Student appreciation of data-driven feedback: A pilot study on OnTask

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Feedback plays a crucial role in student learning. Learning analytics (LA) has demonstrated potential in addressing prominent challenges with feedback practice, such as enabling timely feedback based on insights obtained from large data sets. However, there is insufficient research looking into relations between student expectations of feedback and their experience with LA-based feedback. This paper presents a pilot study that examined students' experience of LA-based feedback, offered with the OnTask system, taking into consideration the factors of students'self-efficacy and self-regulation skills. Two surveys were carried out at a Brazilian university, and the results highlighted important implications for LA-based feedback practice, including leveraging the 'partnership' between the human teacher and algorithms, and developing feedback literacy among learners.

CCS Concepts: • **Applied computing** → **Education**; • **Education** → *Computer-assisted instruction*; Data analytics.

Additional Key Words and Phrases: learning analytics, feedback, learning theories, feedback literacy, OnTask

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1 INTRODUCTION

Feedback is a crucial part of communication between students and teachers in terms of clarifying expectations, monitoring the current progress of learners, and reflecting on the trajectory towards desired learning goals [10]. However, there is robust evidence showing that higher education (HE) institutions struggle to deliver consistent, timely, and constructive feedback that meets student expectations [2, 6]. The inadequacy in delivering effective feedback to students is partly due to conflicts between an increasing focus on 'inclusiveness' and 'personalisation' in HE and yet unmatched capacity of teaching staff to produce feedback that speaks to the needs of individual students in a large cohort [27]. In recent years, research in educational data mining and learning analytics (LA) has shed light on feedback processes in this context.

LA-based feedback is commonly presented in visualisation dashboards to promote self-regulated learning skills [15, 18]. In more recent developments, LA has also been used in ways that can assist teaching staff in providing more contextualised, written feedback at scale. A successful case of this approach is the tool, OnTask, which can be linked to learning data from various sources, such as log data stored on learning management systems, attendance records, and student records, in addition to data imported manually by the instructor. OnTask uses rules in the form of 'if this then that' to help teachers compose personalised messages that are sent to large student cohorts based on parameters relevant to the course design[1] [21]. In this way, OnTask allows feedback to be generated automatically while ensuring the relevance to individual students and direct inputs from instructors.

Although success in using LA to improve student satisfaction and academic outcomes by enhancing feedback provision has been reported [1, 17, 21], this area of work is under-explored especially in the Latin American region where researchers still struggle to move LA from the experimental phase to operation [7]. In order to increase the capacity of a Brazilian HE institution to adopt LA, a pilot study was conducted based on the use of OnTask in three undergraduate courses. So far, existing literature about OnTask has looked at student satisfaction [21], student experience through qualitative insights [16], and the association between feedback experience and learning outcomes [17]. Little research has explored areas such as comparing student expectations of feedback and their experience with OnTask, or looked at the relations between psychological factors (e.g., self-regulation and self-efficacy) and OnTask feedback experience. Our study is intended to address these gaps and this paper presents the results of our first piloting phase, which involved two surveys – one was distributed before OnTask was introduced and the other after. The aim of this phase was to evaluate students' experience of OnTask feedback taking into consideration the factors of students' self-efficacy and self-regulation skills. To this end, our investigation was guided by three questions:

- RQ1: Has students' overall experience with feedback improved after OnTask was introduced?
- RQ2: How might students' self-efficacy and self-regulation associate with how they perceive feedback?
- RQ3: What are the gaps between the perceived importance of feedback and student experience with the feedback generated by OnTask?

2 LITERATURE REVIEW

2.1 Learning analytics in Latin America

Over the past two decades, there has been a significant increase in enrolment in Latin American HE institutions. However, persistent inequality in the society and related challenges in education have surfaced an urgent need to transform the sector to assure educational quality and improve the support to a student population that is increasingly diverse in their socio-economic backgrounds [8]. As part of the HE expansion in Latin America, Brazil was among the countries with the highest increase in the number of public and private HE institutions, and had the highest increase in academic programmes between 2000 and 2013 [9]. Despite the expansion of HE in Brazil, the completion rate within the theoretical duration of an undergraduate programme (4 or 5 years) is only 33%, compared to an average of 39% completion rate in the rest of the world (OECD, 2019).

