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Examining the relationship between reflective writing behaviour and self-regulated learning competence: A time-series analysis

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Abstract. Self-Regulated Learning (SRL) competence is imperative to academic achievement. For reflective academic writing tasks, which are common for university assessments, this is especially the case since students are often required to plan the task independently to be successful. The purpose of the current study was to examine different reflection behaviours of postgraduate students that were required to reflect on individual tasks over a fifteen-week-long higher education course. Forty students participated in a standardised questionnaire at the beginning of the course to assess their SRL competence and then participated in weekly individual reflection tasks on Google Docs. We examined students' reflective writing behaviours based on time-series and correlation analysis of fine-grained data retrieved from Google Docs. More specifically, reflection behaviours between students with high SRL and low SRL competence were investigated. The results show that students with high SRL competence tend to reflect more frequently and more systematically than students with low SRL competence. Even though no statistically significant difference in academic performance between the two groups was found, there were statistical correlations between academic performance and individual reflective writing behaviours. We conclude the paper with a discussion on the insights into the temporal reflection patterns of different SRL competence student clusters, the impact of these behaviours on students' academic performance, and potential suggestions for appropriate support for students with different levels of SRL.

Keywords: Self-Regulated Learning, time series analysis, writing analytics, seasonal decomposition, writing behaviours

1 Introduction and Background

In contrast to many face-to-face learning scenarios, in online learning students are not as restricted in managing their schedules and learning process such as what to study, when to study and for how long [1]. In this aspect, students who are successful in their learning appear to be those who can control their learning process and take an active role in achieving their academic goals [2]. These students are generally referred to as self-regulated learners. The theory of Self-Regulated Learning (SRL) views learning as a self-monitoring and planning process where students monitor the effectiveness of

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their learning methods and adjust them to their needs [3]. There are different theoretical models of SRL that describe regulation phases during learning situations, such as the one proposed by Zimmerman [4] and Winne and Hadwin [5]. Despite the difference in their theoretical backgrounds, there are common phases within them: preparation (forethought), performance and appraisal (self-reflection) [6]. Throughout these phases, students may adopt different strategies for tackling the challenges posed by the learning task. The strategies could be grouped into time management, metacognition, effort regulation, critical thinking, rehearsal, elaboration, organization, peer-to-peer learning and help-seeking [1]. Literature shows that planning (i.e., organization, goal setting, effort regulation, etc.) during the forethought phase and following a good time management strategy during the performance phase are important aspects of SRL that can lead to an improvement in learning [7]. Many studies in the literature analyse how the level of student regulation is related to their performance. For instance, in the study by Broadbent [8] the authors highlighted the importance of time management and elaboration during a MOOC course and a positive relationship between the SRL strategies used by the students and their grades. In another study by Tempeelar, Rienties, and Nguyen [9], it was found that students who use help-seeking strategies by using examples with worked-out solutions achieve higher scores.

A significant approach to studying Self-Regulated Learning is through writing reflections. Reflection is an essential learning process by consciously pondering upon past experience to evaluate and gain new insights which could shape better future actions [10]. As noted by Schunk and Zimmerman [11], self-reflective practices allow students to i) assess their learning progress and the effectiveness of their strategies modify such practices when needed and ii) adjust environmental and social factors to improve their learning settings. For instance, Baggetun and Wasson's study [12] analyses students' use of weblogs for open-ended writing. Specifically, it looks at how SRL manifested in these writings based on four categories: reflection, motivation, ownership, and customization and categorization. The study suggested that weblogging can contribute to SRL in several ways: allowing students to publicly reflect on a topic and initiate conversations about it; building personal knowledge bases by providing relevant links on certain topics; and, providing solutions to challenges that they have encountered. In addition, during the study carried out by Nückles, Hübner and Renkl [13], the authors supported the writing process using prompts to encourage SRL while drafting learning protocols. Learning protocols are artefacts created by students where they are instructed to write down their reflections on previously presented learning contents. Moreover, students should ask themselves what they did not understand and what they could do to improve it. Students received different types of prompts: cognitive prompts, metacognitive prompts and mixed prompts with and without planning of remedial strategies. The results show that prompts are very effective in stimulating cognitive and metacognitive strategies. Providing students with prompts on organisation, elaboration, monitoring and planning increases the use of strategies related to these phases of regulation and improves students' learning protocols.

