performance)? In other words, would higher-performing students see less of an effect on SRL?

Aim and research questions

Despite the growing number of LA-based systems designed to provide feedback to students, there remains a significant lack of research investigating their impact on student learning (Dawson et al., 2017). Especially since the provision of LA-based process feedback to students is still a relatively new innovation, research is needed to examine how students engage with such feedback to modify their learning (Pardo, Poquet, et al., 2017).

The present study aims to understand how process feedback, based on students' learning traces, impacts their SRL and academic performance in a course. To achieve this aim, the study employed a quasi-experimental design to examine the effects of the feedback by comparing data relating to SRL and achievement data over three years in a course. The study looks at SRL through the lens of Winne and Hadwin's (1998) COPES model to understand how feedback can prompt learners to actions (operations) to optimise their learning progress. Moreover, this study aims to discover differential effects of this feedback support due to students' prior academic achievement. In line with these aims, we are guided by the following research questions:

RQ1. What is the impact of LA-based, process feedback on students' (a) self-regulated learning and (b) academic performance in a course?

RQ2. How is self-regulated learning related to course performance in the context of this study?

RQ3. Is there a differential effect of LA-based, process feedback, due to students' prior academic achievement?

Method

Participants

Anonymized data from 784 students over three years (n_{2015} = 266, n_{2016} = 277, n_{2017} = 241) of a first-year introductory biological sciences course were taken for analysis. Students taking the introductory course enrol into a variety of different programs, though most students are from health-related areas. Consistent with other health disciplines (e.g. nursing) there was a higher proportion of female students (70%) to male students in this course. This trend was consistent for the 3 years of examined data (2015, 2016 and 2017). Ethics approval for this study was granted by the University's research ethics committee. Students were invited to participate by providing informed consent and completing the first questionnaire.

Course design and assessments

Across the three cohorts, the course design was the same: based on a blended learning model, involving online weekly activities combined with on-campus attendance in a 3-hour lecture and 1-hour tutorial. The course ran for 13 weeks with students also attending 3 x 2-hour workshop sessions, and 7 x 3-hour Practical sessions. As part of the course activities students were requested to prepare for every Practical session by completing pre-lab activities online in the Learning Management System (LMS). Students were also expected to reinforce their learning in the lectures by completing weekly online activities in an e-book, referred to as *Connect*. Students were informed at the start of the course that *Connect* was an important

component of their learning, and that this platform would host two of their assessments (quizzes) contributing to their final course grade. Overall, the course comprised four assessments whose marks contributed to the final course grade: a mid-term quiz (10% of final grade), an end of term quiz (10% of final grade), practical marks (25% of final grade), and final exam (55% of final grade).

The learning analytics-based feedback system

The LA-based system used to provide feedback to students in the course was *OnTask* (Pardo et al., in press). This tool allows instructors to link learner data from various sources such as the LMS, attendance records, or other e-learning platforms from which log data are retrievable. Data can be in the form of log-trace data; mid-term quiz marks; attendance in face-to-face sessions, that serve as indicators of engagement deemed as relevant to the course. *OnTask* provides an interface to transform these data into different rules for email generation, thereby providing personalised feedback from the instructor for each student based on their own learner data. The rule-based process ensures that the personalised feedback via email is automated yet contextualised to the student and their progress in the course activities. To frame the study firmly within the COPES model, log-trace and attendance data also served to operationalise learning operations, while quiz and other course assessment marks served to operationalise the products of SRL.

OnTask was implemented to provide personalised feedback via email twice over the semester at critical junctures (assessment points) in the course. In providing such feedback, the intent of the course instructor was to foster SRL by encouraging students to engage consistently in their learning, rather than to leave studying towards the exam period. These feedback points were based on students' learning operations determined to be indicators of engagement in the

course, to provide them with greater awareness regarding their progress, as well as specific recommended actions to optimize their learning in the course (see Figure 1 for an example). Thus, the focus was on providing process feedback to students. The first feedback point at week 5 provided information to students on their workshop and tutorial attendance data. In addition, the message reminded students about the importance of attending workshops and tutorials. Finally, the message provided feedback on whether students had registered themselves on Connect; for those who had not already done they were advised to register themselves on to *Connect* as an important part of their learning and revision in the course. The second feedback point at week 8 again provided process feedback in the form of registration and activity data from *Connect,* and also students' performance in Quiz 1. This message again pointed students to using *Connect* as a key revision tool to prepare for the remaining assessments in the course. An example of the email received by students is shown in Figure 1. The email was personalised using relevant students' data—which had been transformed into rules in *OnTask*—in the sections denoted by the braces, while the remaining text without braces comprise generic parts of the email; this was the same for all the students. The Appendix shows examples of the rules from *OnTask* that were used in the email feedback. Figure 2 illustrates the location of the feedback points in relation to the other activities over the course of the semester.

Data sources

As the course had been running regularly since 2012, data from 2015 and 2016 cohorts were used for comparison against the 2017 cohort which experienced the LA-based feedback intervention. While data from 2012-2014 was available, the course design and content over this period was significantly different and did not provide a strong basis for comparison with more recent versions. However, course design and content were the same during the years 2015, 2016

and 2017 making the comparison across these years feasible. All 3 cohorts (2015-2017) were similar in terms of gender proportion (more females) and citizenship (more domestic students). They were also similar in terms of prior academic achievement (as measured by program entry score), and program enrolment, with more students from health versus non-health programs (see Table 1). Program entry score is the percentile score used for Australian University entry, which indicates how well students have performed in their Year 12 (Secondary School) examinations (or equivalent) relative to their peers. Program entry score can act as a measure of a student's prior academic ability. Table 1 provides an overview of the student composition in the course over the three years of comparison.

