ISLS Annual Meeting 2023

Building Knowledge and Sustaining our Community

Montreal, Canada, June 10-15

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Concordia University & Dawson College

16th International Conference on Computer-Supported Collaborative Learning (CSCL)

- Proceedings -

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Using Process Mining to Analyze Tasks Involvement and Collaboration in a Student Generated Questions Activity

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Abstract: In a subject where individual tasks are intermingled with collaborative tasks, complex learning dynamics emerge. When these tasks are performed using a computer tool, the student's interactions leave some evidence traces in the tool. Process mining techniques allow us to analyze these traces and discover and understand these learning dynamics. In this work, we applied process mining to the traces of a computer tool used to implement a student-generated questions activity, in which students propose questions and improve them through collaboration with other students. The study has provided insight into the work habits of the students. It has also shown that students with greater involvement in the activity obtain better academic results. Moreover, some student deviations from the intended process have been detected and an unexpected tendency towards non-collaborative behaviors has also been identified, resulting in an unforeseen aspect of intergroup competition within the activity.

Introduction

Student-Generated Questions (SGQ) is a constructivist strategy that is gaining interest as a learning method (Aflalo, 2018; Ebersbach et al., 2020). As its name suggests, it consists of asking students to develop their own questions about the content being studied. It is often emphasized that this activity promotes self-reflection and self-regulated learning and creates an environment that stimulates the higher levels of learning in Bloom's taxonomy (Yu & Wu, 2016; Teplitski et al., 2018). By creating questions, learners distinguish between the important and incidental content of study materials (Sanchez-Elez et al., 2014; Yu & Wu, 2016). The literature highlights the interest and educational potential of the combined application of SGQs and teamwork techniques, in both conventional learning and flipped classroom contexts (Matalonga et al., 2017). The potential of asking good questions in an educational context can be reinforced by the experience of collaborative development platforms, such as Stack Overflow, which have become an irreplaceable tool in areas such as software engineering. In November 2019, the administrators of Stack Overflow state that "asking questions is easy, but asking good questions is hard" (Chipps, 2019). They recalculated their users' reputation scores, assigning the same points to a good question as to a good answer, to promote good questions.

The workload for teachers in managing a SGQ activity can be considerable, especially if the number of students and the number of questions to be formulated are high. For this reason, having an IT solution that automates the process as much as possible seems essential. In our case, we have developed a specific tool for SGQ (Jaime et al., 2022). The tool guides students in a cycle of activities, some of them designed to be done individually and others to be done as collaborative work. Throughout their SGQ process, the students leave evidence traces in the tool itself. These traces contain information about the process followed by the students in the SGQ cycle. Then, these traces can be studied in order to analyze how the different tasks are produced and in what order, how the collaboration between students takes place, as well as if some deviations from the expected execution of the process are carried out. In this work, we have applied different Process Mining (PM) techniques for examining these traces. PM is an emerging discipline providing comprehensive techniques that can be applied to the field of education (Bogarín et al., 2018; Ghazal et al., 2017). These techniques allow the analysis of underlying processes, wherein advanced procedures can examine the student task accomplishment and collaborative component. More specifically, we used the best-known PM tools, Disco and ProM, which specially dominate in educational PM (Bogarín et al., 2018). Within this context, the objectives of this paper involve the application of several PM techniques to the traces found in our SGQ tool to:

- Better understand student's working habits, detecting students' deviations from the intended process.
- Clusterize students according to their implication with the SGQ methodology, and check if, conforming with the literature, SGQ provides better results in students who made better use of this methodology.
- Mine and analyze collaboration trends both among students and groups of students.