With the increasing adoption of digital technologies in educational contexts, researchers have identified LA as a strategic approach to addressing the challenges in Latin American HE by providing updated or real-time information about a learner's path or risks of dropping out, and prompting timely interventions [8]. A systematic literature review shows that current work around LA in this region focuses on HE (89%), though the development of LA is still at a nascent stage, i.e., at a phase of experimenting with theoretical ideas rather than working on practical applications [7].

A notable effort to increase the sector's readiness for LA in Latin America is the commencement of the LALA project (Building Capacity to Use Learning Analytics to Improve Higher Education in Latin America) [23]. Through a series of consultations with multiple stakeholders, the project identified two important areas of work: defining data protection policies and procedures and strengthening information systems to allow reliable data integration and the delivery of

[1]Details about OnTask are available at: https://www.ontasklearning.org/

timely feedback [12]. Moreover, the project observed a pressing need for quality feedback and timely support to ensure learning success and address the attainment gaps between students with different socio-economic backgrounds [13].

Similarly, an earlier study on perceptions and expectations about LA in a Brazilian HE institution reveals a desire among the students for timely, frequent, and personalised feedback [25]. The authors identified a number of issues with existing feedback provision. For example, the timing of feedback did not offer opportunities for improvement; and grades-only feedback or generic feedback based on replicated written explanations from the textbooks failed to help students bridge the gap between the current progress and desired standards. Based on the unanimous views among the students involved in this study, it is clear that enhancing educational quality with LA needs to first focus on improving feedback quality and experience.

Despite the rising interest in adopting LA to tackle key challenges in HE in Latin America, some of the prominent barriers to field development and adoption are limited researchers in LA in the region, low numbers of early adopters, insufficient understanding of LA, inadequate consultations with key stakeholders, and unclear policy procedures to ensure algorithmic accountability [8, 12]. The pilot study reported in this paper thus sets out to engage teachers and students directly in the use of LA on feedback provision, with the aim to scale the conversation up to the senior management team at the university and to the wider research community in the region and the globe.

2.2 Understanding feedback from learning theories

Feedback plays a crucial role in learning success and the overall learning experience. As such, feedback provision has been an important quality assurance indicator of HE [6]. When evaluating feedback quality, it is important to understand the learning theories that underpin the feedback practice so as to identify appropriate indicators. A systematic literature review by Thurlings et al. [28] identified key characteristics of feedback approaches based on different learning theories: a behaviourist approach to feedback highlights a linear process where certain behaviour can be triggered as a result of given feedback; a cognitivist approach to feedback highlights the cognitive process in which a learner processes and decodes the meanings of received feedback, thus leading to certain outcomes; a social cultural approach highlights interactions between the teacher and the learner in which the former guides the latter into a 'zone of proximal development' – a phase where learners can achieve a certain outcome with support; a meta cognitivist approach emphasises a 'learning to learn' process (e.g., self-regulated learning) in which feedback forms a loop of cognitive development, i.e., the learner continues to update their own cognitive state; and a social constructivist approach similarly emphasises a feedback loop where the learner constructs new knowledge based on interactions with the teacher or peers through feedback and thus continues to update their prior knowledge.

Early LA feedback models have primarily taken a behaviourist approach, especially those that operate as 'alerts', e.g., Perdue Course Signals [1]. Recently, more researchers have reflected on the ineffectiveness of LA feedback taking the viewpoints of other learning theories. For example, some researchers have reflected on the struggles that learners experience in comprehending visual representations of LA-based feedback [22](cognitivist approach); others have taken a meta cognitivist approach and call the attention to ground LA tool design in self-regulated theories [14, 18]. Similarly, the design of OnTask is partly based on a meta cognitivist approach, emphasising the role of multiple agents (teacher, learner, and algorithm) in an iterative feedback loop, which is sustained by both internal (products of self-monitoring) and external feedback (algorithm-assisted human feedback) [20]. Moreover, by leveraging the teacher's efforts with support of algorithms, OnTask emphasises 'collaboration' between the two agents to provide personalised feedback at scale. It is expected that through interacting with the semi-automated feedback, learners will receive teacher guidance that is relevant to their personal development. Thus, to understand the effectiveness of OnTask feedback, we need to incorporate the perspective of a social cultural approach.