To investigate the effect of the process feedback on students' self-regulated learning behaviours (operations), we used log data from the LMS and from the *Connect* e-book. In view of the vast amount of trace data available from students' interaction with the LMS, for the purpose of this study, we focused only on LMS data related to the interaction with prelab activities in order to answer the research questions. As there were 7 practicals students were required to attend over the semester, there were accordingly 7 prelab activities in the LMS that students were strongly advised to complete prior to attending the practical. The prelab activities for each week comprised questions related to the practical, the purpose of which was to enable students to complete the required laboratory work within the allocated class times. Each practical was supported by a dedicated SCORM package that was available through the LMS. The SCORM package comprised a video on the lab topic for the week, followed by a quiz to be completed by students. The package was accessible to students via a link in the LMS. Figure 2 shows the schedule of practical sessions, prior to which students had to complete the online

prelab activities. This schedule and design of the pre-lab engagement and lab sessions were the same across the three cohorts.

Interactions with the prelab activities were recorded with the following event names: Sco launched (student clicked on the link to the SCORM package), Course module viewed (student viewed the content), and Submitted SCORM status (student submitted responses to the questions). As students were allowed multiple attempts for these activities, multiple interactions for students were recorded for each package. For the purpose of this study, we aggregated the interactions for each student for each SCORM package, thus each student had 7 data points related to the counts of interactions with each of the SCORM packages.

Data from the *Connect* e-book were available in the form of reports, showing each student's progress with the required assignments to be completed in conjunction with the lectures each week. The sequence of content in the course and associated assignments in *Connect* were the same over the 3 years, with only minor modifications such as changes to weekly tasks or content distribution based on student feedback from the previous year. We measured *Connect* engagement by obtaining the percentage completion of assignments over the semester. These *Connect* reports could be downloaded according to date range, so it was possible to see whether students had completed the required assignments in a specified time range.

Study design

As this study was implemented in a live course, it was not feasible to do a randomized controlled trial to assign students to treatment and non-treatment conditions. To address the research questions, propensity score matching, PSM, was conducted. This method is employed in situations whereby randomised controlled trials are not possible, as in the current context (Austin, 2011). PSM is a method that creates control and treatment groups from an intervention

study cohort based on their baseline characteristic variables (Mojarad, Essa, Mojarad, & Baker, 2018). In this way, effects of the intervention can be measured with a lower concern for a selection bias. In the study, PSM was employed to match a control group (without feedback) comprising students from the 2015 and 2016 cohorts to the existing experimental group (with feedback) comprising students from the 2017 cohort, removing possible confounding differences that could arise from studying three cohorts. In doing so, PSM enabled us to investigate the effects of the LA-based feedback intervention on self-regulated learning behaviour and performance by examining differences between treatment and control groups, rather than to discover differences between three cohorts.

Matching was performed based on four baseline student characteristics: gender, program type (whether the student was enrolled in a health-related or non-health related program), program entry score, age, and citizenship (whether the student was domestic or international). PSM involves the use of logistic regression to calculate the propensity score of students, with a binary outcome of whether the student had been given the LA-based feedback, and independent attributes being the four characteristics described above. The procedure was carried out using R's *matchit* package.

Data analysis

Students' activity on *Connect* assignments was categorised into 3 blocks of time, to reflect the timing of the feedback points. It was possible to do this for all three cohorts because the timing of each topic and related assignments in the LMS and *Connect* e-book was the same across the three years. Phase 1 was indicated as "pre-Feedback Point 1", Phase 2 was "Post-Feedback Point 1", and Phase 3 was "Post-Feedback Point 2". We calculated the percentage of assignments completed for each phase for each student. For example, if a student completed 5

out of the 8 activities in Phase 2, this was expressed as 62.5%. Accordingly, each student had 3 data points related to *Connect* engagement.

Altogether, the data comprised five demographic variables (age, program entry score, gender, program type, and citizenship), 10 self-regulated learning variables (7 Moodle engagement variables, 3 Connect engagement variables), and 4 course performance variables (Quiz 1, Quiz 2, Practical marks, and final course marks).

To address RQ 1, t-tests were conducted to examine the differences in self-regulated learning behaviour and course performance between treatment (with LA-based process feedback) and control (no feedback) groups created by PSM. In addition, growth mixture modelling (GMM) was conducted to explore heterogeneity in the self-regulated learning trajectories of the treatment and control groups, as measured by activity on the Moodle SCORM packages. We used a zero-inflated negative binomial model as there is an excessive amount of zeros at each time point and the variance was greater than the mean; hence, a Poisson model was not appropriate (Smith & Faddy, 2016). The model estimated the mean, variance, and covariance of the intercept and slope across each known class (2015, 2016, and 2017 cohorts). GMM was only conducted for the Moodle data, as the model produced for *Connect* activity was found not to be appropriate for the data – the procedure generated a warning that "The latent variable covariance matrix in Class 1 is not positive definite", suggesting that the correlation between baseline and linear is greater than 1. Thus, for the *Connect* data, mixed between-within ANOVA was conducted to examine for difference in engagement patterns between treatment and control groups.

To address RQ 2, correlational analysis was conducted between the self-regulated learning and course performance variables, in order to explore how self-regulated learning and

course performance variables might be related to one another. The results of these would also be useful to add further insight into the effects of the feedback.

To address RQ 3, students were divided into quartiles based on their prior academic performance as measured by program entry score, and t-tests were conducted on each quartile separately. This was done to examine more nuanced differences between the groups in course assessment performance.

