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Engagement with analytics feedback and its relationship to self-regulated learning competence and course performance

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Abstract

Incorporating feedback into the learning process is crucial for learners' success. Recent advancements in Learning Analytics (LA) and Artificial Intelligence (AI) have introduced a range of feedback generation and delivery opportunities to improve teaching and learning processes, yet questions remain about how learners engage with such tools and their impact. In this study, we investigated postgraduate students' engagement with analytics feedback in relation to their level of self-regulated learning (SRL) competence and performance in a semester-long (ten-week) course. We specifically focused on the Interactive-Constructive-Active–Passive (ICAP) framework of cognitive engagement. Initially, students were asked to participate in an established SRL questionnaire, based on Zimmerman's theory of self-regulation to evaluate their SRL competence (N = 39). Throughout the semester, their online behaviour data from Moodle and Google Docs was collected and analyzed to form personalised analytics feedback for each student. We examined how students with different SRL competencies engage with analytics feedback and the impact of this engagement on students' course performance. Results indicated that students with high SRL competence actively engage with analytics feedback more than students with low SRL competence. However, students' analytics feedback engagement did not significantly affect their course performance. Additionally, we analyzed students' reflections on the feedback provided to investigate how they perceived it in relation to their learning experiences and performance. Students argued in their reflections that analytics feedback was beneficial in identifying and regulating their online behaviours and providing motivation through objective insights. They also noted limitations in accurately reflecting their behaviours and learning quality, the need for more personalised recommendations and timely feedback, and suggested design improvements to ensure clarity, foster interaction and incorporate tailored, in-depth insights. We conclude the paper with a discussion on future design and research suggestions for ways of monitoring and supporting students' cognitive engagement with analytics feedback interventions.

Keywords: Self-regulated learning (SRL), Learning analytics, Feedback interventions, Cognitive engagement, ICAP framework

Introduction

Advancements in technology have transformed the landscape of higher education. The emergence of digital technologies has offered students opportunities to learn without any time or place restrictions. This flexibility has highlighted students' abilities to effectively control, organize, and manage their cognition, motivation, and behaviours for successful learning outcomes, which are competencies central to self-regulated learning (SRL). As defined by Zimmerman (1990), SRL means becoming a master of an individual's learning process. In academic contexts, regulation of cognition, behaviours, motivation, and environment brings academic success to students (Pintrich, 2000; Pintrich & Zusho, 2002). Extensive research has investigated the impact of SRL competence on engagement with learning content and academic performance (Pardo et al., 2017). For instance, the study conducted by Kizilcec et al. (2017) investigated the effective SRL strategies and their manifestations in online learning behaviours on MOOC platforms, finding that students who applied goal setting and strategic planning accomplished their personal goals and attained higher academic achievement. Similarly, Araka et al. (2022) found that students possessing higher-level regulation competencies achieved higher academic performance. Therefore, research has documented the relationship between self-regulated learning competencies and academic performance, emphasizing the significance of SRL in navigating modern educational settings.

Building upon this foundation posed by the discussion on SRL, research has demonstrated that effective feedback provision through the learning process has an impact on fostering SRL and academic achievement (Broadbent, 2017). Considering the main purpose of feedback is to give information about learning processes and clarify misconceptions to minimize the gap between the current level and the intended level of learning (Hattie & Timperley, 2007; Sadler, 1989), it is an important step to enhance students' learning experience. In educational contexts, as Carless and Boud (2018) stressed, feedback provision is not only related to outcomes but also is related to the learning process itself. In-time, personalized, and reflective feedback can provide insights to students about their learning process, help them regulate their learning, and improve their SRL competence (Azevedo et al., 2022; Lim et al., 2021). Furthermore, experimental research conducted by Ustun et al. (2022) further highlighted the substantial impact of feedback interventions on both academic achievements and SRL competencies.

Learning analytics feedback

Recent advancements in Learning Analytics (LA) have introduced innovative methods to assist students by offering feedback interventions that are both meaningful and relevant to their motivation, cognition, emotion, and behaviours, using data collected from the digital records of their actions and activities. As an application of LA, intelligent intervention systems and dashboards are convenient for presenting or conveying interpreted data to the learners in the form of feedback (Afzaal et al., 2021; Sedrakyan et al., 2020). These results can be integrated into the system as visualizations, notifications, emails, or messages to indicate learning progress (individual or group comparison) (Marquès et al., 2022). Students tend to view their feedback as being context-dependent, which enables them to meet course requirements immediately. However, they may find it difficult to identify the actions recommended in the feedback as examples of effective learning strategies. This leads to not being able to develop SRL competencies from a broader perspective (Lim et al., 2020). In their recent research, Kaliisa et al. (2024) concluded that learning analytics dashboards have been failing to achieve their anticipated impact. LA dashboards tend to be more concerned with making learners aware of their traces in the learning environment rather than focusing on the actions they can take based on that information (Jivet et al., 2018). Therefore, the extent to which learners engage with the feedback provided and the impact of this interaction on their learning outcomes are key questions to be investigated for understanding and improving the effectiveness of analytics feedback interventions.

Further extending the discussion, the efficacy of analytics feedback heavily relies on student engagement with the feedback process. Feedback should facilitate a dialogue rather than merely transmitting information from teacher to student, to build two-way trust and improve motivation to engage with feedback (Yang & Carless, 2013). Since sense-making and engagement with feedback are indicators of feedback literacy, it is important for students to develop this literacy, understand its positive value for their learning process, and integrate it into their learning strategies (Carless & Boud, 2018; Jin et al., 2022). This literacy fosters the necessary attitudes and abilities for students to effectively utilise feedback and implement it in their actions and course performance (Shute, 2008). However, tracking feedback engagement and its effect on learning has been traditionally challenging, particularly in higher education, where interactions between learners and educators might be more limited. Therefore, LA can provide opportunities to monitor students' engagement with the feedback they receive and allow us to be able to track the process after students receive feedback and provide further support as needed (Winstone, 2019).

Interactive-constructive-active–passive (ICAP) cognitive engagement framework

In this paper, we propose the Interactive-Constructive-Active–Passive (ICAP) cognitive engagement framework as a potential framework to investigate the link between analytics feedback and students' engagement with this feedback. In this framework, Chi and Wylie (2014) categorised cognitive engagement into four levels to understand the development of learners' knowledge. At the first and primary level, Passive engagement involves the learner receiving feedback without any observable physical or mental effort beyond viewing or reading. Moving up the hierarchy, Active engagement involves the learner working with the feedback through summarising and annotating without extending beyond the given information. At the Constructive engagement level, learners actively make sense of the feedback by integrating existing knowledge and generating new understanding. The key difference between active and constructive engagement is that, in constructive engagement, the learner refers to additional information, which can be their prior experience or other sources of information. At the pinnacle of the framework, Interactive engagement involves two-way interactions where the learner is not just passively receiving information but actively discussing and questioning the feedback with peers, teachers, or others.