Related work

The different SGQ experiences we found in the literature share several steps in their life cycle. Generally, after providing the materials to students, there is a study phase followed by a question creation phase and a third phase of peer feedback (Aflalo, 2018; Ebersbach, 2020; Yu & Wu, 2016). In addition, some student-made questions are often included in the exam as an incentive to study (Doyle et al., 2019; Ebersbach, 2020). Some authors propose multiple-choice test questions (Hardy et al., 2014; Yu & Wu, 2020) while others use open-ended questions that require students to write their answers (Aflalo, 2018; Ebersbach et al., 2020). It can be also observed that the different SGQ projects use very different strategies, in some cases highly guided (Yu & Wu, 2016) while, at the other extreme, the process is delegated to students with little or no supervision (Hardy et al., 2014).

There is also a wide variety of approaches that choose to work with an automated tool to support the SGQ process. Some experiences seem to have been carried out without any particular support tool (Aflalo, 2018; Ebersbach et al., 2020). Other works use software, such as Hot Potatoes, which are not specifically designed for SGQ activities and that are used from the point of view of a teacher who wants to create questions (Sanchez-Elez et al., 2014). Finally, other works use specific tools designed for SGQ as PeerWise (Hardy et al., 2014). Having a tool that is well adapted to the lifecycle of the implemented SGQ is a considerable relief in the monitoring task which, in our view, should be assumed by the teacher. This includes monitoring compliance with the basic rules of the tasks, managing the collection, organization and provision of feedback, and supporting a follow-up task to identify concepts that are not well understood, among other aspects (Jaime et al., 2022).

In recent years, the use of PM techniques in education has given rise to the term educational process mining (EPM). The most common uses of EPM include understanding educational processes, providing feedback to students and teachers, improving the management of learning objects or analyzing social networks representing students' interactions (Bogarín et al., 2018). At present, there is no well-established methodological approach for how to apply these techniques. Usually, data analyzed with EPM come from educational platforms, are collected in an event log, cleaned, and organized to eventually perform a process discovery (van Eck et al., 2015). Generally, the models obtained are complex and it is difficult to reach clear conclusions (Maldonado-Mahauad et al., 2018). For this reason, clustering techniques (such as trace clustering) are used to pre-process and segment the event log (Bogarín et al., 2018; Domínguez et al., 2021). Regarding the analysis of students' interactions in EPM, the use of Social Network Analysis (SNA) has recently received much interest to extract social structures from event logs using networks and graph theory (Bogarín et al., 2018), resulting in many studies that analyze collaborative settings (Martinez-Maldonado et al., 2013; Premchaiswadi & Porouhan, 2015). However, as far as we are aware, this is the first study that proposes a solution, inspired by teachers' authentic needs, to analyze student's collaboration and working habits in SGQ using EPM techniques.

Methodology

Tool and SGQ cycle

In this section we will explain in brief how we have applied the developed tool and the SGQ lifecycle method as the authors of this work introduced in (Jaime et al., 2022). The tool is built from several components of Google's technology. Google Forms have been used for student input (proposed questions, improvements to third party questions, etc.). The generated questions are contained in public text Google Documents. Some Google spreadsheets are also used to display other information, such as the work plan for each cycle, the activities completed by each student, and so on. The core of the solution are programs written in JavaScript language using the Google Apps Script application programming interface. These programs transfer the information from the forms to the different documents and check compliance with the pre-established work rules.

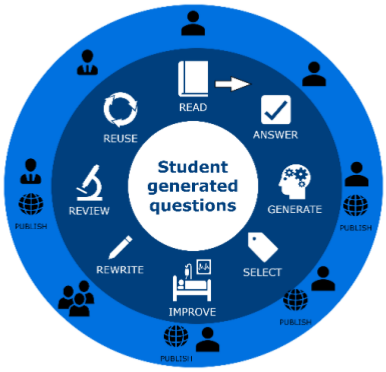
To explain the model, we rely on Figure 1, which represents the steps taken in the SGQ process. All the steps taken for each student or team are registered by the program and automatically graded (except for the *Review*, *Reuse* and *Read* steps). It should be noted that, before starting to work in this way, there is a training period of three to five weeks to understand the different steps and to learn how to ask good questions. Almost all the activities depicted in Figure 1 are individual and are done outside the classroom, while the *Rewrite* activity is done in teams, in the classroom. The same teams are maintained every week. Next, we explain each phase.