Results

The dataset

The PSM produced two equal-sized treatment and control groups (n = 241). Table 2 summarises an overview of demographics of the two groups, self-regulated learning behaviours on the LMS and on *Connect*, and mean course performance results for the different assessments.

RQ1: Feedback effects on self-regulated learning and performance

Effect on self-regulated learning. To examine differences between the treatment and control groups in terms of their learning operations, t-tests were conducted on each of the 7 SCORM activity packages in Moodle as well as on the 3 phases of *Connect* activity (Table 2). The analyses found that specifically for the final SCORM activity package, the treatment group was less active than the control, which is a small effect. The *Connect* activity for all three phases of the study was also significantly lower for the treatment group, with small to large effect sizes. The greatest difference was at Phase 1 followed by Phase 3 and Phase 2.

The GMM analysis showed each group to have comparable intercepts (2015: $\beta_0 = 1.29$, S.E. = -.10; 2016: $\beta_0 = 1.08$, S.E. = -.10; 2017: $\beta_0 = 1.29$, S.E. = -.10). Similar results were also found for the slopes (2015: $\beta_1 = -.14$, S.E. = .02, 2016: $\beta_1 = -.13$, S.E. = .01, 2017: $\beta_1 = -.18$, S.E. = .02), which showed activity on the SCORM packages to decline over time for all three groups

(Figure 3 and Figure 4). In addition, the Wald test of parameter constraints with a value of was not significant ($X^2(4) = 5.40$, $p = .25$), indicating that the decline in activity did not differ according to whether the group had been exposed to the feedback or not.

Because *Connect* data were not suitable for GMM, a mixed between-within ANOVA was conducted to examine differences between treatment and control groups in their engagement with *Connect* over the three phases. While the data satisfied Mauchly's test of sphericity, Box's M test revealed that these data violated the assumption of homogeneity of covariances, hence Pillai's trace statistic was used (Field et al., 2012). The analysis found a significant interaction between group (treatment and control) and phase (Phase 1, Phase 2, and Phase 3), $V = .18$, $F(2,479) = 51.10$, $p < .001$, partial $\eta 2 = .15$. There was also a significant main effect for phase, $V = 15$, $F(2,479) = 41.44$, $p < .001$, partial $\eta 2 = .15$. The main effect of group was also significant, $F(1, 480) = 20.97$, $p < .001$, partial $\eta 2 = .22$ which is a large effect size. These results indicate that students engaged with *Connect* differently over the phases, and that the pattern of engagement differed according to group. The graph of estimated marginal means for completion rate (%) (Figure 5) shows that for the control group, there was a dip in Connect activity in the middle of the semester followed by an in-crease in activity toward the end of the semester. The pattern for the treatment group was reversed, with lower percentage completion rates at the start and then a sharp increase in the middle of semester (coinciding with Feedback Point 1) which was maintained over the rest of the semester.

Effect on course performance. T-tests were conducted on course performance variables to determine differences between the treatment and control groups. The analysis conducted on the two quizzes and on the practical marks found no significant difference between the two groups. However, the difference in final course mark was strongly significant, with the treatment

group achieving higher marks than the group without feedback, which is approaching a moderate effect size.

RQ2. Correlations among self-regulated learning and course performance

Correlational analysis was carried out to explore relationships between self-regulated learning variables and course performance variables (Table 3). All correlations were significant at $p < .01$. The analysis showed that engagement with the online pre-lab activities had small correlations to final course marks, with Pearson's *r* ranging between .19 to .23, while engagement with *Connect* correlated more highly with final course marks, with *r* ranging between .25 to .43, which can be interpreted as small to medium effects. Assessment marks were significantly correlated with each other; the highest correlation being practical marks with final course marks.

RQ3. Differential effects due to prior academic achievement

To uncover possible nuanced effects of the LA-based feedback intervention on students' academic performance in the course, program entry score was divided into quartiles, for the matched groups. As there were 125 cases with missing program entry scores, this analysis was based on 357 cases – the feedback group comprised 177 cases, while the group without feedback comprised 180 cases. Program entry score range for the 1st quartile group was 30.00-65.99 ($n_{feedback} = 36$; $n_{no\ feedback} = 52$). For the 2nd quartile group, the range was 66.00-76.99 ($n_{feedback} = 38$; $n_{no\ feedback} = 39$). For the 3rd quartile group, the range was 77.00-84.49 ($n_{feedback} = 54$; $n_{no\ feedback} = 49$). Finally, for the 4th quartile group, the range was 84.50-100 ($n_{feedback} = 49$; $n_{no\ feedback} = 40$).

Table 4 provides an overview of the quiz marks, practical marks, and final course marks for each quartile. T-tests were conducted on each of these components of course performance.

Final course marks were higher for the feedback subgroups, in the following order of magnitude: quartile 2 ($t(75) = 3.600$, $p < .001$, $d = .82$), quartile 4 ($t(62.615) = 3.208$, $p = .002$, $d = .70$), and quartile 3 ($t(101) = 2.514$, $p = .01$, $d = .49$). To further understand the role played by prior academic achievement in the effect of the intervention, hierarchical multiple regression was used to test the LA-based feedback intervention to predict final course grades, after controlling for the influence of program entry score. Preliminary analyses were conducted to ensure no violation of the assumptions of normality, linearity, multicollinearity and homoscedasticity. Program entry score was entered at Step 1, explaining 11% of the variance in final course mark. After entry of the group variable (experimental vs control) at Step 2, the total variance explained by the model as a whole was 16%, $F(2, 354) = 35.55$, $p < .001$. In the final model, program entry score recorded a higher beta value (beta = .31, $p < .001$), than the group variable (beta = .24, $p < .001$).