In previous literature, the ICAP framework was mainly used to assess learners' cognitive engagement with learning materials by categorising students' learning behaviours

(Chi & Wylie, 2014). For instance, Wu et al. (2023) utilised artificial intelligence and computer vision to automatically assess students' engagement with STEM education materials through the framework. In another study, a model developed by Liu et al. (2022) used the Bidirectional Encoder-Decoder Transformer-Convolutional Neural Network (BERT-CNN) Natural Language Processing (NLP) method to automatically detect learners' cognitive and emotional engagement with the ICAP framework in MOOC discussions.

Since analytics feedback interventions themselves are used as learning materials for students to better understand and improve their own learning (therefore becoming a learning material), the ICAP framework can also provide a valuable conceptual framework for categorising students' engagement behaviours with analytics feedback. Building on the framework, Fahid et al. (2021) explored an adaptive learning environment that provided ICAP-inspired feedback and remediation and illustrated how data-driven models can optimise feedback delivery to promote students' cognitive engagement levels. By adjusting the feedback, these models could create more engaging learning environments while supporting engagement and promoting SRL (Vosniadou et al., 2024).

While levels of the framework indicate knowledge construction with a hierarchical order of Interactive > Constructive > Active > Passive, here we propose these categories as potential proxies of different depths of engagement with analytics feedback. In previous LA studies, engagement with analytics feedback was measured to a certain extent but lacked a comprehensive approach. In many studies, analytics feedback was sent to students, but students' engagement with this feedback was not monitored (i.e., Iraj et al., 2020). In some studies, feedback engagement is monitored in a relatively superficial manner. For instance, in the study of Suraworachet et al. (2023), analytics feedback was provided mid-term to observe behavioural changes in students' interaction with a reflective writing task. The analytics feedback provided was only monitored to observe the extent to which students viewed the feedback. In other studies, students' engagement with automated writing feedback was measured by collecting self-report data from students on their experiences with the feedback (Shibani et al., 2022; Tsai et al., 2021). Other researchers explored the process of feedback engagement by conducting interviews with students to gain insights into their behaviours and experiences (Lim et al., 2020). As Chi and Wylie (2014) argued in their original study, Interactive level engagement behaviours' characteristic descriptor is a dialogue (i.e., the constructive participation of every agent); thus, it can be achieved through discussions with peers or others about the feedback received. Changing our perspective on analytics feedback engagement from Passive to measuring different degrees of quality in the engagement- Active, Constructive, and Interactive is necessary to understand students' engagement with analytics feedback (Vytasek et al., 2020). To comprehend such a multifaceted nature of engagement, we should incorporate multiple data sources across all levels of cognitive engagement.

This study aims to understand how students with varying self-regulated learning (SRL) competencies engage with personalised analytics feedback and its impact on their course performance. We adopted a data-driven approach to gather and examine trace data generated by students during their interactions with analytics feedback, while also asking for their feedback regarding the analytics feedback itself, to be able to judge their level of engagement with the analytics feedback and to understand how they perceive it in the context of their learning process. Understanding the multifaceted impact of analytics feedback on students' regulation of learning, engagement levels, course performance, and perceptions can improve the design and implementation of the feedback to enhance its effectiveness, potentially leading to enhanced learning experiences and better learning outcomes for students. More specifically, in this study, we aim to answer the following research questions:

RQ1 How do students with different levels of SRL competence engage with the analytics feedback provided?
RQ2 What is the relationship between students' engagement with analytics feedback and their course performance?
RQ3 How does the analytics feedback affect students' learning behaviours in the course?
RQ4 What are the students' perceptions of analytics feedback in relation to their learning experiences and behaviours, and what recommendations do they offer for enhancing feedback effectiveness?

Methodology

Educational context and participants

The context of this study was a face-to-face postgraduate course in Educational Technology. During the 10-week course, topics related to educational technology design were presented to thirty-nine students (11 male and 28 female) from various backgrounds, including computer science, education, and design sciences. The age distribution of the cohort included 2 students younger than 22 years, 11 students aged 22–25 years, 17 students aged 26–30 years, and 9 students over 30 years. These students shared a common experience with the course's technological resources, including learning management software, collaborative documenting tools, and synchronous meeting tools, and they possessed comparable levels of understanding of statistical analysis and programming. Notably, their SRL competence was assessed to be above average (explained in detail in Sect. "SRL Questionnaire and Clustering of Students"). Institutional ethics approval was received for the study, and at the beginning of the term, all students were informed about the study to opt in, and written consent forms were collected from all participants.

The learning design implemented in the course was based on the flipped classroom model, referring to an instructional strategy where lecture content is provided before class while in-class time is dedicated to discussions, collaborations, and more hands-on experiences. Throughout the semester, the course took place on Tuesdays, and students were expected to: (1) finish the readings provided on Moodle, an online learning management platform; (2) watch a pre-recorded lecture video about the subject of the week; (3) participate in a debate on an online discussion platform on Moodle; (4) write an individual reflection on the weekly learning experience on Google Docs (GDocs); and (5) write a critical essay to submit at the end of the term. The course performance of students was calculated by averaging students' grades on the two assignments for the course: weekly individual reflections and a critical essay submission.

Personalised analytics feedback provided to students was based on their Moodle and GDocs interaction logs. The analytics feedback (i.e. Figures 1 and 2) was prepared in a bespoke web application for the module and sent to students in the mid-term, right after the first half of the course. Six weeks of data, including week 0 (preparatory week), were presented to students in the form of line graphs, heat maps, bar charts, and total counts of engagement (clicks on resources, video views, debate posts, and edited number of characters in reflection). Also, under each sub-section, students received written feedback summarising the visuals, further motivating, and suggesting sources to improve their related skills. The web application also offered the option for students to export their data (Moodle and GDocs logs) and perform an analysis by themselves. At the end of each page, students were asked to provide feedback on the feedback they received via a short survey.