First: *read/view*. The material of the subject (which always includes a text and sometimes some videos) is presented and published by the teacher. A weekly plan for the SGQ process is also published, the first task of which is to read the text and watch the videos.

Second: *answer*. Students answer a teacher-made questionnaire of between 4 and 9 questions about the material. It is advisable to consult the material provided, which can be used to answer the questions. The aim of the activity is to show several sample questions and to encourage reflection on what has been read or watched.

Third: *generate*. Each student prepares and publishes one test-type question that in his or her judgment is relevant to the topic. The question must meet certain restrictions (medium-high difficulty, answers without references to other answers, no double negation...), and its wording comes from the part of the material assigned to the team in the weekly plan. A deadline is set for completing the first three steps. In each question the team to which the author belongs is visible, but not the author himself/herself. Each part of the material will have questions from several teams (2 or 3 in our case), although exceptionally, a part can be worked by only one team. All students can see all the questions generated.

Figure 1
The weekly phases of the SGQ, starting with read and moving to the right to reuse



Fourth: *select*. Each student votes on the most interesting questions (2 or 3) of her or his part.

Fifth: *improve*. Each student can make suggestions to improve the questions selected in her or his part. Suggestions for improvement are incorporated into the published questions. In the weekly plan there is a deadline for this task and some time is allowed for authors to understand the suggestions before tackling the next step.

Sixth: *rewrite/acknowledge*. Each team meets at the last weekly class session with the task of considering suggestions to their questions and agreeing and proposing final versions. They select 2 to 4 questions from each part, taken from among the best rated. Students may acknowledge the two best improvements (as first and second-best improvements) that their peers have made to each one of their questions, which increases the mark earned for the improvement. A minimum of two final submitted questions by each team is required, but more questions are permitted.

Seventh: *review*. The teacher reviews the questions and corrects those that still contain problems. Accepted questions are graded with a distinctive symbol (gold, silver, or bronze medal) depending on its quality. If the question has many problems, it is labelled as a "cancelled", and it is returned to the students to submit an improved version. The accepted versions are published in a text document.

Eighth: *reuse*. Questions that are published and quality-certified by the teacher have dual use; they are a tool for study and reflection, and there is a commitment that some of them will be selected for the exam.

PM procedure

Based on the Process Mining Project Methodology PM^2 (van Eck et al., 2015), in the planning stage we established the objectives as stated in the Introduction. Subsequently, in the extraction phase, we extracted the event data from the SGQ tool in a spreadsheet, after having cleaned unnecessary data. The activities considered in the study were those explicitly related to the elaboration of questions (i.e., from the *Generate* phase to the *Review* one, also including the acknowledgement of improvements, to analyze recognition of peers' suggestions). The resulting spreadsheet was imported into Disco and ProM to finally obtain the event log ready for use in subsequent stages.

Afterwards, we performed two analysis iterations, each including the corresponding data processing, mining and analysis, and evaluation stages. In both iterations we applied concrete PM techniques provided by Disco and ProM. In the first iteration, we performed a data processing stage where, aimed at further analyzing collaboration trends among students, and following an approach similar to the one presented by Martinez-Maldonado et al. (2013), we enriched the data by adding contextual information to the SGQ actions performed by the students, classifying them as follows: (1) *Owner* actions, which refer to the actions carried out by students on their own questions (such as when a student *Selects* a self-generated question), (2) *OwnTeam* actions, that refer to the actions performed by students on questions generated by the team they belong to, and (3) *Other* actions, which refer to the actions carried out by students on questions generated by a team different from that they belong to. Also, aimed at analyzing collaborative trends, we applied a compliance-based filtering to the log to keep those

SGQ activities where collaborative aspects are not compromised (that is, we just consider the *Select* and *Improve* steps since they are free to be performed under the *Owner-OwnTeam-Other* actions).