As mentioned above, engaging in writing reflection practices about the learning process may provide benefits for learners, and supporting students during this process by enhancing their SRL strategies can improve their results. Unfortunately, it is very

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difficult for teachers to gain insight into their students' writing process, which could be one of the reasons why they only provide feedback on the final product [14]. Therefore, it is necessary to use tools that can provide meaningful information about the students' writing process to i) understand students' reflective writing behaviours, and ii) provide timely support to the students [14]. There are many tools developed to support writing instruction and assessment including automated essay scoring systems to assess writing quality [15], automated writing evaluation systems to provide feedback and correction suggestions [16] and intelligent tutoring systems that can provide automated feedback and provoke students' reflection through questions [17]. Even so, most of the tools are research-based and therefore, not pervasively available. Moreover, educators and students might lack experience using educational technology tools that are not familiar to them or might find it challenges to setting up and implementing these tools in real-world settings.

In this study, we applied time-series analysis to examine the temporal reflective writing behaviour of students with varying SRL competence levels (according to their self-reported data) to better understand their reflection processes. Contrary to most previous research, we explored students' reflective writing behaviours using trace data from a commonly used, user-friendly and easily accessible cloud platform (Google Docs). The supportive insights from reflection behaviours could generate a model to predict students' performance and therefore pave the way towards educational technology solutions that can provide personalised support and trigger timely interventions aimed at students with different levels of SRL competence. As noted by Zimmerman [18], there are different profiles of regulation among students (i.e., experts and novices) and it is possible to support them according to their regulation level. More specifically, this study aims to answer the following main research questions:

RQ1) How do students with different levels of SRL competence approach their reflective writing tasks?

RQ2) To what extent do students with high SRL competence approach the individual reflective writing tasks more systematically?

RQ3) What is the relationship between students' individual reflective writing behaviours and their performance?

2 Context of Study

2.1 Educational Context

The study was conducted within an online selective MA module called 'Design and Use of Technology for Education' (DUTE). Over the 15-week course, students were introduced to topics related to educational technology design and had to collaboratively work on their chosen educational challenges and propose a technological solution to overcome them. To illustrate, they might select a challenge of an assessment at scale and propose artificial intelligence (AI) as a solution. Within each week, students had to 1) read the weekly materials on the weekends, 2) participate in the class debate expectedly by Monday, 3) study lectures released on Tuesday, 4) organize an online weekly group meeting preferable between Wednesday and Friday to discuss their design case, and 5) individually reflect on what they have learnt, what went well and what needed to be improved via a single Google Docs every week, preferably before the next week started. This study focused on the 5th weekly task (Individual reflective writing task). The module started on 28 Sep (week 1) to 7 Dec 2020 (week 10) with a pause in the middle from 9-15 Nov 2020 (after week 6) known as the reading week. The final submission was on 11 Jan 2021 (5 weeks later). There were nine weeks in total for students to reflect upon since the first week was an orientation week. This reflection part accounted for 40% of the students' overall grade. The feedback was provided twice: formative feedback on the use of evidence, tone, misconceptions, suggestion for improvement and a balance between personal experience and academic practice at mid-term (week 6) and summative feedback of the final grade at the end. Both types of feedbacks were provided and marked by three reviewers. For the final grade, thirty-five percent of the students were double marked, achieving high inter-rater reliability (96%).

Participants. There were 54 students enrolled in the course but only 42 students completed it. They were mixed gender (65% female vs. 35% male), varied backgrounds from pedagogy (60%), multidisciplinary (20%), technology (5%) to others (14%), and based in different time zones. On average, students reported moderate familiarity with the collaborative writing tool used in this study (Google Docs). At the beginning of the study, ethical approval was received through the institutional processes.

2.2 Data Collection Tools

As mentioned above, we decided to collect student's individual reflective writing behaviours using Google Docs (http://docs.google.com). It is an online collaborative web-based platform for word processing. There are various platforms for reflective writing tasks such as Input Log. However, installation and activation are required and this might not be practical for real-time teaching and learning contexts where reflective writing happens at students' personal computers. Google Docs, on the other hand, can keep track of every change by chronologically storing versions of the file (called 'revisions') in the cloud database. Each revision has a unique and auto-incremental identification number. However, Google Docs occasionally merges revisions for space optimization purposes[1] which results in minor changes or some revisions lost. Moreover, Google Docs stores revision history as a file that requires pre-processing to extract changes but in combination with Draftback (http://draftback.com), an open-sourced Chrome extension, it can offer extracted data and save processing time. As a result, given the popularity, the accessible analytics and student and educators' familiarity with it, students were invited to reflect weekly on Google Docs which were processed with Draftback for generating analytics on students' writing behaviours.