SRL questionnaire and clustering of students

To measure students' SRL competence, they were asked to complete a questionnaire at the beginning of the course. A meta-analysis of SRL (Sitzmann & Ely, 2011) was used as the basis for the development of the questionnaire consisting of four dimensions, which are goal setting (GS, N = 5), effort (E, N = 3), self-efficacy (SE, N = 9), and persistence (P, N = 13). These dimensions were found to explain the highest variance in learning performance when combined. Previous research also measured the inter-item reliability of the questionnaire and reported the Cronbach Alpha values of each dimension as (GS = 0.67, E = 0.68, SE = 0.89, P = 0.87) (Suraworachet et al., 2021). The K-means clustering method was used to divide students into groups. The best clustering results were achieved with k = 2, with a low SRL competence cluster (N = 18) and a high- SRL competence cluster (N = 21) as indicated by the Silhouette score and the Elbow heuristic method. To identify

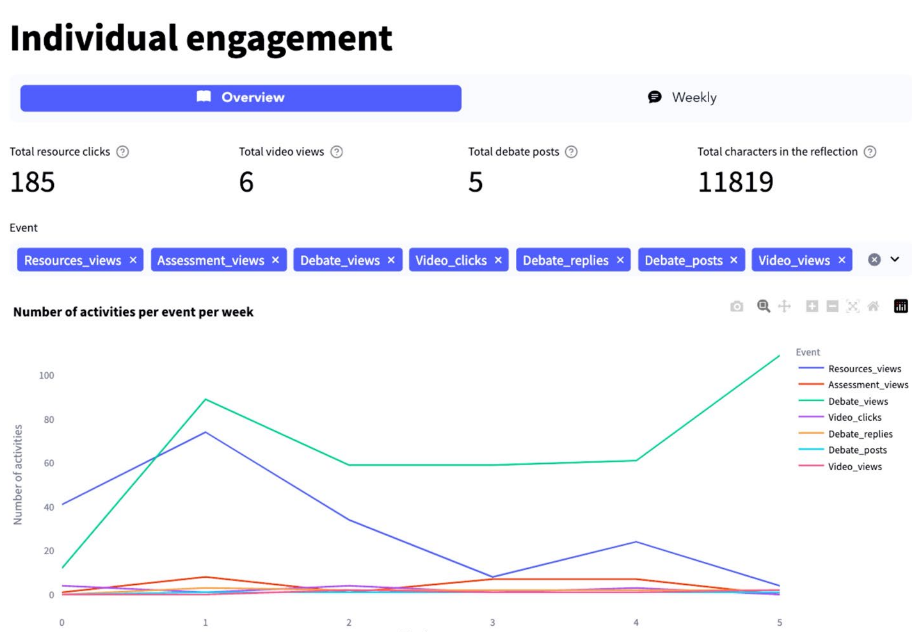

Fig. 1 Sample feedback dashboard presenting a student's overview engagement with seven proxies and their distribution across five weeks

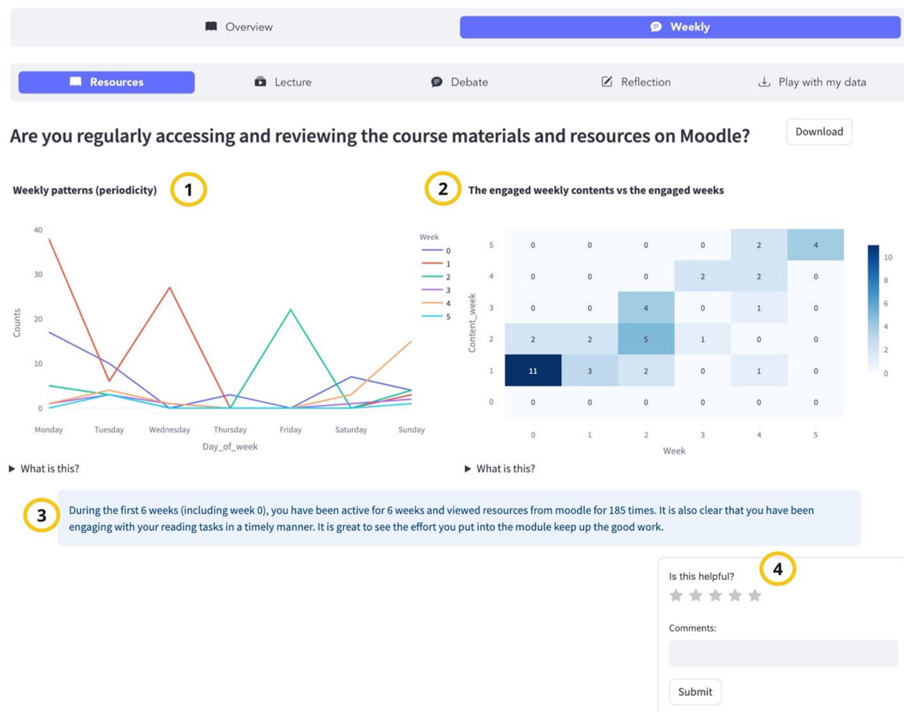

Fig. 2 Sample feedback dashboards (cont. page) presenting students' weekly resource engagement in terms of (1) the total number of engagements with resources, (2) timeliness, whether they engage each week's content within the same week, (3) verbal explanations of the visualisations, and (4) feedback survey about analytics feedback

the differences in the percentage of SRL competence across students who engaged with the analytics feedback, Chi-square tests were applied.

Logs data collection and analysis

Two steps of log data collection and analysis were performed in this research. Firstly, to give students information about their learning process in terms of online activities for the first half of the semester, we prepared feedback content by gathering and analyzing logs of interactions with Moodle and GDocs (Zhou et al., 2021). Based on the features explained in Table 1, the students received personalised feedback in the form of visualisations followed by qualitative comments from the educator. A rule-based approach was formulated based on behavioural features to write qualitative comments for each student (see details in supplementary documents).

Secondly, to investigate students' engagement with analytics feedback, clickstream data was collected from the web application used to present feedback to students (Fig. 3). After preprocessing and analysing the collected data, three main features were derived: (1) feedback view- the number of times that a student visited the feedback pages, namely: overview, lecture, debate, resource, and reflection; (2) overview page interaction- the number of times that a student interacted with the feedback filtering options presented on overview page line graph 'number of activities per event per week' (Fig. 1); and (3) download data- the number of times that a student downloaded their data for further analysis. These three main engagement behaviours were derived from theoretical

Table 1 Descriptions of behavioural features and sources of data to derive these behaviours

Source of Data	Behavioural Features	Description
Moodle logs	Resource clicks and Resource clicks late	The total number of times that a student clicks resources provided in Moodle or clicks them in later weeks
	Video clicks and views	The total number of times that a student clicks and views lecture videos
	Debate views, posts and replies	The total number of times that a student views, posts and replies to debate questions in Moodle
	Assessment clicks	The total number of times that a student clicks the assessment-related content
Google Docs logs	Avg Str Count Per Day	The average number of contents edited (characters) in a student's reflective writing task per day
	Total Active Day	The total number of active days that a student has active engagement with reflective writing task
	Avg Str Count Per Week	The average number of contents edited in a student's reflective writing task per week
	Total Active Week	The total number of active weeks that a student has active engagement with reflective writing task