For the mining and analysis stage, we used the Disco Fuzzy Miner algorithm (Bogarín et al., 2018) on the event log to visualize the behavior of students while performing the SGQ process. Additionally, Disco gave us functionality to investigate the SGQ process from the statistics perspective, while the application of the Fuzzy Miner algorithm gives an understanding about the process flow. Social Network Analysis (SNA) was also applied to the event log to understand how students worked together. The analysis was conducted with the ProM Mine for the Working-together Social Network plugin (Claes & Poels, 2013) to determine who works with whom. Also, the ProM Guide Tree Miner (Claes & Poels, 2013) plugin was applied as a process diagnostic technique. This plugin uses an agglomerative hierarchical clustering and needs to be told how many clusters to obtain. For the evaluation stage, the findings of the analysis were evaluated, relating them to ideas for improvement that would make it possible to achieve the objectives of the study. The clusters obtained were statistically analyzed using complementary data on academic performance.

Those clusters gave us insight to obtain a different perspective on the event data so that, after a careful investigation of such clusters, we perform a second analysis iteration phase aimed at studying how the students included in such clusters behaved regarding collaborative actions (*Owner-OwnTeam-Other*). In this case, we added to the event log additional information inferred from the resulted clusters and used the Disco Fuzzy Miner algorithm to mine the interaction processes in such clusters.

Subject

The SGQ method was applied to a course entitled “Transversal Workshop: Databases and Information Systems” in the fourth year of a Computer Science Engineering degree during the 2021-2022 academic period. A total of 53 students attended the course, distributed in 10 teams of 5 students (except for 3 teams of 6 students). The course has various assessment types. Firstly, five text exams evaluated the theoretical part of the subject which supposes 60% of the final grade. Secondly, different practical deliverables should be made throughout the academic year which supposes 20% of the final grade. Finally, the SGQ activity supposed 20% of the final grade.

Results and discussion

Data analysis

Disco identifies that students generated 286 different questions (which correspond to the process instances or traces), which included 1995 events (classified into 7 different activities), with the mean time case duration of 3.7 days for each SGQ cycle. The tool also showed us that, while all students participated at least by generating questions, the total number of activities in which each student has participated is uneven, ranging from 11 activities (the student with lowest participation) to 69 (the student with highest participation). Focusing on the mean participation of each student per question, this varies from 1 to 3.29 activities per question. The participation also remains uneven among teams, varying from 124 to 248 activities. The average participation per team in each question also differs among teams, with a range from 4.39 to 6.64 activities per question.

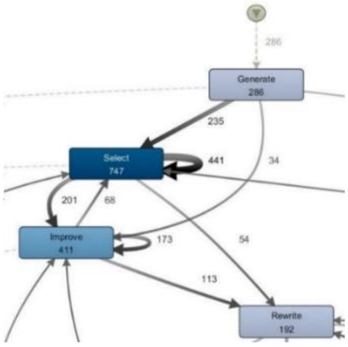
The results presented in the remainder three subsections serve to address, correspondingly, each objective formulated in the study.

Data process

An excerpt of the discovered fuzzy model is depicted in Figure 2, where the tool was set to show all activities and all pathways. The color of the events (dark—more, light—fewer) and the thickness of the pathways (thicker—more) represent the frequency in the log. From the 286 generated questions, 253 were selected by students as interesting questions (88.46%). More specifically, the *Select* activity turned out to be the most frequent activity with 747 times (see Figure 2), which means that each question got around three votes on average. After the *Select* phase, 51 questions were not considered to continue the process (20.15%), despite having been voted on. Afterwards, 191 questions were proposed for improvement, so that each question had around two suggestions for improvement on average (411 *Improve* instances). From such questions, 167 were finally rewritten, which showed that each question had around one or two reformulations (192 *Rewrite* instances).

