Machine-learning-based software to group heterogeneous students for online peer assessment activities

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Abstract. Since the academic year 2017/2018, a peer assessment activity was included in the online Genomics laboratory for the master's degree course in Biological Sciences of the University of Camerino, with the aim of improving learning outcomes and soft skills in students, such as team building and critical thinking. Creating groups in university courses is not easy because of the large number of students, that leads teachers to realize groups totally randomly, a procedure that is not always effective. One of the factors that influences the success of collaborative learning is the creation of heterogeneous groups based on the students' behaviors. Despite little improvements, the online genomics laboratory highlighted some gaps. Random groups didn't ensure that each group was composed of heterogeneous students, and it leads some students to have a bad perception of the peer review activity, negatively affecting their engagement and motivation. This work proposes a new Machine Learning Approach and the realization of a specific software, able to create effective heterogeneous groups to be involved in the online peer assessment process, in order to improve learning outcomes and satisfaction in the students. The aim is to check the improvement of the peer assessment effectiveness using heterogeneous groups compared to random groups of students. Two editions of the online laboratory of Genomics were analysed, examining the students' results and perceptions to verify the impact of the Machine Learning approach designed in this work.

Keywords: On-line Peer Assessment, Working group, Machine learning.

1 Introduction

Universities promote innovative teaching that allows an improvement of learning in terms of knowledge and soft skills, including the student as an active actor in the training process.

Collaborative activities such as peer assessment are effective teaching methodologies since they improve learning outcomes by promoting active learning [1]. They also develop the students' social skills such as decision making, communication, collaborative and critical thinking [2][3].

Peer assessment is a collaborative learning technique based on a critical analysis by learners of a task or artefact previously undertaken by peers [4]. In the peer assessment process, students reciprocally express a critical judgment about the way their peers performed a task assigned by the teacher and give a grade to it. Furthermore, students provide their peers with detailed qualitative feedback to guide and help them in the constructive revision of their work for the teacher evaluation.
To produce the feedback, the students use a rubric [5], which is a schema of the criteria for assigning marks for each step of the task. The rubric is usually prepared by the teacher in collaboration with the students themselves, thus promoting metacognitive reflection on the quality of the task or artefact to be produced.

The literature shows how peer assessment supports and improves learning, both for the students who receive the feedback and those who give it, because the activity triggers self-assessment and critical reasoning with a focus on the tasks produced by both [6].

Since the academic year 2017/2018, a collaborative activity of peer assessment, used as an evaluation process with a training function, was included in the online laboratory of Genomics for the master's degree course in Biological Sciences of the University of Camerino (Italy), thanks to the use of digital technologies. This experimental procedure was entirely conducted online, using the University's Moodle e-learning platform. Analysing the students' perceptions related to this collaborative activity carried out in all the past editions, some critical issues emerged on the composition of the reviewers' groups, selected randomly.

Groups were entirely created by a Moodle plugin which automatically and randomly provided the distribution of users in different groups, based on the teacher's preferences (number of groups and users for each group). Due to the random selection, the teacher did not pay attention to including students of different levels of knowledge and abilities into the groups. This unbalanced distribution of students led to creating groups with excellent students and groups with students showing difficulties in the study.

Despite little improvements of learning outcomes in the collaborative activities based on random groups, this teaching method highlighted some gaps:

1. Random groups didn't ensure that each group was composed of heterogeneous students.
2. Because of random groups, some students have a bad perception of the peer review activity, negatively affecting their engagement and motivation. [7]

Ensuring the heterogeneity of the students in terms of cognitive resources (based on the tests results achieved during the course path and interactions with other peers), characteristics (gender and provenience) and behaviours (how they used the tools in the e-learning platform) is essential for maximizing success in group works [8].

In university courses, forming optimal heterogeneous groups of students for collaborative activities is not always an easy task. Usually, different approaches don't always guarantee the formation of heterogeneous groups, such as random selection, automatic selection, and teacher selection [9]. The last approach could guarantee the realization of heterogeneous groups. It consists in the selection of students, by the teacher, based on pre-established characteristics, such as knowledge, skills, interests and learning style

[10]. However, for the university teachers, the identification of different profiles of students who attend the classroom, influenced by certain characteristics and behaviours, is complicated, not only for the high number of participants, but also for the relatively short duration of the courses that do not always require a mandatory attendance. Different works show how the use of models help teachers to define students' behaviours related to their learning process [11].

Some Machine Learning algorithms, such as Clustering, reveal their usefulness for their ability to group similar student's types through specific behavioural indicators such as "presence coefficient", "study coefficient", and "activity coefficient" [12]. The weakness in the online learning environments is the lack of a specific software that easily allows the creation of these groups automatically, facilitating the teacher's work.

For this purpose, a computer-based application was created to allow the artificial-intelligent creation of heterogeneous groups, using unsupervised Machine Learning techniques [13] applied to the Learning Analytics produced by the students during their attendance of an online course in the Moodle platform [14]. The software firstly defines different clusters of students (each cluster includes students with similar behaviours in the online path) and then heterogeneous groups (each group includes students belonging to different clusters). For the first scope, K-means clustering algorithm was chosen for its effectiveness in grouping students based on online behaviour in e-learning courses [15]. Alternatively, the realization of heterogeneous groups required an algorithm specifically developed, that includes in each group at least one student belonging to a different cluster, ensuring heterogeneity. This software application was implemented in the academic year 2020/2021 in the Genomics online laboratory (composed by international students from: Africa, India, China, and Italy), in order to automatically create heterogeneous groups of students for the collaborative activity of the peer assessment.