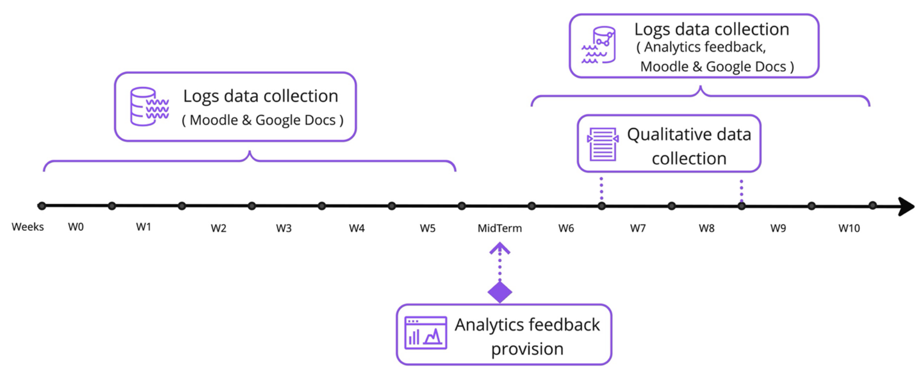

Fig. 3 Research design

considerations of cognitive engagement and are roughly aligned with the ICAP framework's engagement stages (Chi & Wylie, 2014). At the most basic level, if students merely view the visualisations without further interaction or reflection, their engagement is categorised as passive. The effectiveness of analytics feedback at this level can be evaluated based on how well it attracts students' attention (i.e., Feedback View feature). When students begin to interact with the feedback through simple actions like clicking to reveal more information or filtering data, they exhibit active engagement. While it is potentially more beneficial than passive engagement, it may still lack the depth of cognitive processing associated with higher engagement levels. Incorporating interactive feedback visuals at this level might encourage exploration (i.e., Overview Page Interaction feature). Constructive engagement refers to students generating insights or connections not provided in the feedback. We can evaluate the analytics feedback at the constructive engagement level by examining how it provokes thought, encourages reflection, and supports the generation of new knowledge (i.e., Download Data feature and Reflective Writing explained in Sec. "Qualitative Data Collection on Students' Engagement with Analytics Feedback and Analysis"). The highest level of engagement, according to the framework, is interactive engagement, where students collaborate with peers or instructors to discuss and interrogate the analytics feedback. This level of engagement could foster the deepest cognitive processing and learning. The aim of interactive engagement is that feedback should serve as a catalyst for discussion with peers and promote a collaborative interpretation of data (i.e., Peer discussions about the analytics or student-AI interaction to discuss analytics feedback). However, our study did not incorporate the interactive engagement level and thus could not evaluate its impact within the scope of this study.

In the final analysis, the three main features were used to calculate the feedback engagement score. The K-means clustering method was conducted to divide students into two groups: the low analytics feedback engagement group (N = 29) and the high analytics feedback engagement group (N = 10) with the Silhouette Score = 0.58. To answer the posed research questions related to the differences between the low and high SRL competence students' engagement scores and the relationship between these scores and students' course performance measured with their grades, we ran inferential statistical tests between the means of variables. To determine the extent to which parametric assumptions about the data sets are met, we performed the necessary tests. When the assumption of normal distribution was violated, the Mann–Whitney U tests and Wilcoxon Signed-Rank tests were conducted. Otherwise, independent samples and one sample T-tests were used. Finally, a post-hoc power analysis was conducted using observed effect sizes in the G*Power tool (Faul et al., 2007) to assess the statistical power of the study and determine the reliability of detected effects.

Qualitative data collection on students' engagement with analytics feedback and analysis

Students were asked to write around 1000 words (500 words in week 7 & 8 as part of weekly subjects) individual reflections on the potential and value of the analytics feedback they received, focusing on their thoughts and feelings about the feedback, its impact on their learning experiences and behaviours, as well as any suggestions for improving the feedback's relevance and usefulness (Fig. 3). As described in Sec. "Logs Data Collection and Analysis", it was aimed to complement students' constructive engagement with analytics feedback and collect feedback on the analytics feedback provided. The task prompts in these weeks encouraged students to think about specific aspects of the feedback, such as its strengths, limitations, impact on learning, and improvements. In total, thirty-nine reflective writings were collected to explore students' perceptions of analytics feedback and their suggestions for enhancing its effectiveness. We employed inductive thematic analysis to identify recurring themes and codes related to students' perceptions and recommendations (Braun & Clarke, 2006). Independent analysis by three researchers ensured the auditability of the findings, yet no interrater reliability was calculated due to the reflective nature of the text and the interpretative nature of the analysis.

Results

RQ1. How do students with different levels of SRL competence engage with analytics feedback? To determine whether there is a difference in students' engagement with analytics feedback between low-SRL and high-SRL students, a Mann–Whitney

U test was conducted. As seen in Table 2, the results indicate that although high SRL students (N = 21, M = 6.19) appeared to engage more with analytics feedback than low SRL students (N = 18, M = 5.28), there was no significant difference in analytics feedback engagement score between the two SRL groups (U = 165, p = 0.496). We also analysed the feedback engagement features separately to further investigate the differences. The results revealed that there was a significant difference in feedback overview page interaction behaviour, which is an indication of students' active engagement, (U = 136, p = 0.034) between high SRL and low SRL students with a small effect size, but no significant difference was found in passive and constructive engagement features; feedback view (U = 170, p = 0.592) and download data (U = 150, p = 0.228). The result of the Chi-Square test showed that the percentage of feedback engagement behaviour was not different across the low and high SRL students, $\chi 2$ (1, N = 39) = 1.478, p = 0.777.

A post-hoc power analysis was conducted to determine the achieved statistical power for the Mann–Whitney U-tests. Using the observed *effect sizes* and sample sizes (N = 18 and N = 21), power calculations indicated low statistical power across all features. Specifically, for feedback engagement score (effect size = 0.12), the achieved power was 0.07; for overview page interaction (effect size = 0.34), the power was 0.18; for feedback view (effect size = 0.09), the power was 0.06; and for download data (effect size = 0.19), the power was 0.09. Although the overall power was low for the majority of features, the significant difference observed in active engagement underscores its potential importance, warranting further investigation in future research.

RQ2. What is the relationship between students' engagement with analytics feedback and their course performance? We explored the relationship between students' engagement with the analytics feedback provided and their academic grades. To compare the mean academic scores of students in low and high analytics feedback engagement conditions, a Mann–Whitney U test was conducted. To align the institutional grades (A (4), B (3), C (2), D (1), E (0), F (0)) with the analysis, the grades were transformed into a 0–100 scale. There was no significant difference between those students with high feedback engagement (N = 10, Md = 64.75) and those with low feedback engagement (N = 29, Md = 65.73); U = 135, p = 0.748 (effect size = 0.05). These results suggest that analytics feedback had no effect on course performance measured by students' final grades in the module. These results suggest that analytics feedback did not have detectable effect on course performance as measured by final grades, although the test was underpowered, which may have contributed to the nonsignificant findings.