The last phase in which students participate is the *Acknowledge* phase. Students acknowledge the improvements suggested by their peers 167 times (for 111 questions), of which 115 came directly from the *Rewrite* phase (they correspond to the first best improvement), and 52 instances again came from the *Appreciate* phase (second best improvement). Further exploration in Disco showed that from the 167 questions that were finally rewritten (*Rewrite*), 130 questions (77.38%) had previously received proposals for improvement (*Improve*), which shows that a significant percentage of questions (37 questions, 22.62%) where rewritten without having previously received any suggestion for improvement. Also, in 19 out of such 130 questions with suggestions for improvement (*Improve*) and rewritten (*Rewrite*), the question owner team did not acknowledge such suggestions.

Figure 2
The resulting fuzzy map created by Fuzzy miner Disco for SGQ data



Finally, the teacher came into play assessing the quality of the questions, thus correspondingly accepting or cancelling them (*Accept/Cancel* phase). There were 111 accepted questions, from which 76 corresponded to questions that were acknowledged. From these 111 accepted questions, 19 were awarded a gold medal (17.08% of those accepted), 35 received a silver medal (31.48%), and 57 got a bronze medal (51.43%). It should be noted that 14 gold medals (73.68%), 28 silver medals (80%) and 34 bronze medals (59.65%) came from questions which acknowledged suggestions of improvement. That is, most of the best quality questions acknowledge peer-supplied improvements. 73 questions reached the *Cancel* state, from which only 23 questions were given a second chance, returning to the *Rewrite* state (31,51%), thus showing that many of the questions were not reworked. Specifically, from the 73 questions cancelled at some time, 17 were finally accepted and 56 questions ended up cancelled.

Furthermore, the model helps us reveal further intriguing facts concerning student behavior. More specifically, it shows us that some students deviate from the intended process steps, skipping expected steps or performing actions when they no longer had any influence on the question. Examples of these observed unexpected sequences are the following (some of them presented in Figure 2): *Generate>Improve* (34 instances-questions), *Improve>Select* (68 instances, 54 questions), *Accept>Improve* (2 instances-questions), and *Cancel>Select* (2 instances-questions). Some of this unexpected behavior can be explained based on students' isolated behaviors. For example, the 34 votes received after the *Improve* state could correspond to either students who rushed into making improvements without having finished the selecting period, or votes performed in late stages when such a period had finished.

Cluster analysis according to students' log events

Following the criteria and procedure indicated in the previous section, two clusters were obtained by applying PM to the log of SGQ events. We chose a two clusters solution, since adding more clusters results in new clusters appearing by segregation of one of these two, which were very similar in their activity and number of events. More specifically, the first cluster, which we call Low Activity (LA), includes 23 students with less activity, where such an activity is concentrated in the first phases of task construction (generating and selecting questions). The mean activity of this cluster is 24. The second cluster, on the other hand, High Activity (HA), corresponds to the 30 students with more activity occurring throughout all phases. This cluster has a mean activity of 48.1.

A comparative study was done of the grades obtained by the clustered students on the different assessments, which is presented in Table 1. This study shows that both clusters have significant differences in the results obtained in the theoretical part of the subject; the LA cluster has a mean grade (standard deviation) of 6.40 (1.41), while the HA cluster have 7.05 (1.24) ($t = -1.729$, $p = .045$*, Cohen's d = -0.49). More specifically, in all test exams, the cluster that worked more on the SGQ activity obtained better academic results. This improvement was around half a point difference in the first 4 exams and more than 1 point in the last exam (t = -2,340*, p = .012, Cohen's d = -0.64). This is not the case, however, for the grades obtained in the deliverables from the practical part of the subject, where the cluster HA had a better grade, but by less than two-tenths of a point. This indicates that students benefit not only from the SGQ part, but also from the theory part (probably better prepared thanks to the SGQ). This benefit is not reflected in the practical part, to which the SGQ has no relation. These results agree with other works in the literature who applied this method and who observed improvements in learning (Sanchez-Elez et al., 2014; Hardy et al., 2014), although these works do not delve deeply into the tasks performed by the learners and the relationships that occur between them through techniques such as PM. As for the application of PM to collaborative settings in education, the closest study to ours was presented by Premchaiswadi & Porouhan (2015) which principally consists in analyzing student's collaborative behavior captured during a distance multi-user concept mapping activity. However, this work mainly differs from ours in that this study applies a manual clustering strategy to segment the group of students and it does not provide a statistical analysis using complementary data on academic performance.