Both the meta cognitivist approach and the social cultural approach highlight the role of the learner as an active agent who decodes feedback messages and translates the meanings into a particular outcome, which reflects the development of the learner's knowledge, beliefs, or skills [3, 28]. Thus, evaluations of OnTask feedback cannot simply see feedback as information or a product, nor can evaluations treat feedback as one-way teacher transmission. Instead, evaluations of OnTask need to see feedback as a dialogic processes in which expectations are clarified, and meanings are interpreted and negotiated [6]. In this process, students are expected to exercise their feedback literacy by transforming external feedback into internal feedback and deploying it in a productive way [4].

According to Carless and Boud [5, p. 1316], feedback literacy is 'the understandings, capacities and dispositions needed to make sense of information and use it to enhance work or learning strategies'. They propose a model of four inter-related features to describe student feedback literacy: appreciating feedback, making judgments, managing affect, and taking action. In particular, the feature of appreciating feedback highlights a recognition of the value of feedback in learning and an awareness of the learner's own role in taking productive action in response to feedback [4]. Similarly, Winstone et al. [31] argue that the effectiveness of feedback for learners not only depends on their comprehension of the information, but also the awareness of the function of feedback, the motivation to act on feedback, and the perception of one's agency to enable changes. Thus, when designing approaches to evaluate student experience with OnTask feedback in the current study, it was deemed essential to consider existing dispositions of students, including their perceived value of feedback in learning, their self-regulated learning skills, and self-efficacy.

3 METHODOLOGY

3.1 Survey design

The pre-OnTask survey contains 26 questions measured at a 7-point Likert scale; 17 of these questions evaluated student experience with existing course feedback, i.e., performance of course feedback, and 9 questions evaluated their general attitudes towards feedback. The survey design draws on a number of feedback models Butler and Winne [3], Carless and Boud [5], Hattie and Timperley [10], Nicol and Macfarlane-Dick [19], Pardo [20], covering the following themes: overall experience, knowledge & beliefs, domain knowledge, strategy knowledge, motivational beliefs, goal-setting, tactics & strategies, mental and behavioural products, self-monitoring, teacher-student interactions, and feedback appreciation/ awareness (http://bit.ly/2m9BkKH). The post-OnTask survey includes the 17 questions of course feedback performance from the pre-OnTask survey at a 7-point Likert scale, forming the 'performance' scale (performance of OnTask feedback). In addition, we added 17 more questions to the post-OnTask survey to evaluate student perceptions of the importance of different aspects of feedback. These questions form the 'importance' scale (importance of feedback), and each question is designed to match the corresponding question of the 'performance' scale (https://bit.ly/2THGXwS). The post-OnTask survey also includes 7 items of self-efficacy scale and 12 items of the self-regulation scale of the Motivated Strategies for Learning Questionnaire (MSLQ)[24]. Both the pre- and post-OnTask surveys were first developed in English and later translated into Brazilian Portuguese by a native speaker.

3.2 Study context

The survey was distributed among students from three courses at the Computer Science Department of a Brazilian public university. Two of the courses targeted undergraduate students from first and second year, each focusing on topics related to software engineering (SE) and introduction to virtual learning environments (VLE) respectively. The third course focused on text mining (TM) and it was offered for the third and fourth year but was also open for postgraduate students to enrol. All of these courses were delivered face-to-face with a similar course design, i.e., the topics were divided into 14 weeks with an activity at the end of each week.