Discussion and conclusions

This study aimed to examine the impact of LA-based, process feedback on students' self-regulated learning and academic performance within the context of a health science course. To this end, we used PSM to match a control group to the treatment group, based on demographic characteristics of three cohorts of students who took the course. The analysis employed multiple data sources, including log data generated from the LMS and the *Connect* e-book, as well as student performance in the assigned course assessment.

Impact on self-regulated learning

The first research question examined the change in self-regulated learning operations as measured through online self-study behaviour that may occur through student receipt of process feedback based on their learning activity data. As shown by the mixed between-within ANOVA, the feedback did have an impact on students' online self-study behaviour. Compared to the

control group, the treatment group had a more sustained engagement with the e-book from the period after the first feedback point until the end of the semester. The emphasis of both feedback points were on the importance of the e-book, with the email message at Feedback Point 2 specifically mirroring to students the level of their engagement with the e-book. Hence, this result implies that the external feedback provided additional evidence for students to monitor their task engagement and to align their operations with the recommended learning actions (Butler & Winne, 1995). In terms of COPES, this feedback can be seen as a more explicit standard for students to evaluate and then adjust their operations (Winne, 2014) – in this case their operations to interact with the e-book. Thus, the process feedback afforded by students' online learning behaviour seems to have fostered or at least nudged students toward more regular study. This was precisely the intention of the instructor (Author 2): to encourage students to engage in regular study over the semester as opposed to concentrating study efforts in the study vacation just before the examination period. In contrast, the GMM analysis showed that the way students engaged with the pre-lab SCORM activities in Moodle was the same, regardless of whether students received the LA-based process feedback or not. This may be expected as the feedback messages were not explicit about this task. Since this was not brought to students' attention, there was no reason offered in the feedback messages for them to re-evaluate their operations with respect to this task.

Impact on course performance

The t-tests showed that the treatment group demonstrated higher final course grades than the control group. As the e-book was instrumental to students' learning in the course, and having demonstrated that e-book engagement increased over the semester relative to the two years prior, the higher academic performance could be a result of the adjusted learning operations by

students. Additionally, the correlation analysis found medium correlations between *Connect* engagement and final course mark; this suggests that the feedback was associated with students' learning behaviour, which was then positively associated with the students' final learning outcome.

The finding that the treatment group achieved higher final course grades even though they recorded much lower *Connect* activity, is worthy of discussion. It is possible that students in the experimental group had engaged in untracked and offline "embedded tasks" which learners could perform as part of COPES (Winne, 2014), and which have not been measured. The conflicting findings of lower levels of online learning activity and yet higher academic performance by the treatment group relative to the control group, may be due to these unobserved "embedded tasks", such as offline study behaviours (studying with a physical textbook, or engaging more in peer learning). In addition, students may have also interacted with other contents in the LMS, which were not examined in this study. An alternative explanation may also be found in the study by O'Connell & Lang (2018), who suggested that personal email reminders which they designed, increased students' cognitive effort during study time. Their experimental study also found that students who had received the personalized reminders performed significantly better at the end of the course. For the present study, that the feedback had fostered greater cognitive effort in students from the treatment group is also possible, because the messages could have caused students to pay more attention to their learning in the course. Further investigation should test this hypothesis by directly asking students about how the feedback emails impacted their cognitive effort.

Differential effect due to prior academic achievement

The split-file analysis based on program entry score indicated that students at the higher end of prior academic achievement benefitted more from the feedback system, judging by their final course marks. The result was especially notable for the second and third quartile groups. The process feedback could have given this group of students the kind of information necessary for making their learning operations more effective. More investigation into students' interpretation of the feedback could be conducted to verify this. It is also notable that the feedback did not appear to impact the academically weakest group (based on their program entry score). With regards to this group, it will be interesting to know how the feedback affected their self-efficacy as well as other self-beliefs and goals. From the framework of self-regulated learning, self-efficacy is hypothesised to be an important motivational variable driving learning strategies (Butler & Winne, 1995; Zimmerman, 2000): if students do not feel confident in their ability to succeed in their learning, they will likely feel unmotivated to carry out the necessary learning strategies, which, in this case, were the use of Connect and the online pre-lab SCORM activities. Furthermore, these students may not have perceived the value of the recommended learning tasks, which therefore led to failure to follow up on the feedback, and ultimately a less optimal learning result. However, this remains to be validated in further research. If the above interpretations are supported, for students at lower levels of prior academic achievement, it may therefore be necessary to have conversations with them to help them know how to utilise the feedback and to overcome feelings of inadequacy associated with it (Pitt, 2017). As suggested by Orsmond and Merry (2013) from their own qualitative study of students' perceptions of tutor feedback, students at lower academic achievement may have difficulty interpreting feedback to inform their own self-regulation. Overall, the findings of differential impact show that it cannot

be assumed that all students will automatically take actionable intelligence from personalised feedback to inform their learning (Harks et al., 2014), and that specifically low performing groups of students may need more and different kinds of support to help them make their learning more effective. Furthermore, the results highlight the need to understand the 'dialogic process' of LA-based feedback (Carless, 2016), how learners interpret the information presented to them.

This study bears some similarity to the earlier study by Dodge, Whitmer and Frazee (2015) which also employed LA-based, feedback through email messages. While their study found no real impact on students' academic performance, the current study has provided some empirical evidence of what changes, and for whom, when process feedback support based on LA is implemented in a course setting. The results suggested that the feedback could have changed the operations in students' self-regulated learning, and ultimately, their academic performance in the course. However, the findings also suggest that the beneficial outcome is limited to students who need a little more guidance to push them further, and has a limited effect for students at the lowest levels of prior achievement.