Table 1
Mean (Standard deviation) of the grades for the deliverables, for the SGQ activity, for the different exams, and for the final marks in the two review clusters (grades on a 10-point scale)

	LA	HA	Statistics	Cohen' d
N	23	30		
Deliverables	7.93 (1.27)	8.1 (0.5)	n.s.	-0.18
SGQ	7.27 (1.3)	8.61 (1.15)	t = -3.942***	-1.08
Theoretical part	6.4 (1.41)	7.05 (1.24)	t = -1.758*, p = .045	-0.49
Exam 1	5.99 (2.26)	6.47 (2.2)	n.s.	-0.21
Exam 2	6.97 (2.15)	7.39 (1.88)	n.s.	-0.21
Exam 3	6.94 (1.59)	7.59 (1.46)	t = -1.522, p = .067	-0.42
Exam 4	7.14 (1.77)	7.6 (1,75)	n.s.	-0.26
Exam 5	5.13 (1.92)	6.24 (1,53)	t = -2.340*, p = .012	-0.64
Final mark	6.87 (1.08)	7.57 (0,87)	t = -2.535**, p = 0.06	-0.71

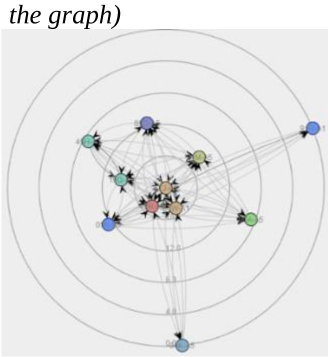
*p < .01, **p < .01, ***p < .001, Statistics: Student' t test

Level of interaction results

We have analyzed intergroup interactions at two different levels: by identifying how students work together during the different SGQ cycles and by analyzing the type of collaboration trends.

In the first case, we filtered the log by only considering, for each SGQ cycle, the activity performed by those teams working on the same part of the material. This resulted in different event logs, one per each cycle and group of teams working on the same part of the material. After applying the ProM Mine for a Working-together Social Network technique, we had found that for each cycle and group of teams, most of students had more tendency to work in group in the assigned tasks of the process, being closely clustered together (see Figure 3). However, it is also observed that there are one or two students who hardly contribute any task with someone else during the SGQ process (they are slightly connected with the cluster).

Figure 3
Social network based on working together between two teams (students most involved together in SGQ paths are more central in the graph)