Table 2 Mann–Whitney U-test of analytics feedback engagement behaviours compared between two SRL groups

	Low SRL (N = 18) Md (IQR)	High SRL (N = 21) Md (IQR)	U	p	*Effect size*
Feedback engagement score	3.00 (7.25)	4.00 (8.50)	165	0.496	0.12
Overview page interaction	0.00 (0.00)	0.00 (2.50)	136	0.034*	0.34
Feedback view	20.0 (52.75)	22.00 (44.00)	170	0.592	0.09
Download data	0.00 (1.25)	1.00 (1.50)	150	0.228	0.19

*p is significant at the 0.05 level (2-tailed)

The module assessment consisted of two parts, so we also conducted separate tests for each of them to investigate their relationship with analytics feedback engagement. The results revealed that there were no significant differences in students' individual reflective writing task grades between those students with high feedback engagement levels ($N = 10$, $Md = 65.48$) and those with low feedback engagement levels ($N = 29$, $Md = 76.20$); $U = 132$, $p = 0.675$ (effect size = 0.07), and in their critical writing task grades between those students with high feedback engagement level ($N = 10$, $Md = 59.52$) and those with low feedback engagement level ($N = 29$, $Md = 57.13$); $U = 137$, $p = 0.796$ (effect size = 0.04). The results indicate that the analytics feedback has no effect on students' reflective writing assignment and their critical writing assignment. However, the post-hoc power analysis indicated that the tests had insufficient power to detect differences at these engagement levels, with power values all below 0.06. Therefore, the null effects may reflect both a genuine lack of impact of analytics feedback on performance and the very low statistical power, which makes it difficult to detect subtle differences.

RQ3. How does the analytics feedback affect students' learning behaviours in the course? A Wilcoxon Signed-Rank Test was conducted to compare the behaviour of high and low feedback engagement groups between the first and second half of the semester. In the low feedback engagement condition, significant decreases from the first to the second half of the semester were observed in the number of resource clicks, $Z = -3.180$, $p = 0.001$; video clicks, $Z = -1.732$, $p = 0.001$; debate views, $Z = -1.295$, $p = 0.001$; debate posts, $Z = -0.594$, $p = 0.001$; resource clicks late, $Z = -2.165$, $p = 0.005$ and total active week, $Z = -0.153$, $p = 0.011$. However, no significant differences were noted in assessment clicks, $Z = -3.111$, $p = 0.124$; Avg Str Count Per Day, $Z = -0.945$, $p = 0.345$; Total Active Day, $Z = -1.373$, $p = 0.170$ or Avg Str Count Per Week, $Z = -0.945$, $p = 0.345$ (Table 3). Moreover, a post-hoc power analysis was conducted for the low feedback engagement group to determine the achieved statistical power of the Wilcoxon Signed-Rank Tests, which were chosen due to the non-normal distribution of our data. The achieved power varied depending on the effect size of each feature: for resource clicks (effect size = 0.59), power was 0.47; for video clicks (effect size = 0.32), power was 0.29; for video views (effect size = 0.19), power was 0.23; for debate views (effect size = 0.24), power was 0.47; and for debate posts (effect size = 0.11), power was 0.40. These results suggest that while the study had sufficient power to detect large effects, it was underpowered for reliably identifying smaller effects, indicating that caution is needed when interpreting the nonsignificant findings for features with smaller effect sizes.

In high feedback engagement condition, significant decreases from the first to the second half of the semester were also observed in the number of resource clicks, $Z = -2.803$, $p = 0.005$; video clicks, $Z = -2.096$, $p = 0.036$; debate views, $Z = -2.803$, $p = 0.021$ and debate posts, $Z = -2.565$, $p = 0.010$. However, no significant differences were noted in video views, $Z = -1.838$, $p = 0.066$; assessment clicks, $Z = -0.912$, $p = 0.362$; resource clicks late, $Z = -1.886$, $p = 0.059$; Avg Str Count Per Day, $Z = -1.274$, $p = 0.203$; total active day, $Z = -0.479$, $p = 0.632$; Avg Str Count Per Week, $Z = -1.274$, $p = 0.203$ or Total Active Week, $Z = -0.302$, $p = 0.763$. The findings suggest that high feedback engagement can help students stay more engaged with their Moodle and reflective writing activities (Table 4). However, the post-hoc power analysis for the high feedback engagement group revealed low power across most features. Specifically, for resource clicks (effect

Table 3 Wilcoxon Signed Ranks tests of Moodle and reflective writing engagement behaviours between the first and second half of the semester compared in low analytics feedback engagement condition

Moodle and GDocs features		**Low feedback engagement (N = 29)**			
		Md (IQR)	**Z**	***p***	***Effect size***
Resource clicks	First half	135 (82.5)	− 3.180	0.001**	0.59
	Second half	48 (30.5)			
Video clicks	First half	15 (10)	− 1.732	0.001**	0.32
	Second half	10 (9.5)			
Video views	First half	6(4.5)	− 1.000	0.287	0.19
	Second half	5 (5)			
Debate views	First half	145 (182)	− 1.295	0.001**	0.24
	Second half	65 (81)			
Debate posts	First half	5 (1)	− 0.594	0.001**	0.11
	Second half	3 (3)			
Assessment clicks	First half	10 (11)	− 3.111	0.124	0.58
	Second half	7 (9.5)			
Resource clicks late	First half	11 (11)	− 2.165	0.005*	0.40
	Second half	3 (8)			
Avg Str count per day	First half	1285 (1694)	− 0.945	0.345	0.18
	Second half	614.45 (1205.75)			
Total active day	First half	6 (6.5)	− 1.373	0.170	0.25
	Second half	5 (6.5)			
Avg Str count per week	First half	7497 (9892)	− 0.945	0.345	0.18
	Second half	3584 (7034)			
Total active week	First half	4 (2)	− 0.153	0.011*	0.03
	Second half	3 (2)			

**p* is significant at the 0.05 level (2-tailed)

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

size = 0.89) and debate views (effect size = 0.89), the achieved power was 0.46, while for debate posts (effect size = 0.81) it was 0.40. The remaining features exhibited power levels below 0.40, indicating a limited capacity to detect smaller effects in this condition.