The present study made use of propensity score matching to remove possible selection bias in a situation where randomised control trial was not viable. The matched groups formed by logistic regression of a binary outcome (whether the student experienced the intervention or not) against available student characteristics facilitated a rigorous analysis to study the impact of this student-facing LA-based feedback on students' learning behaviours and academic performance, which are currently areas in need of more rigorous research. However, PSM is not without its limitations. Foremost, the procedure is limited to observed covariates; in this study, we selected available demographics such as gender, program entry score, and program-type as factors to

assign cases to treatment and outcome groups. We acknowledge that there may be other latent variables that could result in hidden bias (Shadish, Cook, & Campbell, 2002), and therefore affect the differences between the groups.

Implications for SRL research

This study provides empirical evidence of the theorised effect of feedback on SRL (Winne & Hadwin, 1998). Using the COPES model as a framework in this study provides insights into the benefits of using an LA-approach to feedback. LA uses trace data from learner interactions with the online learning environment. These interactions can be seen as operations of learning, as described in the introduction. In our study, the feedback targeted students' operations of learning, by employing trace data from *Connect* and reporting this usage back to students. This external feedback provided a standard by which students could evaluate their progress. To some extent, the result of the higher completion rate in *Connect* assignments after Phase 1 for the treatment group suggests that these students, on average, had adapted their operations based on this new standard. In this sense, the feedback had the effect of disrupting students' own standards in the evaluation of their progress, providing for them a new standard for their learning, and prompting them to adjust their operations. The results therefore point to the cyclical nature of SRL: based on the external standard provided by LA-based feedback, students evaluate and adjust their operations in order to optimise their performance, resulting in new products for evaluation in the next learning iteration.

This study also highlights the importance of employing suitable engagement metrics for providing feedback to students, in such a way that will improve SRL and optimise their learning in the course – this is a challenge for contemporary higher educators working with big data in education (Pesare, Roselli, & Rossano, 2017). The main online engagement metric employed for

feedback provision in this study related to the *Connect* e-book. Accordingly, the result showed an impact on this, but not on the pre-laboratory activities in Moodle which were also part of the students' learning activities for the course. This suggests that any metric chosen for feedback brings that particular operation into students' metacognitive awareness, causing them to evaluate this new information, with the result that other important operations might be lost.

Finally, the findings in this study also potentially inform the feedback model for data-rich learning experiences proposed by Pardo (2017). In particular it supports the role of multimodal evidence in the feedback process. In the context of this study, learners (Agent B in the model) engaged in the learning process, producing multimodal evidence in the form of attendance records, online engagement data from the LMS and the e-book, as well as mid-term quiz marks. The agent (Agent A in the model) processed these data using the 'measure and compare stage', with the aid of *OnTask*. Importantly, these data were made relevant to students by making it clear to them where they stood in relation to expected behaviour and consequent success in the course. In other words, the LA data provided explicit standards (*S* in the COPES model) for students to evaluate their learning operations. The results lend some support to the proposition that this LA-based feedback at least prompted students to adjust their learning operations (*O* in the COPES model), thereby closing the loop. What still needs to be evaluated in this model, is the extent to which the feedback caused a re-appraisal of the learners' internal knowledge, beliefs and attitudes, as well as goals. For instance, is it possible that learners could respond to the feedback solely in terms of their strategies and tactics, without necessarily changing their internal representations? Future studies could examine more closely how these internal representations are affected by the LA-based feedback.

The study in the paper contains certain limitations. Firstly, we have examined the fine-grained data available from the LMS logs to measure the extent to which any observed change is sustained over for example one week or over a longer time period. The potential of educational data mining can be harvested to examine the impact of LA-based feedback on students' specific self-regulated learning behaviours online (Winne & Baker, 2013; Zhou & Winne, 2012). For example, future studies could employ a process-mining approach such as that conducted by Beheshitha, Gašević, and Hatala (2015) or Sonnenberg and Bannert (2015) to explore how students' temporal sequence of events change after receipt of feedback. Secondly, as explained earlier, we chose to employ a cohort analysis rather than a randomized controlled trial to explore impact of the intervention. In doing so, it cannot be concluded that the LA-based feedback system was the direct result of the outcomes. More data from the stakeholders' (i.e. students') perspective is needed to make firmer conclusions about the link between the intervention and the outcomes.

To address the above limitations, future works may consider : 1) conduct more in-depth analysis of log-file data to examine changes in students online learning behaviour after feedback at 1-week and 1-month periods; 2) conduct focus groups with students to investigate the students' perspectives of how they interpreted and acted on the feedback, to triangulate with the quantitative results; 3) collect more data about the students' motivations, academic background, and other learner characteristics that might moderate the way students respond to the feedback.

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Tables

Table 1

Cohort comparability (2015-2017)

Student composition	Year		
	2015 (n = 266)	2016 (n = 277)	2017 (n = 241)
% of females	70	71	70
% of domestic students	93	95	91
% from health-related programs	69	73	73
Program entry score (Median)	77	79	78

Note. Program entry score was not available for all students at the time of study; this data was only available for domestic students who used their High School Certificate results as a basis for entry to the University. For this variable, $n_{2015} = 198$, $n_{2016} = 217$, $n_{2017} = 177$.