Draftback provides a statistical summary of the writing sessions and visualizations, namely a timeline of the activity and change locations in the document (see Fig. 1). Since this plugin is open-sourced, we modified the extension to be able to export the extracted data in the csv format for further analysis. Draftback data contained information about: (1) type—of change made whether the contents were inserted or deleted, (2) starting index—of the document in which the contents were inserted/deleted, (3) ending index—of the document in which the contents were

[1] https://developers.google.com/drive/api/v3/change-overview

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inserted/deleted, (4) string—the actual contents that were inserted but this field is blank when the contents were deleted, (5) revision number—an incremental number recorded by Google Docs to refer to a particular change, (6) user ID—Google account ID of the person who made the change, and (7) timestamp—recorded time of when the change was made.

Fig. 1. Statistical summary and visualization provided by Draftback. The top part shows the timeline of the activity (red dots represent editing actions and the blue shade refers to the document length) whereas the second part shows the edited location within the document. The bottom part contains a summary of the writing sessions.

2.3 SRL Questionnaire and Clustering students according to their SRL Competence

At the beginning of the module, students were asked to fill in a standardised self-report questionnaire about their SRL levels. Four aspects of SRL namely goal-setting (GS), effort (E), self-efficacy (SE) and persistence (P) were shown to be together accounted for the highest variance of learning performance in a well-validated meta-analysis of SRL and academic performance [19]. Questionnaire items were then selectively gathered from GS [20], E and P [21] and SE [22] to maintain optimum length and coverage of SRL dimensions and were adapted accordingly to the context. The inter-item reliability was tested per dimension (Cronbach' Alpha: GS = 0.796, E= 0.879, P=0.891, SE=0.902). Students' scores on these dimensions were clustered with the K-means clustering approach [23] to categorise students with different levels of SRL competence. To maximize the average centroid distance with high interpretability of the clusters, three clusters (average centroid distance =-0.674) were selected: (1) high SRL cluster (25 students), (2) medium persistence & effort, low goal setting & self-efficacy group (5 students), and (3) medium goal setting & self-efficacy, low persistence & effort group (10 students). Similar to previous SRL competence comparison studies in the field [24], we merged clusters 2 and 3 into the low competence SRL group and created one high competence SRL cluster (25 students) and one low SRL competence students (15 students).

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3 Methodology

3.1 Pre-processing

Out of 42 students, 2 students were excluded because they did not submit the reflections via Google Docs. As a result, 40 students remained for processing. Another three students submitted the weekly reflections through multiple Google Docs, thus merging was performed. Additionally, the changes that did not belong to the students (e.g., the reviewer accidentally edited the document) or the changes that were made after the submission date, were filtered out. In the end, the resulting dataset described approximately 600000 editing actions (revisions) in total.

3.2 Derived Features

Two datasets were created to be investigated: the 'Activity' dataset composed of the actual changes that students have made and timestamps, 'Student' dataset contained information related to students, their SRL level and their grade. For each editing action described in the 'Activity' dataset, two features were added. By integrating timestamp and students' timezones, we inferred (1) DayOfWeek_local—day of the week in which the change happened at the student's local timezone. By considering the type of changes, starting index and ending index, (2) strCount—number of letters added or deleted was counted regardless of the change types. For individual students, seven features were derived: (1) TotalRev— number of total revisions, (2) FinalStringCount—number of strings in the final document, (3) AvgRevPerDay—the average number of revisions made per day, (4) AvgStrCountPerDay—the average number of strings added/deleted per day, (5) TotalActiveDay—number of days that students have made changes (possible 99 days), (6) AvgStrCountPerWeek—the average number of strings added/deleted per week, and (7) TotalActiveWeek—number of weeks that students have made changes (possible 15 weeks). Apart from the two datasets, a time-series 'Date' was created. It has dates as indexes (from the first day of the course to the submission date) and clusters as columns: all students, students with high SRL competence (cluster 1) and students with low SRL competence (cluster 2). This time-series data contained an average number of strings added or deleted per day (AvgStringCountPerDay) for comparison across clusters.