RQ4. What are students' perceptions of analytics feedback in relation to their learning experiences and behaviours, and what recommendations do they offer for enhancing feedback effectiveness? Students' reflections on the feedback provided were analysed to investigate how they perceived it in relation to their learning experiences and performance. The thematic analysis of reflective writings indicated three main themes emerging from students' reflections on the feedback provided:

The effectiveness of feedback Sixty percent of the students frequently expressed a "positive" impact of the analytics feedback on their "motivation" and observed it as a "valuable" and "insightful checkpoint" enabling them to "self-monitor and evaluate" their learning process and identify "areas of improvement" and "patterns". Commenting on the strengths of analytics feedback, one of the students said that "*[analytics feedback] underscores the pivotal role of fostering an environment where students actively and continuously interact with learning materials*" (S1). They also addressed some concerns regarding analytics feedback being "generic", not reflecting their specific learning preferences and quality of learning and being limited in guiding

Table 4 Wilcoxon Signed Ranks tests of Moodle and reflective writing engagement behaviours between the first and second half of the semester compared in high analytics feedback engagement condition

Moodle and GDocs features		High feedback engagement (N = 10)			
		Md (IQR)	Z	*p*	*Effect size*
Resource clicks	First half	171 (97)	− 2.803	0.005*	0.89
	Second half	88.5 (72.75)			
Video clicks	First half	22 (12)	− 2.096	0.036*	0.66
	Second half	13.5 (12)			
Video views	First half	8.5 (3.75)	− 1.838	0.066	0.58
	Second half	6.5 (2.75)			
Debate views	First half	241 (64)	− 2.803	0.021*	0.89
	Second half	127.5 (97.5)			
Debate posts	First half	5 (1.5)	− 2.565	0.010*	0.81
	Second half	4 (1.5)			
Assessment clicks	First half	15.5 (15.25)	− 0.912	0.362	0.29
	Second half	10 (15)			
Resource clicks late	First half	9.79 (17.12)	− 1.886	0.059	0.60
	Second half	2.18 (11.90)			
Avg Str count per day	First half	1737.84 (1993)	− 1.274	0.203	0.40
	Second half	741.57 (2116)			
Total active day	First half	6.5 (8.5)	− 0.479	0.632	0.15
	Second half	7.5 (7.25)			
Avg Str count per week	First half	10,137.4 (11,650)	− 1.274	0.203	0.40
	Second half	4325.8 (12,260)			
Total active week	First half	4 (1.25)	− 0.302	0.763	0.10
	Second half	4 (2)			

* *p* is significant at the 0.05 level (2-tailed)

suggestions. Several students were not sure "*how increasing the number of event views and click counts translates into learning performance or engagement*" (S9, S17, S26, S30, S33 and S36) when asked about the limitations of analytics feedback.

Impact on learning and behaviours Students reflected on how analytics feedback prompted reconsideration of learning behaviours, adjustments to study routines, and increased engagement. It played an encouraging role in timely preparation and participation in weekly learning activities, despite concerns over data quality and relevance to actual learning outcomes. One student commented "*I suddenly realised that it would be a good way to better understand the content by viewing the video again after class.*" (S26) to express the impact of analytics feedback on Moodle behaviour. Another student stated "*It [analytics feedback] helps me to change my learning behaviours to plan and work on the reflection [individual reflective writing task] earlier by taking notes and points I would like to put in the reflective journal during lessons*". However, some of the students discussed that increased engagement with the module resources and activities does not automatically translate to deeper learning or better learning outcomes, emphasising a need for more than statistics to change learning behaviour.

Recommendations (i) Feedback Design. Students argued that timing of the feedback is important as providing consistently and strategically timed feedback could improve learning behaviours and outcomes. They highlighted the importance of delivering feedback early in the term or weekly. Since students were significantly concerned about the emphasis on the quantity of viewing/clicking on learning platforms and submission over the quality of learning and reflective writing, they propose feedback to be tailored to “individual needs”, “in-depth with more data sources,” “relevant” and “including improvement suggestions”. One student proposed that the analytics feedback “*can provide additional suggestions focusing on how to make improvements instead of solely describing superficial information.*” (S27) (*ii) Dashboard Design.* The main issues that students had about the interface design were confusion and interpretation difficulties of feedback, such as heatmap visualisations. Students suggested enhancing the dashboard by following the interface design principles, utilising a progressive disclosure feature to focus the core of feedback while additional information is accessed as needed, and providing scaffolding elements such as reminders and notifications to improve interaction. For instance, a student summarised these issues as “*The synchronisation of design elements elevates the overall learning journey.*” (S6). There were also some suggestions for integrating data literacy training and guidance on the dashboard interface to support analytics feedback interpretation.

These results indicate that while analytics feedback was valued for promoting regulation of learning and motivation among students; more personalised, timely, and actionable feedback was considered essential. This includes reconsideration of feedback content and provision, as well as enhancing analytics dashboard design to improve student engagement and their overall learning experience.

Discussion

Analytics feedback bears the potential to convey timely and personalised interventions to improve learning if only students engage with it effectively. Reporting data to students regarding their interactions with various learning activities as feedback is not enough to promote students’ learning (Jivet et al., 2018). Feedback requires cognitive engagement and sense-making, as well as regulation of one’s own behaviours to take actions to foster learning. Although several researchers investigated the analytics feedback engagements of students using different methods, a deeper level of understanding of feedback engagement is needed to better understand the extent to which students benefit from it. In this study, students’ engagement with personalised analytics feedback and its relationship with the level of SRL competence and course performance were investigated via a data-driven approach (Kaliisa et al., 2024). More specifically, the number of views and interactions on provided feedback and downloads for further exploration, as well as students’ submission of feedback about the analytics feedback, they received, were all used as proxies of analytics feedback engagement to interpret its relationships to students’ SRL competence, their course performance, and learning behaviours throughout a semester.

High SRL students engage more actively with analytics feedback

Our first research question investigated whether students with different SRL competence levels exhibit different engagement behaviours with analytics feedback. Students with high SRL competence engaged more with the overall summary page of analytics feedback than those with low SRL competence. Although this difference was statistically significant, it should be interpreted with caution due to low statistical power resulting from a small sample size. One possible interpretation is that students are more than passive recipients of feedback. Rather, they actively process feedback, which is a crucial step towards learning and deeper cognitive engagement. Although high SRL students on average engaged more with the analytics feedback, there was no statistically significant difference found in other levels of engagement. This indicates that the students with low and high SRL competence might have similar engagement levels with feedback which is a result that contrasts with existing theoretical hypotheses (Pintrich, 2000; Zimmerman, 1990). Our initial hypothesis was that low SRL students may lack accurate self-monitoring skills to check course pre-determined goals and the extent to which they are on the right track although they require further external guidance, feedback, and support to observe how they are engaging with the course requirements (Pintrich, 2000). On the other hand, students with high SRL competence might be more aware of their own learning process and confident with the self-monitoring skills they think they may be keen to confirm their engagement with the course activities and to improve their learning process further by taking advantage of every opportunity presented to them (Eilam & Aharon, 2003; Pintrich & Zusho, 2002). As strategic learners, students with high SRL competence tend to utilize various learning materials as opportunities for learning and development, so they may think of analytics feedback as well (Kizilcec et al., 2017). As an implication, evidenced by results and recommendations derived from students' reflective writings, incorporating more engaging and interactive features, filters, sliders, buttons and links into the analytics feedback dashboard might encourage more active engagement and motivation (Sedrakyan et al., 2019). Moreover, leveraging the interface design principles for usability and data storytelling features for clarification of any complex data in analytics feedback design can facilitate effective communication and interpretation (Martinez-Maldonado et al., 2020; Pozdniakov et al., 2023). The guidance on how to interpret the data and training on data literacy utilised inside the analytics dashboard might scaffold the engagement. Finally, it is worth mentioning that in the full-time postgraduate study program at the higher education institute, we investigated, all students' overall engagement and course performance levels were similar and high. This lack of diversity in the relatively small sample size and potential ceiling effect of overall high engagement might have also influenced the results observed. Our findings require further investigations, recognising and mitigating the limitations of the current study by implementing the suggestions, to be confirmed.