Table 2

Comparison of attributes, online engagement, and course performance, after propensity matching (SDs in brackets)

Attribute	LA-based feedback (n = 241)	No LA-based feedback (n = 241)	Sig.
1. Age	19.74 (4.58)	19.82 (4.73)	
2. Program entry score (mean)	56.15 (35.71)	55.06 (34.24)	
3. % of females	69.7%	70.1	
4. % from health-related programs	73.4	74.7	
5. % of domestic students	91.3	92.5	
6. Moodle 1	5.98 (5.70)	6.87 (9.59)	t (480) = 1.25, p = 0.21
7. Moodle 2	5.23 (6.06)	5.58 (8.66)	t (480) = 0.52, p = 0.60
8. Moodle 3	2.09 (2.47)	2.15 (2.78)	t (480) = 0.26, p = 0.80
9. Moodle 4	2.41 (3.52)	2.76 (5.09)	t (480) = 0.87, p = 0.38
10. Moodle 5	2.11 (2.68)	2.45 (3.39)	t (480) = 1.22, p = 0.22
11. Moodle 6	2.09 (3.24)	2.63 (3.96)	t (480) = 1.64, p = 0.10
12. Moodle 7	1.65 (2.46)	2.39 (4.02)	t (480) = 2.42, p = 0.02, d = .22
13. Connect Phase 1	.09 (.19)	.47 (.35)	t (480) = 14.42, p < .001, d = 1.35
14. Connect Phase 2	.25 (.27)	.32 (.25)	t (480) = 2.87, p = 0.004, d = .78
15. Connect Phase 3	.27 (.32)	.55 (.39)	t (480) = 8.70, p < .001, d = .27
16. Quiz 1 marks (%)	72.10 (22.31)	69.83 (22.47)	t (480) = -1.11, p = 0.266
17. Quiz 2 marks (%)	68.77 (28.32)	64.62 (28.06)	t (480) = -1.62, p = 0.11
18. Practical marks (%)	71.83 (18.70)	69.10 (20.09)	t (480) = -1.54, p = 0.12
19. Final course mark (%)	71.21 (18.77)	61.86 (21.23)	t (480) = -5.12, p < .001, d = .47

Note. Moodle variables (7-12): values refer to the average number of interactions performed by students. Connect variables (13-15): values refer to the percentage of required assignments completed within the phase.

Table 3

Correlations between self-regulated learning and course performance variables (n = 784)

	1. Moodle 1	2. Moodle 2	3. Moodle 3	4. Moodle 4	5. Moodle 5	6. Moodle 6	7. Moodle 7	8. Connect Phase 1	9. Connect Phase 2	10. Connect Phase 3	11. Quiz 1 marks	12. Quiz 2 marks	13. Practical marks	14. Final course mark
1.		.37**	.35**	.34**	.31**	.37**	.39**	.21**	.19**	.25**	.17**	.16**	.17**	.19**
2.			.42**	.36**	.46**	.38**	.32**	.14**	.20**	.21**	.12**	.16**	.20**	.18**
3.				.54**	.46**	.43**	.35**	.18**	.18**	.25**	.16**	.20**	.21**	.23**
4.					.51**	.51**	.33**	.19**	.17**	.20**	.13**	.14**	.20**	.21**
5.						.60**	.40**	.22**	.21**	.32**	.14**	.17**	.24**	.23**
6.							.43**	.25**	.23**	.32**	.16**	.19**	.24**	.23**
7.								.23**	.13**	.27**	.11**	.16**	.20**	.18**
8.									.30**	.52**	.22**	.19**	.25**	.22**
9.										.47**	.28**	.25**	.34**	.31**
10.											.32**	.42**	.43**	.43**
11.												.60**	.57**	.71**
12.													.67**	.79**
13.														.86**
14.														

** Correlation is significant at the 0.01 level (2-tailed).

Table 4

Assessment performance by group, quartiled by program entry score

Group	Quiz 1		Quiz 2		Practicals		Final course marks	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
				1st quartile				
With feedback	61.11	29.28	53.65	36.06	60.48	24.27	59.10	24.68
No feedback	63.20	25.83	57.85	31.68	62.00	21.55	54.14	22.05
Sig	*t(86) = -.353, p = .73*		*t(86) = -.577, p = .57*		*t(86) = -.308, p = .76*		*t(69.379) = .969, p = .336*	
				2nd quartile				
With feedback	71.96	18.01	67.67	24.73	73.26	11.06	71.73	12.35
No feedback	68.12	20.84	62.42	25.92	66.88	17.74	58.76	18.55
Sig	*t(75) = .862, p = .39*		*t(75) = .909, p = .37*		*t(75) = 1.887, p = .06*		*t(75) = 3.600, p = .001**, d = .82*	
				3rd quartile				
With feedback	72.27	21.64	72.38	24.60	73.65	16.17	73.06	16.24
No feedback	70.09	19.86	64.76	27.20	72.29	17.73	64.38	18.82
Sig	*t(101) = .531, p = .60*		*t(101) = 1.493, p = .14*		*t(101) = .408, p = .68*		*t(101) = 2.514, p = .01*, d = .49*	
				4th quartile				
With feedback	81.63	10.96	77.32	21.04	80.33	12.03	79.95	12.06
No feedback	76.34	16.02	68.25	22.72	78.25	17.49	68.70	19.32
Sig	*t(87) = 1.846, p = .07*		*t(87) = 1.952, p = .05*		*t(87) = .664, p = .51*		*t(62.615) = 3.208, p = .002**, d = .70*	