3.3 Time series analysis of students' reflective writing behaviours

To answer the research questions posed, we needed an analysis approach to explore the commonalities and differences between different clusters of students' writing behaviours, and potentially build models that would help us predict their future outcomes. Such explorations are particularly difficult for time-dependent data. In this study's context as students were free to reflect at any particular point in time, these voluntary and time-dependent behaviours can most appropriately be explored using time series analysis [25]. Time series analysis is very common for economic forecasting yet rarely implemented in learning sciences and education despite the time-dependent characteristics of the collected data [26]. Compared to other common techniques in social sciences such as regression analysis, time series analysis provides an opportunity to explore time-dependent behaviours such as long-term trends or short-term fluctuation as seasonality which could further help to identify the causes of the temporal

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patterns. Two major characteristics of time series data are trend and seasonality. Trend refers to a long-term changing direction of the data. While an upward trend refers to an increasing mean over time, a downward trend conversely refers to a decreasing mean over time. On the other hand, Seasonality is a recurrent short-term pattern found over a fixed period of time. Concerning the research questions: RQ1) How do students with different levels of SRL competence approach their reflective writing tasks?, trends of the reflection behaviours at multiple frequencies (e.g., day of the week and over the period of observation) will be explored. For the second research question: RQ2) To what extent do students with high SRL competence approach the individual reflective writing tasks more systematically?, seasonality will be extracted and investigated. For the final research question, RQ3) What is the relationship between students' individual reflective writing behaviours and their performance?, a correlation analysis will be used.

4 Results

4.1 Overall individual reflective writing behaviours

To observe the overall reflection behaviours more clearly, the trend was extracted from the time series data across clusters using 7-day and 30-day rolling means as shown in Fig. 2. Visual inspection of the average string count per day showed a steady trend across 14 weeks and increased exponentially towards the final week. Whereas the trend plot of cluster 1 was steady, cluster 2's trend showed higher variance and a distinct trend especially a seasonal increase during week 9.

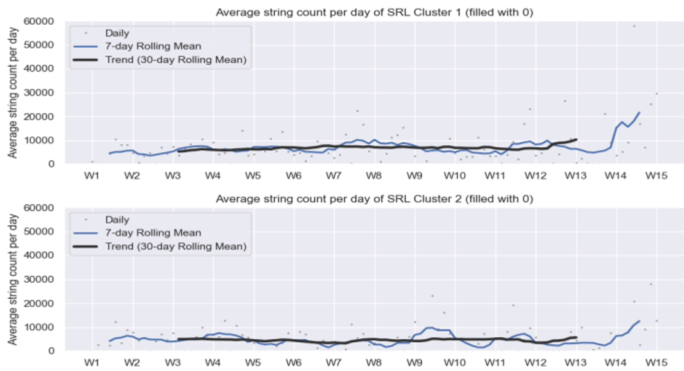

Fig. 2. Plot of Average String Count Per Day, 7-day and 30-day rolling mean of cluster 1 and 2

To investigate further, the average string count per day across 15 weeks and the two clusters are compared in Fig. 3. This analysis confirmed that the trend of cluster 1 tends to be steadier. On the contrary, cluster 2 revealed a different trend with lower number of reflections (denoted by the sparser number of asterisks) and a lower number of edited contents (denoted by the lower magnitude) in general. More specifically, cluster 1 showed more editing frequency (93 times) with a larger amount of edited contents (M=7927.07) as compared to cluster 2 (70 times, M=6945.93). During the 10-week studying period, cluster 1 reached its local peak on week 7 (the week after the midterm feedback) whereas cluster 2 followingly reached this peak on week 9. Considering the break period before the final submission, the global maxima was located at the end of the course (Week 14) in any group.