In Brazilian face-to-face courses, instructors usually provide oral feedback in class instead of sending written messages. Thus, for the initial seven weeks of the courses, the instructors in this study continued the same feedback practice each week. From week 8, the instructors adopted OnTask to write personalised feedback messages until the end of the course (seven weeks in total). They sent a weekly feedback message based on a quiz carried out at the end of each week. It is important to note that most of the instructors were new to OnTask. The lack of experience with the tool could have influenced the feedback messages sent to students, consequently the outcomes of the survey.

The questionnaires were sent to a total number of 112 students. Instructors shared the pre-OnTask survey after the end of the 7th week of the course (mid-October 2019), and the post-OnTask survey after the 14th week, which was before the final exam (mid-December 2019). Participation in the survey was anonymous and voluntary, though a prize draw of two GitHub vouchers (worth 30 Brazilian reais each) was offered as an incentive for the participation in each survey. In total, 61 students (response rate=54.4%) and 48 students (response rate=42.8%) responded to the pre-OnTask and post-OnTask surveys, respectively. Table 1 summarizes the collected information about the participants.

Table 1. Participant Information.

Survey	Genre	Level	Course
Pre	Male: 55; Female: 6; Others: 0	Undergraduate: 57; Master: 4	SE: 13; VLE: 10; TM: 38
Post	Male: 40; Female: 6; Others: 1	Undergraduate: 45; Master: 3	SE: 0; VLE: 13; TM: 35

3.3 Analysis approaches

We carried out an exploratory data analysis to identify emerging patterns in student perceptions of the importance of feedback and the performance of feedback pre- and post the introduction of OnTask, for different groups of students. Considering the small sample size, the exploration of data focuses on using descriptive statistics and visualising the distribution of relevant variables. To address RQ1, we used boxplots to investigate the overall students' perception of feedback performance before and after the introduction of OnTask. This analysis focused on exploring the distribution of the students' answers to the 17 questions the two surveys had in common, as indicated in Section 3.1.

To address RQ2, a three-step analysis was performed. First, we computed the students' self-efficacy and self-regulation scores following the recommendations proposed by Pintrich et al. [24] on how to analyse the MSQL questionnaire. Next, we grouped the students based on their responses to the self-efficacy and self-regulation questions provided in the post-OnTask survey. The clustering process included a silhouette analysis to identify the optimal number of groups; then, the traditional k-means algorithm was applied[32]. Second, we applied the Weight of Evidence (WoE) method [30] to select those questions from the feedback importance and performance scales which were the most distinctive between the identified student groups. WoE ranks features (i.e., students' answers) according to their importance to the prediction of the dependent variable (i.e., groups of students). Accordingly, we used WoE to estimate the predictive power of the students' answers about their perceptions of feedback importance and the performance of the feedback provided by OnTask (independent variables) in relation to the clusters generated in the previous step (dependent variable). Students' responses to the questions that proved to have high predictive power were used to further examine the student groups in a way similar to the one applied for the first research question, namely using boxplots to examine the distribution of the students answers.

Finally, to address RQ3, we explored the differences in the students' expectations of feedback and experience with OnTask feedback. The main goal of this final analysis was to examine the gap between feedback expectations (based on the importance ratings) and the experience with OnTask feedback (the performance ratings) using the same groups of students identified through clustering in the context of RQ2. In particular, we plotted mean values of students' answers to feedback importance questions against mean values of their answers to feedback performance questions, and we did that separately for the two student groups. That allowed us to get an overall view into how much expectations and experience with feedback were aligned, while controlling for the students' self-reported self-efficacy and self-regulation.

4 RESULTS

In response to our fist research question, we did a visual exploratory analysis of the students' responses to the questions related to the perceived performance of feedback before (pre-OnTask survey) and after (post-OnTask survey) the introduction of OnTask. Figure 1 presents the distribution of scores per question on both surveys. The figure shows that the students' perceptions of the quality of the feedback were generally very positive. The average score per question was between 4.77 (Q11) and 5.80 (Q1) on the pre-OnTask survey and between 4.85 (Q17) and 5.92 (Q2) on the post-OnTask survey. There are several questions with similar medians and the overall distribution. Pre-OnTask survey scores were higher for questions Q7 ("The course feedback that I have received shows me my current progress"), Q9 ("... deepens my domain knowledge"), and Q13 ("...helps me develop and adjust my learning strategies"), compared to the students' responses to the same questions on the post-OnTask survey. On the other hand, when compared to pre-OnTask survey responses, post-OnTask survey scores were somewhat higher only for questions Q2 ("...makes me feel that my instructor cares about me") and Q11 ("...helps me build my self-confidence").