*Difference significant at p < .05 ** Difference significant at p < .01



Figure 1. Example of OnTask email sent to students in a course

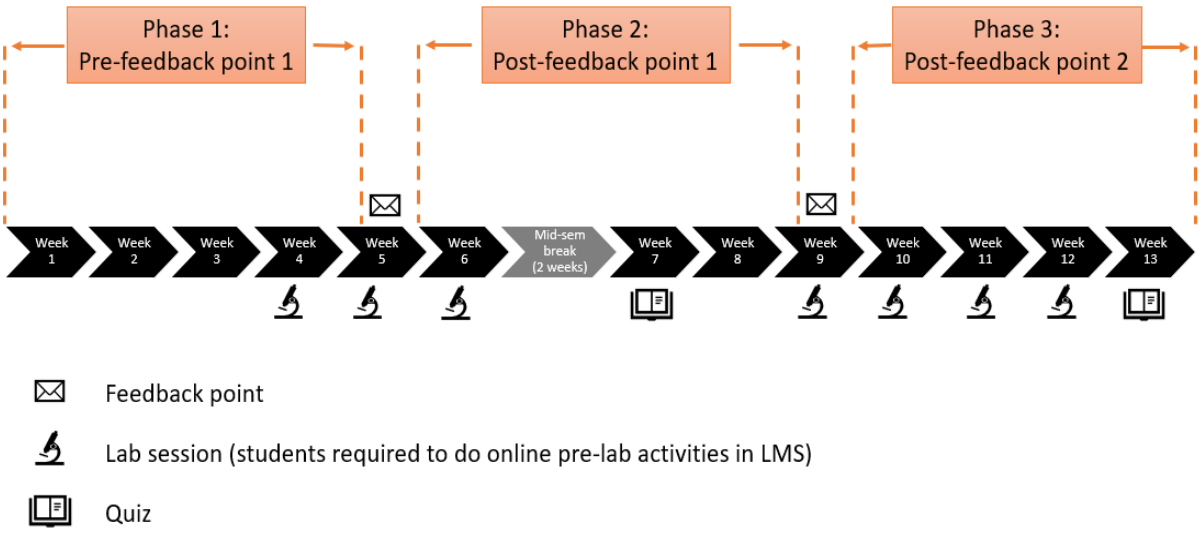


Figure 2. Scheduled feedback support (mailouts) over the semester in the course. Week 13 is followed by a two-week study vacation and then summative examination

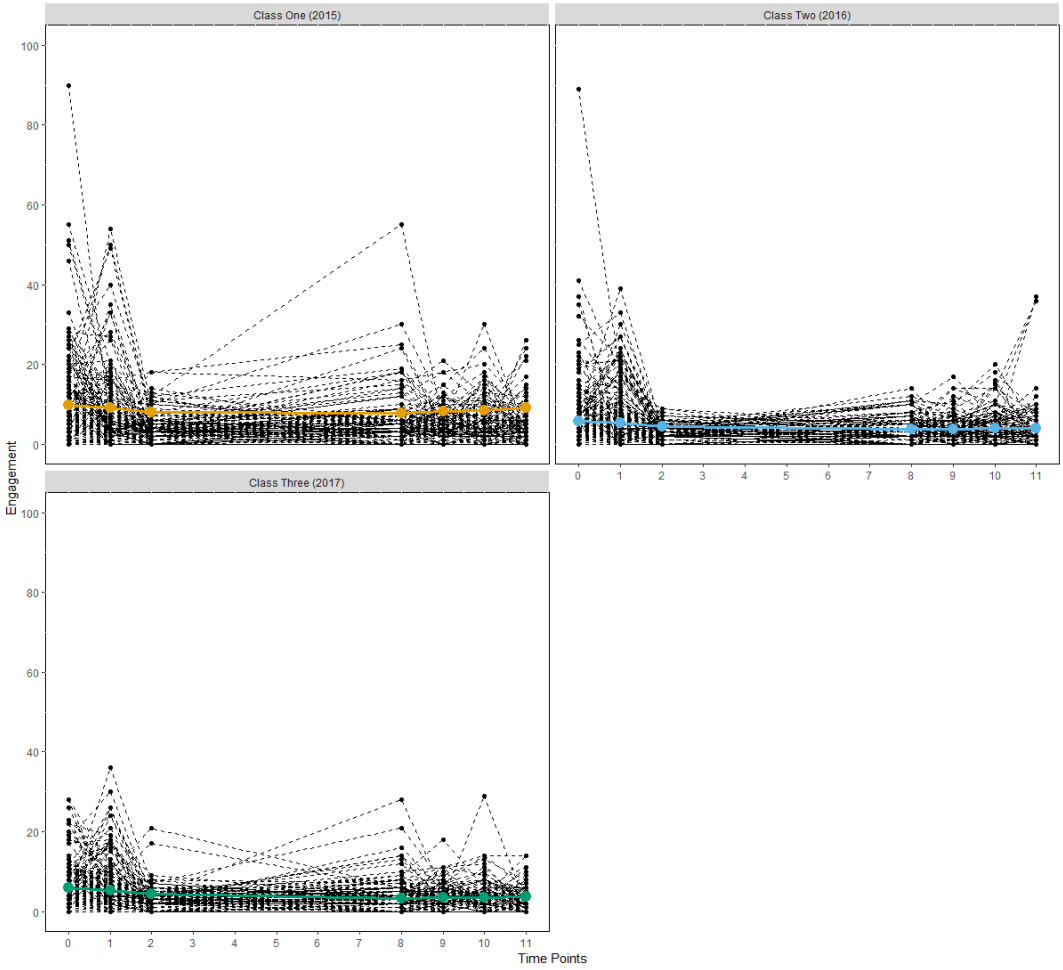


Figure 3. Individual trends in activity over 7 SCORM packages in Moodle for three classes