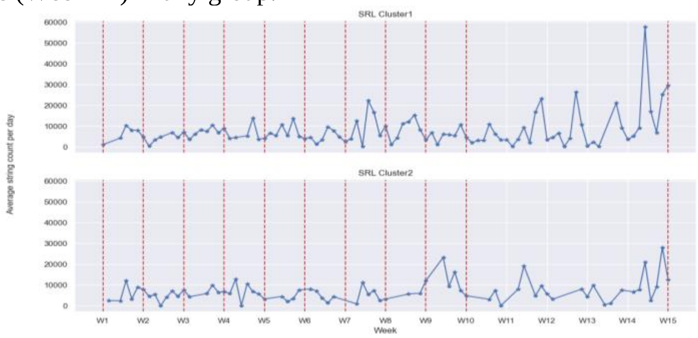

Fig. 3. Average string count per day across different clusters in which the multiple dotted red lines represent Monday of the week, the final dotted red line refers to the final submission date and the asterisks (*) show the number of edited contents on a particular day

Apart from daily trends throughout the course, reflecting behaviours were explored as weekly interactions to see the overlap between the actual behaviours and the anticipated weekly tasks of the module. Fig. 4 demonstrated the average string count on each day of the week across clusters. In general, both clusters reflected the most on Monday. While this number dropped significantly to the lowest on Tuesday (lecture day of the week in the course), it progressively increased towards the end of the week. Among these days, cluster 1 had a higher amount of average string count than cluster 2 except on Wednesday where cluster 2's average string count slightly surpassed cluster 1's.

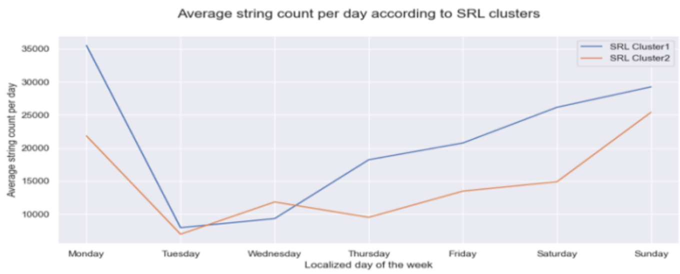

Fig. 4. Average string count for each day of the week across clusters (localized time zones)

4.2 Systematic reflection patterns

Apart from the overall trends above, seasonal decomposition as a part of time series analysis was applied to investigate recurrent short-term patterns of students' writing behaviours. The seasonal decomposition of cluster 1 and 2 are illustrated in Fig. 5 (upper) and Fig. 5 (lower), respectively. Aligned with the above results, both clusters adopted similar trends, yet higher variance was observed in cluster 2's seasonal model. When considering the extracted seasonalities in Fig. 5 (upper), cluster 1's seasonality had a similar cycle as found in the aforementioned 'day of the week' graph (Fig. 4). In other words, the interaction in terms of the average number of string counts was lowest at the beginning of the week (Tuesday) and raised towards the end of the week

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(Saturday). Compared to cluster 2, the extracted seasonality was more fluctuating which can be seen as multiple peaks (Fig. 5 (lower)). The seasonality detection should be considered in accordance with the residuals to ensure its validity. The normally-distributed and zero mean residuals suggest randomness and hence supports the validity of the seasonality model extracted.

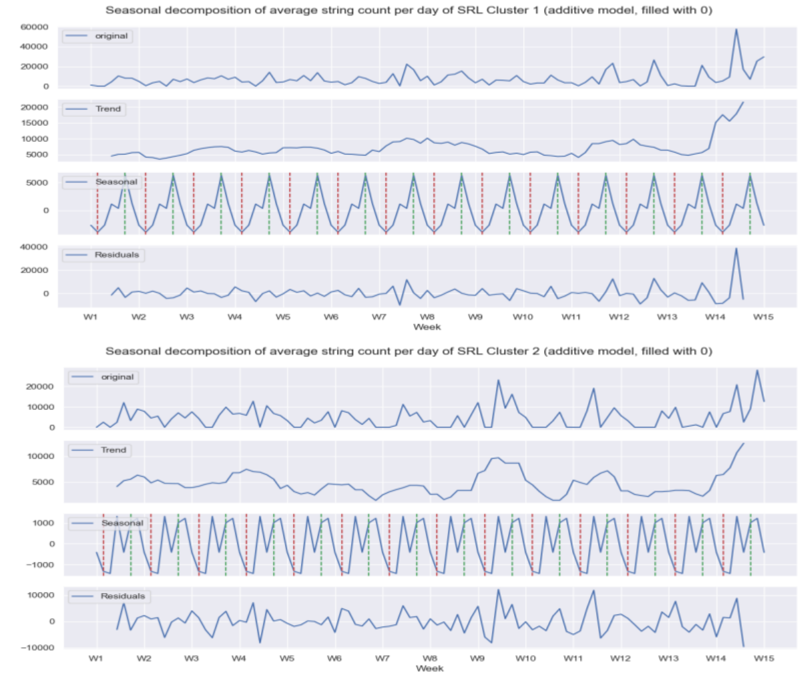

Fig. 5. Seasonal decomposition of the average string count per day of cluster 1 (upper) and cluster 2 (lower) which displayed the original, trend, seasonal and residuals components from top to bottom, respectively. In the seasonal component, red and green dotted lines refer to Tuesday and Saturday of the week, respectively.