Engagement with analytics feedback enhances study behaviours but does not improve students' course performance

The second research question explored the relationship between students' engagement with analytics feedback and their course performance. In contrast to our hypothesis, a statistically significant difference was not found between the final grades of students who had high analytics feedback engagement and those who did not. The result aligned with the findings of Kaliisa et al. (2024) research, concluding that learning analytics dashboards often do not delivered on their promises on course performance. Additionally, since the assessment had two parts, we also investigated the impact of feedback on the two parts separately. The feedback seemed to have no significant impact on students' individual reflective writing activities and their critical writing activities. Due to the learning design features of the course, the individual reflective writing assignments were weekly assignments, whereas the critical writing assignment was an end-of-semester assignment that particularly measured students' content acquisition and critical thinking skills. Although there was no significant impact of analytics feedback on performance, it encouraged students to regularly study and interact with the module content over the semester as reflective writing was the one pointed out mostly. Previous research has indicated that the quality of a student's writing and their grades are closely related to the regularity of their engagement with writing tasks, rather than the amount of writing completed within a limited time period (i.e. cramming) (Suraworachet et al., 2023). Also, the differences in the nature of assignments as a result of learning design might have led to the differences observed (Rienties et al., 2015). Therefore, engagement with analytics feedback may have encouraged students to develop a regular study routine and dedicate more time and effort to their reflective writing tasks with spaced practice (Toppino & Cohen, 2010), but not necessarily have led to higher grades on these assignments. Besides, we should reconsider how the level of engagement, as defined in the ICAP framework, impacts students' performance. Whilst active engagement was evident from research question one, the absence of direct impact on performance may stipulate the necessity of higher levels of cognitive engagement, such as constructive and interactive, to observe measurable effects on performance (Fahid et al., 2021). Future studies should take into account and investigate the impact of different analytics feedback engagements on different performance assessment tasks, individual reflective writing and critical writing assignments, as well as controlling for the learning design features of the course to evaluate their specific impact. For example, a study could examine the relationship between the depth of students' engagement with analytics feedback features, 'reflection' and 'assessment', and individual reflective writing assignment, or the relationship between 'debate', 'download data' and 'assessment', and critical writing assignment.

Analytics feedback can help mitigate the typical mid-semester drop in module engagement

The third research question examined the effects of analytics feedback on the module engagement behaviours of students between the first and second half of the semester after the feedback was provided. After receiving the analytics feedback, a decrease in students' engagement with module activities was observed, irrespective of their level of self-regulated learning competence or their engagement with the analytics feedback provided. This is somehow expected as students' behavioural engagement with the module activities tends to decrease as the required workload and content difficulty increase and the novelty and motivation drop. However, whilst we observed significant differences in students' late resource clicking behaviours and total active weeks of reflective writing between the first and second half of the semester among students who have low engagement with the feedback, there were no significant differences found in the same features among those who have high engagement. Our results show that the drop in engagement behaviours of students who have high engagement with analytics feedback was less dramatic, indicating that those students better managed their engagement with the course activities (Sedrakyan et al., 2019). As students reported in their reflective writing, the analytics feedback impacted their individual reflective writing strategies and they interacted with course materials on time (Suraworachet et al., 2023). Although the feedback provided did not appear to be enough to maintain students' engagement with all the course activities in the second half of the semester, it appears to have mitigated the mid-semester engagement drop of students to a certain degree.

Effective analytics feedback, when personalised and timely, boosts motivation, self-regulation and cognitive engagement

The final research question focused on how students perceived analytics feedback regarding their learning experiences and addressed their recommendations to improve the effectiveness of feedback. The positive impact of analytics feedback on motivation, self-evaluation and self-monitoring perfectly aligns with the principles of self-regulated learning theory (Zimmerman, 1990), becoming a master of an individual's learning process. This result highlighted the importance of analytics feedback to foster such an environment for students that supports regulating their cognition, behaviours, motivation, and affect, contributing to learning and academic success (Pintrich, 2000). However, students expressed that the feedback should be more reflective of individual learning strategies. Especially, those who have high self-regulated learning competence stated that they are already aware of their learning process and tend to find feedback too broad to be relevant to them. This is exemplified by Jivet et al. (2020) study demonstrating how students' goals and self-regulated learning competence influence their interpretation and sense-making process of analytics feedback information and highlighted the need for collecting and evaluating data on how they engaged with different features to understand students' sense-making process which can result in further informing the learning design. Considering student's levels of SRL while constructing feedback may be valuable for further specifications of the feedback to be more relevant to the needs of students with different SRL competencies (Aguilar et al., 2021; Matcha et al., 2020).

An additional key recommendation to enhance analytics feedback was the content of written feedback provided along with the visualisations. It should provide more suggestions on how to improve instead of mere descriptions while explaining the rationale and feedback construction decision process (Pardo et al., 2019). For example, one student commented that besides the editing frequency, feedback should include strategies "*focused on nurturing critical thinking and enriching reflective writing depth would significantly benefit students*". These specific improvement suggestions might not only aid the regulation of learning but also make feedback feel more relevant and applicable to the learning context (Lim et al., 2021).

Another emerging recommendation was the importance of timing of analytics feedback. Students suggested that constant and strategically timed feedback, whether delivered early in the semester or every week, could enhance learning behaviours. In the literature on feedback, the question of whether formative feedback should be provided delayed or immediately has been hotly debated for years as being a powerful mechanism in learning (Hattie & Timperley, 2007). It should be determined based on task difficulty, desired learning outcomes, students' prior knowledge, retention of procedural or conceptual knowledge or promoting learning transfer (Shute, 2008). Therefore, to observe changes in behaviour, it is important to give students time to monitor and evaluate their learning process early and continually (Sedrakyan et al., 2020). The insight also compliments the ICAP framework, where timely feedback encourages students to engage actively with course content and reflect constructively on their learning.