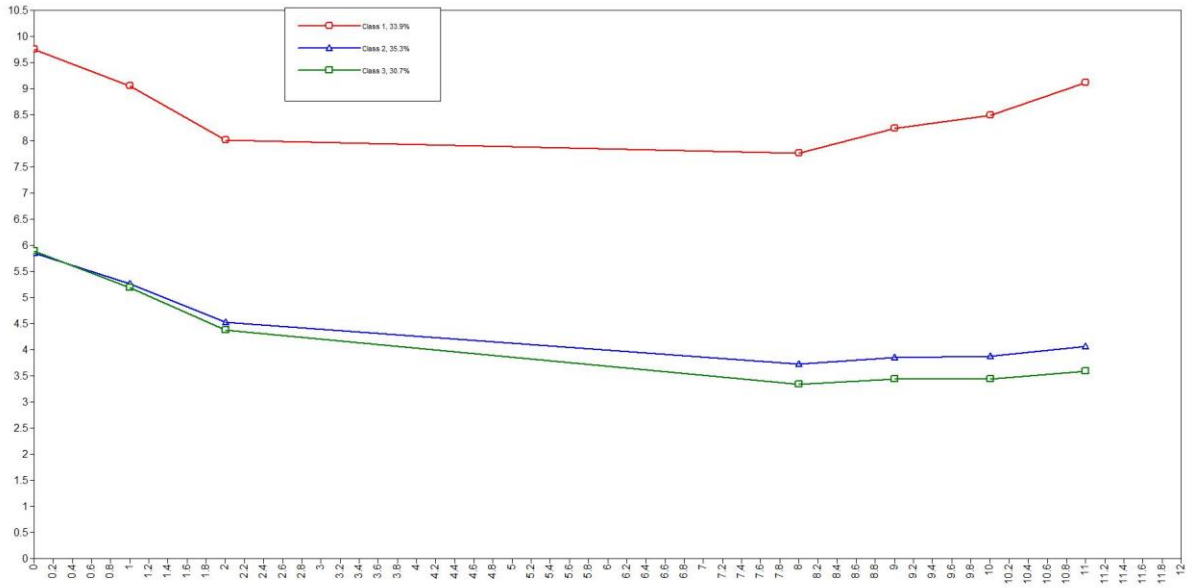


Figure 4. Estimated mean trend in activity over 7 SCORM packages in Moodle for three classes (Class 1 – 2015; Class 2 – 2016; Class 3 – 2017)

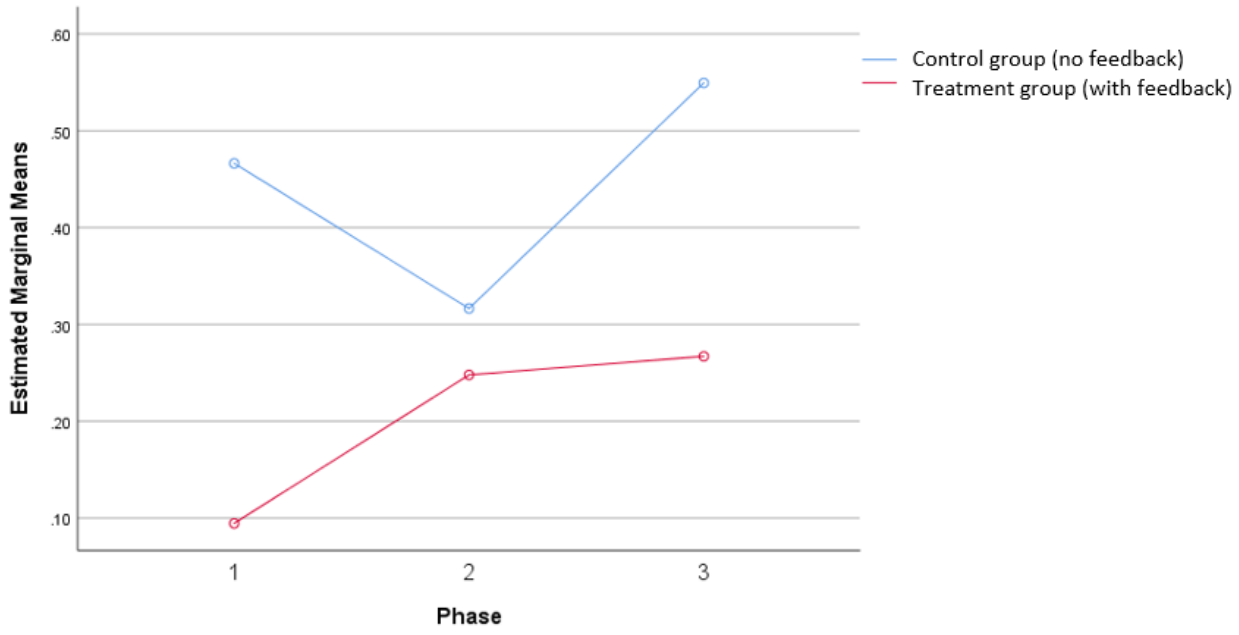


Figure 5. Estimated marginal means for completion rate of *Connect* e-book activities over 3 phases

APPENDIX. Example rules for messages providing process-oriented feedback, based on learner activity data and course performance

Condition	Feedback message
Connect registration status = Registered	I can see that you have registered for *Connect*, which is fantastic.
Connect registration status = Not registered	I have noticed that you haven't registered for *Connect*. It's important that you do this ASAP. The weekly learning modules will help you develop a good foundation knowledge in this course, furthermore the *Connect* platform will be used to complete our summative assessment, Quiz 1 in a few weeks time. If you haven't registered for *Connect* you will be unable to complete the quiz.
Quiz performance = Passed quiz	Quiz 1 marks were distributed last week, and you will have noticed that you have passed Quiz 1. Well done! Irrespective of your grade, it's important that you reflect on your performance in Quiz 1 by working through the solutions via the *Connect* website.
Quiz performance = Failed quiz	Quiz 1 marks were distributed last week, and you will have noticed that you did not pass Quiz 1. It is important that you reflect on how you went in Quiz 1 by working through the solutions via the *Connect* website.