4.3 Academic Performance

At last, to investigate the differences between the reflection scores between two clusters, an independent sample t-test was used. There was no significant difference (t(38)=-0.047, p=0.936) in academic performance between cluster 1 (M=2.04, SD=0.49) and cluster 2 (M=2.05, SD=0.54). To get a better sense of the relationship between the individual reflective writing behaviours and academic performance Pearson's r correlations were calculated. Table 1 shows the correlation coefficients between the reflection score calculated from two parts of the rubric criteria for reflective writing, and the computed features from reflection behaviours: total number of revisions, final string count, average revisions per day, average string count per day, total active day, average string count per week, and total active week. There were moderate and significant correlations between the reflection scores and the total number of revisions (r_s=0.484, p<.01), the average revisions per day (r_s=0.423, p<.01) and the total active weeks (r_s=0.417, p<.01). On the other hand, the reflection scores and the

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final string count (r_s=0.374, p<.05) and the total active day (r_s=0.387, p<.05), were found to be statistically significant yet weakly correlated.

Table 1. Correlation matrix between student performance and reflection behaviours

	Reflection Score	TotalRevisions	Final String Count	AvgRev PerDay	AvgStr Count PerDay	TotalActiveDay	AvgStr CountPerWeek	TotalActiveWeek
Reflection Score	1.00	**.484****	**.374***	**.423****	.037	**.387***	.215	**.417****

*** Correlation is significant at the 0.01 level (2-tailed)*
** Correlation is significant at the 0.05 level (2-tailed)*

5 Discussion

RQ1: How do students with different levels of SRL competence approach their reflective writing tasks?: According to the overall trends, students tended to reflect more after the reading week in which the mid-term feedback was provided and increased their efforts towards the end of the course as the submission date approaches. Comparing between the high and low SRL competence groups, the high SRL group tended to have a higher frequency of reflective writing behaviours and a higher quantity of contents written while reflecting. One potential interpretation of these results is that students with high SRL competence were also able to regulate their reflective writing behaviours better. A higher amount of interaction after the reading week, when there were no lectures and students were sent their mid-term feedback on their writing tasks, may be associated with students' reactions to their feedback. One interesting observation is that, whilst these trends can easily be spotted right after the feedback for the high SRL group, such higher interaction was delayed by two weeks for the low SRL group. Timely reaction to feedback was a representative behaviour of the high SRL group. According to the observation from the reflection data, out of twelve interactions from low SRL students within week 9, three students reflected on the contents before the reading week, another three students reflected on the contents of the week before and the last six reflected timely on the current week.

Looking at the weekly interactions, both clusters of students had the lowest reflection behaviours on Tuesdays (when the course lectures took place) and gradually increased their reflective writings towards the end of the week. This aligned with the anticipated learning activities of the module in which students were expected to study the lectures on Tuesdays and reflect during the week. Despite the higher reflection contents of students with high SRL throughout the week, an interesting reflection pattern was observed on Wednesdays. Wednesdays were the only day of the week that students with low SRL outperformed students with high SRL in terms of the amount of reflective writing content produced. Based on a further investigation of the actual reflection contents, we found out that 5 out of 6 students with low to medium SRL competence showed catching up behaviours after Tuesday's lectures in which they reflected on the contents of the week before rather than the current week. These results are aligned with the SRL theory, which suggests that students with high SRL competence tend to approach their learning tasks more timely and strategically to achieve their goals [8].