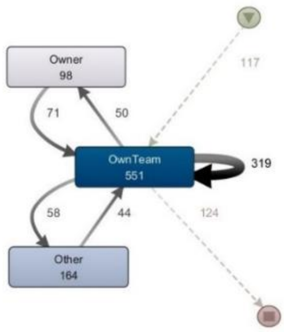
In the second case, we focused on those SGQ activities where intergroup interaction was possible and where collaborative aspects were not compromised. For this task, we followed a two-phase filtering proposal. First, we again maintained any activity carried out by groups of teams working on the same part of the material on a weekly cycle. Second, from all the activities involved in the SGQ strategy, we kept those actions performed individually (*Select* and *Improve*). Then, we used the Fuzzy Miner algorithm to mine the intergroup interactions focusing on *Owner-OwnTeam-Other* actions, resulting in the fuzzy graph presented in Figure 4 (again, all activities and all pathways were considered). This graph shows that there was a total of 813 events in the *Select-Improve* category, and the most significant trace of the interaction corresponds to those actions performed by students on questions created by the team they belong to (*OwnTeam* action), representing 67.77% of the activity and an absolute frequency of 551 times. The frequency of actions performed on students' own questions (*Owner* action) represents 12.06% of students' actions (absolute frequency of 98 times), while actions performed on questions from other teams (*Other* action) represents 20.17% of the actions. Thus, the technique allowed us to realize that the activity performed on questions designed by other teams is very low compared to the activity of students performed on questions created by their own teams (which is almost 80% of the interventions). Therefore, it can be inferred that students tend to follow non-collaborative behaviors, perhaps because they incorporate an unexpected intergroup competition aspect to the SGQ activity, avoiding actions that could benefit other teams.

Considering these results, we decided to investigate whether HA and LA groups have different levels of interaction. For this task, we used again the Disco Fuzzy Miner algorithm to mine the interaction processes in both groups. Upon inspection in the resulting fuzzy graphs, we realized that, as expected, the total amount of activity was notably higher in the HA group compared to the LA group (HA has an absolute frequency of 614 times, more than 20 activities per student, against 199 times of the LA group with less than 10 activities per student). In addition, a higher concentration of activity tending to favor one's own team is observed in LA (about 90%) than in HA (about 75%). From these data, we can conclude that the HA group has a higher level of collaboration with respect to LA.

Finally, to know if the level of participation contributes to an improvement in the quality of the questions elaborated by the students, we have further analyzed the number of medals of each type received by each group (both HA and LA). Following a strategy similar to the one presented above, we observed that the number of medals received by the HA group is higher than that of LA. More specifically, almost three times more (on average per student) in the case of gold medals, six times more for silver medals, and over four and a half times more for bronze medals.

Figure 4

The resulting fuzzy graph focusing on Owner-OwnTeam-Other actions



Conclusions

In this work we have applied techniques from process mining to analyze the tasks performed by a group of students in a subject in which a SGQ activity is included, supported by an IT tool. Each student should develop a cycle of activities both individually and in teams. This tool tries to guide students and facilitates the management of all the activities. The traces that the students leave in the tool contain information about the effective process followed by the students in the SGQ cycle. These traces allowed us to analyze, by means of process mining techniques, how the different tasks are performed and in what order, how collaboration among students occurs, as well as whether there are any deviations from the desired process.

Specifically, the model helped us reveal that, although most questions are generated following the intended cycle of activities, some students deviate from the planned process, skipping some expected steps or performing an action when it no longer had any influence on the question. Moreover, two types of students can be defined depending on the amount of activity. Whereas the group of students with higher student generated activity (HA) obtains better grades in the theoretical part of the subject and elaborates more quality questions, the grades in the practical part (not related with the student generated activity) remains similar in both groups. Finally, it can be inferred that students tend to follow non-collaborative behaviors, avoiding collaboration with members of a different team; behavior that is more pronounced among the groups of students with less activity (LA). All the insights gained from the evaluation were used to suggest improvements in the SGQ tool.

We believe that the methodology applied in our context can be generalizable to other contexts in which complex process of interactions among students occurs.

References

Aflalo, E. (2018). Students generating questions as a way of learning. *Active Learning in Higher Education*, 22(1), 63–75.

Bogarín, A., Cerezo, R., & Romero, C. (2018). A survey on educational process mining. *Wiley Interdisciplinary Reviews: Data Mining and Knowledge Discovery*, 8, e1230.

Chipps, S. (2019, November 13). We're Rewarding the Question Askers. *Stack Overflow Blog*. https://stackoverflow.blog/2019/11/13/were-rewarding-the-question-askers/

Claes, J., & Poels, G. (2013). Process Mining and the ProM Framework: An Exploratory Survey. In M. La Rosa, & P. Soffer (Eds.), *Lecture Notes in Business Information Processing*, 132. Springer, Berlin, Heidelberg.