Overall, the results of qualitative data analysis complemented our understanding by presenting how analytics feedback helped students to level up in the cognitive engagement spectrum. Students not only interacted with the feedback but also used it to reflect on and improve their learning behaviours, and constructive engagement. Additionally, recommendations about feedback and dashboard design can aid the transition between the levels of framework, for instance, passive to active and eventually to the highest level of cognitive engagement, interactive. However, we would like to note that the categorisation of features of the ICAP framework was more of an exploration rather than a rigorous test of hypotheses with a strict linear hierarchical order. Indeed, the framework holds promise for delving deeper into the levels of cognitive engagement and determining actionable steps to meet the requirements of each level, proposing valuable implications for analytics feedback provision and enhancement. Future studies can expand this research by including the interactive level cognitive engagement measures such as discussion about analytics feedback with peers or Artificial Intelligent chatbots.

Implications for analytics feedback provision and practice

To effectively leverage analytics feedback in higher education, it is crucial to recognise and cater to the diverse SRL competence among students. Feedback mechanisms should be specifically tailored to address individual learning needs, providing insights for those with lower SRL competence while challenging and confirming the strategies of more self-regulated students. This personalisation ensures that feedback is not only relevant but also promotes a sense of ownership and engagement in the learning process.

Enhancing the interface design of LA dashboards is another crucial aspect while presenting analytics feedback to students. A user-friendly and interactive interface can transform passive data reception into an engaging learning material. Analytics feedback elements such as interactive visualisations and contextual information can help clarify complex data, making it accessible and understandable to students of various competence levels. By encouraging students to interact with their feedback actively, we can promote higher levels of cognitive engagement—from active to constructive and interactive engagement as outlined in the ICAP framework. The use of such designs can make learning more engaging, as well as give students greater control over their learning processes, potentially leading to deeper insights and better academic performance.

Furthermore, the timing and relevance of feedback are essential for maximising its effectiveness. Feedback should be delivered in a way that aligns with the students' learning activities and at times when it can have the most significant impact. Strategic timing can enhance the likelihood of feedback being used effectively, as students are more likely to integrate insights into their learning processes. Additionally, continuing monitoring and adjusting the feedback based on feedback engagement data can help educators refine their feedback strategies, to remain effective in the teaching process. This dynamic approach to feedback provision can help maintain student engagement and motivation throughout their educational journey.

Limitations and future research

We recognise that this study has certain limitations that need to be acknowledged which also provide opportunities for future research. First, there were technological constraints of the current platform in providing interactive engagement opportunities for students with analytics feedback. While students could actively engage with feedback, its explanations and suggestions, and they could construct response feedback to it, there were limited interactive engagement opportunities for students, thus missing a whole dimension of the ICAP framework. Feedback is not merely a presentation of information on one's performance or understanding (Hattie & Timperley, 2007) but should allow interactive engagement for students to challenge (i.e., Open Learner Models (Bull & Kay, 2010)), make sense of and take actions on their learning processes (Carless & Boud, 2018). In addition to performance-oriented feedback, it is necessary to tailor the feedback to coordinate with students' learning goals and regulatory mechanisms to better support their development (Sedrakyan et al., 2020). The integration of scaffolding techniques, such as tooltips or step-by-step guides, can be implemented into an analytics feedback platform, empowering students to explore and utilise its full potential along with the data literacy training. Moreover, natural language processing (NLP) approaches can be implemented to further improve the platform and provide students with interactive engagement opportunities with analytics feedback. By leveraging scaffolding techniques along with NLP approaches, the platform can be enhanced to aim to facilitate students' development of self-regulation competencies, enabling them to actively engage with analytics feedback, make informed decisions, and ultimately improve performance. Second, the platform recorded student interaction logs to a certain extent, resulting in limited feedback engagement proxies presented in this study. We acknowledge that these may not comprehensively capture students' engagement with the analytics feedback, which should be further improved. Apart from log data, multi-modal data sources (i.e., eye-tracking data, performance testing or interview) could also be integrated into the results as well as shed light on how students engage with the analytics feedback through different measures. Third, the analytics visualisations of learning engagement were exploratorily proposed. They would further benefit from iterative co-design sessions with learners to improve while maintaining their pedagogical requirements (Martinez-Maldonado et al., 2015). Fourth, future research could build upon our findings by conducting a comprehensive correlational analysis to examine how specific feedback attributes, such as timeliness, content relevance, and mode of delivery relate to academic outcomes (Hattie & Timperley, 2007). While our study focused on measuring the effects of engagement with analytics feedback on academic performance, an investigation into how specific analytics feedback attributes correlate with academic metrics such as grades, assignment completion rates, and overall course performance could provide additional insights. This direction would extend the current study's focus on engagement patterns within the ICAP framework and offer a deeper understanding of analytics feedback's role in shaping academic success. Finally, although it was a ten-week-long intervention, this study was conducted in specific contexts with a relatively small sample size ($N=39$) which makes it difficult to reach the statistical power needed and cannot be generalised to other settings. A post-hoc power analysis, conducted to assess the adequacy of our sample size for robust statistical analysis, revealed limited power (estimated power < 80% at $\alpha=0.05$) to detect small to moderate effect sizes, consistent with the effects observed in this study. Given that the study was carried out in a real-world educational setting, we had little control over the sample size. Therefore, future research, including large-scale studies, is needed to study students' engagement with analytics feedback and its impact on various learning processes and outcomes to understand more about ways of providing meaningful and effective feedback for students.

Conclusion

In this study, postgraduate students' engagement with analytics feedback and its relationship to SRL competence and course performance was investigated in the context of a ten-week-long course. The results showed students with high SRL competence may engage with analytics feedback more actively compared to their low SRL competence peers. Moreover, we also observed that although analytics feedback can support students' monitoring skills to stay engaged with course activities, the engagement does not necessarily lead to significant grade improvements. Engagement with analytics feedback, self-regulated learning and the ICAP framework intersected in a rich area of study with substantial implications for learner success and educational practitioners. The findings of this study contribute to the ongoing dialogue on the efficacy of analytics feedback in higher education and ways to improve students' engagement with it. Although, analytics feedback interventions are notoriously challenging to be designed in a way that is impactful, supporting students' engagement with analytics feedback is an initial necessary, yet not sufficient, step towards achieving their impact on student learning.

Abbreviations

SRL	Self-regulated learning
LA	Learning analytics
AI	Artificial intelligence
ICAP	Interactive-Constructive-Active–Passive

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Author Contributions

All authors contributed to the development of the materials, the design of the study intervention, data analysis, and manuscript writing. All authors have read and approved the final version of the manuscript.

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Availability of data and materials

The datasets used and analysed during the current study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate

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Competing interests

The authors declare that they have no competing interests.

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