RQ2: To what extent do students with higher SRL competence approach the individual reflective writing tasks more systematically?: Based on the seasonal decomposition analysis, students with high SRL competence exhibited more periodic patterns weekly: reflecting the lowest on Tuesdays and the highest on Saturdays. However, students with lower SRL competence showed more random behaviours. In other words, students with high SRL approached their reflective writing task more systematically. One potential explanation for this observation is that students with high SRL competence are better at planning and enacting their tasks by deploying time management strategies. Therefore, they tend to plan when they will do the task to better ensure task completion rather than do the task when it was necessary (e.g., right before submission deadlines) [27]. Although the type of data analysis we have undertaken in this study doesn't help us answer such "why?" questions, they lead to hypotheses that should be explored with further qualitative investigations in future research studies. Perhaps, more importantly, these results highlight the value of structuring individual reflective writing tasks in ways that would allow students to approach them more systematically. To achieve this, there are multiple forms of metacognitive scaffolding that can be incorporated into the task itself such as static predefined questions or dynamic support within the learning environment [28]. At the learning design level, since the results highlight the value of regularity in individual reflective writing behaviours, once reflective writing tasks are set, students can be regularly reminded about the expected contributions as well as being supported on how to do so (i.e., prompt-embedded templates sent to students every week on certain times).

RQ3: What is the relationship between students' reflective writing reflecting behaviours and their academic performance?: Even though there was no statistically significant difference between academic performance and students' SRL competence as measured through self-declared data, there were significant correlations found between academic performance and certain reflective writing behaviours such as the total number of revisions, final string count, average revisions per day, total active day, and total active week. Surprisingly, average string count per day and average string count per week had no correlation with students' performance. One potential interpretation of this result is that the reflective writing behaviours that relate to organisational behaviours are more fundamental to academic performance than the amount of reflective writing itself. In other words, high performing students appeared to make more regular visits to their reflective writing tasks and they spread their writing across days and weeks. However, they didn't necessarily write significantly more than low performing students. Recognising the limitations of such correlational interpretations, we suggest that further research in more controlled designs and with potential content analysis of individual reflective writing pieces should be conducted to draw more conclusive results.

5.1 Limitations and Future Research

Before we conclude, it is important to note that even though permissions were given, it is undeniable that collecting log data from Google Docs might introduce privacy concerns for students due to its invasiveness and high granularity of collected data [29]. As a result, multiple methods to ensure transparency have been applied in our study

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such as available information on data collection and objectives, choices to opt-in/out and recognition of tracker (ibid). Moreover, our recent study [30] suggested that participants reported concerns over being monitored by the system only at the beginning of the course and the perceived effects were reduced as the module progresses. More importantly, as the reflecting engagement was not a part of the summative assessment, monitoring such behaviours might be neglectable for them. Apart from the ethical issues, this study involved a relatively small number of students from a single course. Therefore, the results might not be generalized into other contexts due to the context-specific nature of the SRL processes. Besides, previous research highlights the potential content-specific [31] and context-specific [32] nature of students' SRL behaviours. More studies are required to explore consistency in the reflection patterns across domains and learning design. Moreover, the log data captured from Google Docs is limited and might overlook other significant aspects of the writing process such as duration of pause, document formatting and mouse movement. Another limitation concerns the selected proxy to represent students' reflection behaviours. In this study, the number of strings added/deleted was used to represent the number of reflection interactions. However, this proxy might not be a good presenter in situations where students frequently cut-and-paste the contents. Thus, other proxies such as the number of the writing sessions or time consumed on the tasks could further be explored. Regarding the current analysis, we currently only focus on the low-level quantity measures of students' reflecting behaviours whereas most SRL research infers SRL processes from the contents of reflection which could provide more information about students' thinking processes. Their reflective writing behaviours in combination with reflective contents could reveal more insights into how students plan and enact the task. This aligned with the recent participatory research in the design of the writing analytics tools that the experts expected higher level and content-related feedback to support writing processes and assessment [14]. Future work should also focus on analytics from the individual reflective writing contents of students.

6 Conclusion

This exploratory study investigated the reflection behaviours of postgraduate students with different levels of SRL competence over the fifteen-week module in an ecologically valid educational setting. Data on fine-grained reflection writing were retrieved from Google Docs and analyzed using time series decomposition. The results showed that students with different levels of SRL competence present different reflective writing behaviours. Students of high SRL competence carried out the task more frequently, and produced greater quantities of writing, and did so in line with the expectations of the modules. Regarding students with lower SRL, they appear to be catching up and presenting more random reflection behaviours. Moreover, time-series analysis shows that both low SRL and high SRL competence students' reflective writing behaviours fit well in certain seasonal trends with low residuals. This exploration opens up future opportunities for early prediction of less productive reflective writing behaviours and timely interventions from educators, learners themselves and/or educational technology.

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