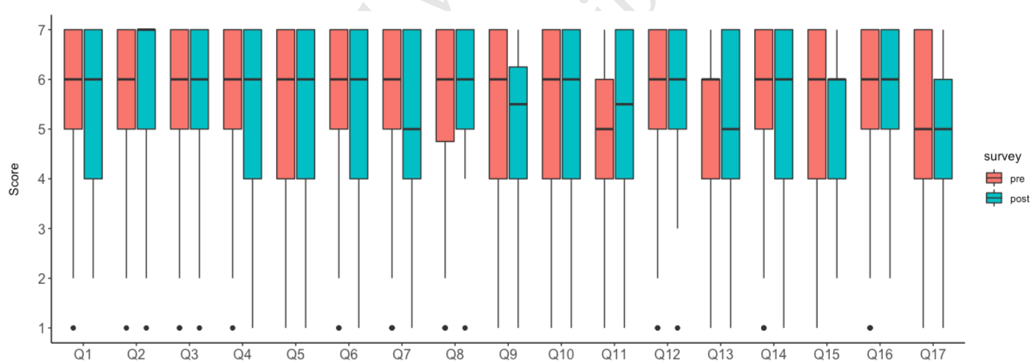

Fig. 1. Boxplots of responses about the performance of feedback in the pre-OnTask and post-OnTask surveys

Before clustering the students, as required for our second research question, a silhouette analysis was performed. It indicated that two was the best value for the number of clusters, reaching a silhouette of 0.48. Figure 2 shows the results of the clustering process, where the axes represent self-efficacy and self-regulation scores (obtained from the corresponding MSLQ sub-scales). The figure suggests that the students reported higher scores for self-efficacy than for self-regulation. It also suggests that, when compared to the students in Cluster 1 (red), students in Cluster 2 (green) tended to report higher values on both scales analysed. The students in Cluster 2 concentrated their scores in 5-7 and 3.5-6.5 for self-efficacy and self-regulation, respectively. On the other hand, Cluster 1 presents scores with higher spread: 1.5-6 for self-efficacy and 2-5.5 for self-regulation.

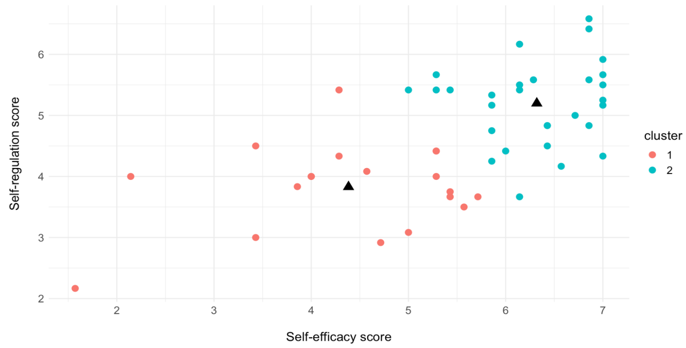

Fig. 2. Student clusters based on their answers to the MSLQ self-efficacy and self-regulation questions (each node represents a student and the triangles are the means of the groups).

The Weight of Evidence (WoE) technique suggested that questions Q6 and Q7 from the feedback importance scale (importance of feedback in learning) and questions Q4, Q14, Q15, and Q16 related to the performance of feedback had a strong predictive power. To examine the two identified student groups in terms of their responses to these questions, we generated violin plots, as shown on Figure 3. The figure reveals that, when the two clusters are compared, the students in Cluster 2 (high self-efficacy, high self-regulation) had higher scores on all the questions except for the performance scale of Q4 ("The frequency of the course feedback is appropriate"). Moreover, the scores of cluster 1 were generally more spread than those of cluster 2.