Domínguez, C., García-Izquierdo, F. J., Jaime, A., Pérez, B., Rubio, Á. L., & Zapata, M. A. (2021). Using Process Mining to Analyze Time Distribution of Self-Assessment and Formative Assessment Exercises on an Online Learning Tool. *IEEE Transactions on Learning Technologies*, 14 (5), 709–722.

Doyle, E., Buckley, P., & Whelan, J. (2019). Assessment co-creation: an exploratory analysis of opportunities and challenges based on student and instructor perspectives. *Teach. High. Educ.*, 24(6), 739–754.

Ebersbach, M., Feierabend, M., & Nazari, K. B. B. (2020). Comparing the effects of generating questions, testing, and restudying on students' long-term recall in university learning. *Applied Cognitive Psychology*, 34(3), 724–736.

van Eck, M. L., Lu, X., Leemans, S. J. J., & van der Aalst, W. M. P. (2015). PM^2: A Process Mining Project Methodology. *Lecture Notes in Computer Science*, 9097, 297–313.

Ghazal, M. A., Ibrahim, O., & Salama, M. A. (2017). Educational Process Mining: A Systematic Literature Review. *Proceedings of the European Conference on Electrical Engineering and Computer Science*, 198–203.

Hardy, J., Bates, S. P., Casey, M. M., Galloway, K. W., Galloway, R. K., Kay, A. E., Kirsop, P., & McQueen, H. A. (2014). Student-Generated Content: Enhancing learning through sharing multiple choice questions. *International Journal of Science Education*, 36, 2180–2194.

Jaime, A, Domínguez, C., Blanco, J. M., & Sánchez, A. (2022). Preguntas generadas por estudiantes: una solución online para supervisar la aplicación sistemática del método. In *La innovación como motor para la transformación de la enseñanza universitaria* (pp. 171-182). Universidad de La Rioja.

Maldonado-Mahauad, J., Pérez-Sanagustín, M., Kizilcec, R. F., Morales, N, & Munoz-Gama, J. (2018). Mining theory-based patterns from big data: Identifying self-regulated learning strategies in massive open online courses, *Comput. Human Behaviour*. 80, 179–196.

Martinez-Maldonado, R., Yacef, & K., Kay, J. (2013). Data Mining in the Classroom: Discovering Groups' Strategies at a Multitabletop Environment. *Proceedings of the International Conference on Educational Data Mining*, 121–128.

Matalonga, S., Mousques, G., & Bia, A. (2017). Deploying Team-Based Learning at Undergraduate Software Engineering Courses. *Proceedings of the IEEE/ACM 1st International Workshop on Software Engineering Curricula for Millennials*, 9–15.

Premchaiswadi, W., & Porouhan, P. (2015). Process modeling and decision mining in a collaborative distance learning environment Definitions and context. *Decis Anal*, 2.

Sanchez-Elez, M., Pardines, I., García, P., Miñana, G., Román, S., Sánchez, M., & Risco, J. L. (2014). Enhancing Students' Learning Process Through Self-Generated Tests. *Journal of Science Education and Technology*, 23, 16–25.

Teplitski, M., Irani, T., Krediet, C. J., Di Cesare, M., & Marvasi, M. (2018). Student-Generated Pre-Exam Questions is an Effective Tool for Participatory Learning: A Case Study from Ecology of Waterborne Pathogens Course. *Journal of Food Science Education*, 17, 76–84.

Yu, F., & Wu, W. (2020). Effects of student-generated feedback corresponding to answers to online student-generated questions on learning: What, why, and how? *Computers & Education*, 145, 103723.

Yu, F., & Wu, C. (2016). The effects of an online student-constructed test strategy on knowledge construction. *Computers & Education*, 94, 89–101.

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