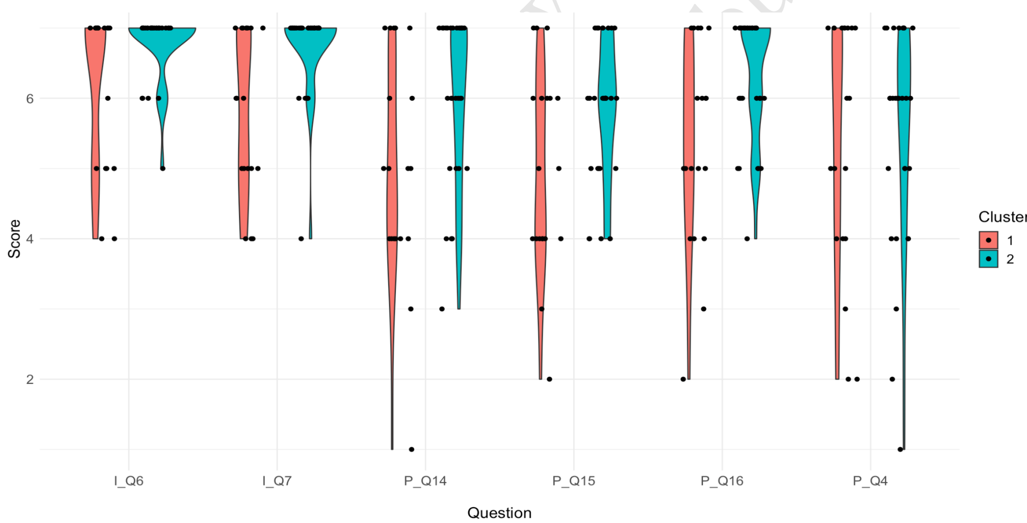

Fig. 3. Violin plots of the student's clusters in terms of the strongly predictive question (WoE) (the violins represent the distribution of the students' scores on the given questions).

To address our third research question, we graphed the average scores on questions related to the importance and performance of the feedback, separately for students in Clusters 1 and 2. Figures 4 and 5 show that student perceptions of the importance of feedback is generally higher than their experience with OnTask feedback (perceived performance), and scores among students in Cluster 2 are less spread than those among Cluster 1. Moreover, students with higher

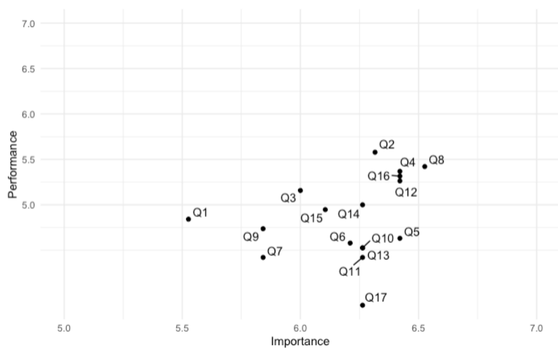

Fig. 4. The average scores for feedback importance and performance as perceived by students in cluster 1

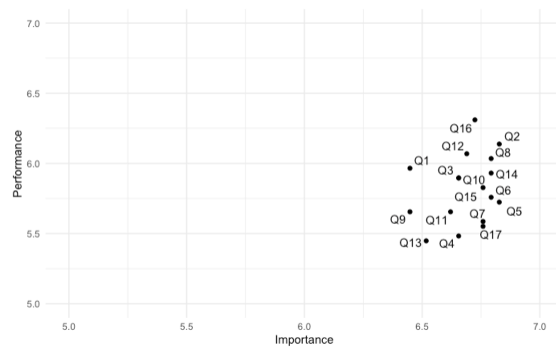

Fig. 5. The average scores for feedback importance and performance as perceived by students in cluster 2

self-efficacy and self-regulation scores (Cluster 2) demonstrated higher appreciation of feedback importance and more positive experience with OnTask compared to the students in Cluster 1. On the other hand, Figure 4 shows that Q17 (feedback identifies the learner's strengths and weakness) may be an area that is worth dedicating more effort to, especially among students with lower self-efficacy and self-regulation, as it received a high average rating on its importance but the lowest rating on OnTask performance.

5 DISCUSSION

This pilot study set out to evaluate student experience with OnTask-generated feedback and compared that with the perceived importance of feedback in learning. In response to RQ1 (*Has students' overall experience with feedback improved after OnTask was introduced?*), we found that the two items that scored higher in the post-OnTask survey, compared to the same items in the pre-OnTask survey, are both related to the affect-level (relationship with the teacher and self confidence), whereas the three items that scored lower are related to cognitive (domain knowledge) and meta-cognitive development (self-regulated learning). In response to RQ2 (*How might students' self-efficacy and self-regulation associate with how they perceive feedback?*), we found that students with high self-efficacy and self-regulation (Cluster 2) tended to have higher appreciation of feedback and more positive experience with OnTask compared to the other students. This phenomenon was also observed when inspecting the questions with strong predictive power of group membership (Figure 3). We took a similar approach to inspect RQ3 (*What are the gaps between the perceived importance of feedback and student experience with the feedback generated by OnTask?*), and found that both clusters of students rated the importance of feedback higher than OnTask's performance in each of the inspected aspects. Nevertheless, all the items of the 7-point performance scale received an average rating higher than 5, showing high satisfaction with the feedback received through OnTask. In terms of areas that may require particular attention in the future implementation of OnTask, frequency of feedback and learning strategy development scored lower than other aspects among students with higher self-efficacy and self-regulation (Cluster 2), and the 'feeding back' aspect of feedback (identifying the learner's strengths and weakness) particularly requires attention when composing feedback for students with lower self-efficacy and self-regulation (Cluster 1).

Overall, this pilot study has a number of important implications for LA-based feedback. Firstly, the comparison of student feedback experience before and after OnTask showed that despite a certain level of automation, OnTask generated feedback was able to facilitate a relational process, which is key to continuous dialogue between the teacher and the student Price et al. [26] as well as to keep the latter motivated [11]. This may be due to the 'partnership' between the teacher and the algorithms in the creation of feedback through OnTask. In other words, this pilot study suggests that by leveraging human elements, OnTask can address students' and teachers' concerns about LA replacing human interaction and make up for what dichotomous metrics cannot capture with the teacher's professional expertise and local knowledge in feedback provision [29]. Secondly, the fact that OnTask scored lower in assisting the students to develop domain knowledge and self-regulated learning and to identify the learner's weakness and strengths suggests a need to inspect further both the teacher's feedback literacy and the parameters adopted to compose feedback on OnTask. As also mentioned in the methodology, the teacher's familiarity with the tool may also affect the quality of the feedback.

Thirdly, the fact that students with high self-efficacy and self-regulation had higher expectations and more positive experience with feedback concurs with the literature that the dispositions of learners play a key role in their engagement with feedback, and that the appreciation of feedback is a sign of emerging feedback literacy [5]. Thus, it is important that strategies for feedback practice provide opportunities to build students up in this area, and that evaluations of feedback quality recognise varying feedback literacy among students, especially when evaluations are based on students' perceptions [4]. For example, although all the students rated the frequency of OnTask feedback similarly on the performance scale (Q4), the students with high self-efficacy and self-regulation (Cluster 2) attributed higher importance to this aspect (Figures 4 & 5). This gap should not be interpreted as OnTask under-performing, as the results clearly showed a high rating of the performance. Instead, the gap shows an endeavour among a group of students who demonstrated growing feedback literacy through their desire for improvement on the basis of feedback [5] and their willingness to invest efforts in seeking and dealing with feedback [10].

6 LIMITATIONS AND FUTURE WORK

Due to the pilot nature of the study, we took an exploratory approach to investigate data collected from a small sample. Although the findings only present views of a relatively small student group, they provide important implications in terms of human-machine interactions, feedback evaluations, and areas of improvement specific to OnTask adoption that are worth further studies. Our future work will explore these areas further through focus group interviews.

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