The aim of this work is to check the improvement of the effectiveness of the peer assessment activities using heterogeneous groups (created by the software developed), compared to random groups, answering to the following questions:

1. Does peer assessment based on heterogeneous groups enhance the improvement of students' performance compared to the same activity based on random groups?

2. Does the use of the heterogeneous groups influence an improvement in students' perceptions compared to the same activity that required random groups?

A uniform and substantial improvement both for the students' works (after the quantitative/qualitative feedbacks given by the peers) and for the students' perceptions (related the quality of the feedback received) was obtained in the Genomics laboratory edition 2020/2021 that used the intelligent software, described in this work, for the creation of heterogeneous groups of students.

2 Methodology

2.1 Description of the activities

The on-line Genomics laboratory is supplementary to the classroom learning. It allows students to perform genetic sequence analyses starting from real experimental data. The course consists firstly of teaching materials (as video tutorial, slides, pdf documents, video experiments) to be attended in self-learning, and then a second part characterized by a collaborative activity that require working groups. A specific gene-sequence case study, that contains one gene represented by exons and introns, is delivered to students belonging to the same group. After the self-study of teaching materials, each student has to perform individually the analysis of the sequence performing a task that requires the submission of an essay characterized by questions related to the gene-sequence case assigned.

In the first part students had to work individually and only in the second part they have to interact with the other students of the same group, during the collaborative activities. Once concluded the elaboration of the task, each student had to upload their final report using the Workshop module of the Moodle platform to start the on-line peer assessment. This activity promotes mutual assistance among the students with different levels in competence and knowledge and in addition develops soft skills, such as critical thinking, sense of responsibility and time scheduling. In this activity each student performed two peer assessments to colleagues' reports and, after considering feedback received, can decide if edit or not his task.

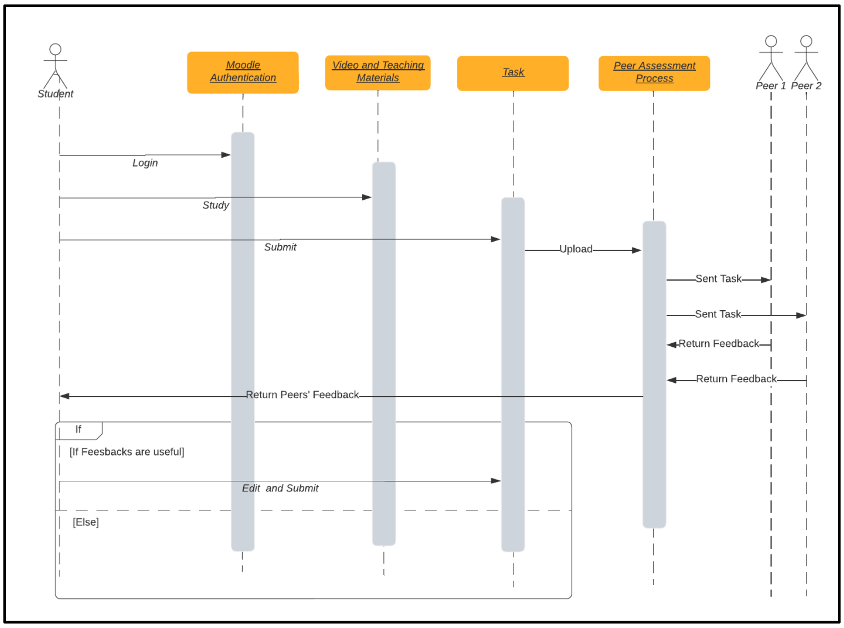

Fig. 1. Sequence diagram of the flow of the peer assessment activity.

Each student during the evaluation phase filled a rubric, already tested in past editions of the Genomics Laboratory course [7], writing quantitative and qualitative judgements related to the task processed. The rubric consists in a set of clear criteria used to help teachers and students to focus on what is valued in a subject, topic, or activity [16]. For the quantitative judgement, students must evaluate the task of the peer giving a score, with a maximum value of 30. For the qualitative evaluation feedback with tips was required that could help peers in improving their tasks, before the last submission, that will be assessed by the teacher.

2.2 Participants

In the past edition of the on-line Genomics Laboratory 41 students (23 females and 18 males), composed of Italian, Chinese, African and Arabian people, participated in the course. 8 Groups of 5-6 people were created totally randomly.

The participants of the new edition of the on-line course were 41, characterized by 26 females and 15 males. Students came from all over the world, such as Italia, Netherland, Albania, Africa, Arabia, and China and through the Machine Learning software aimed to the creation of heterogeneous groups, they were sorted in 8 groups, 7 composed by 5 people and 1 group by 6 people.

The participation was voluntary, and students actively participated in the on-line activities. At the end of the laboratory an extra-point was added to the final score of the Genomics exam for students that completed the course-path, including the submission of the task and the realization of peer review.

2.3 Machine learning approach

Teachers involved in totally on-line courses can find difficulty profiling student behaviour to create successful heterogeneous workgroups for collaborative activities, based only on monitoring students' Moodle Log data.

For this reason, in the past editions of the on-line Genomics Laboratory course, the creation of groups was totally random, and not always effective for the peer assessment processes because it didn’t ensure the heterogeneity in each group.

In the last edition of the on-line course, a Machine Learning approach was performed to create heterogeneous groups of students, with the aim of improving the learning outcomes in students involved in collaborative activities. The software, already tested, consisted in the execution of the K-Means unsupervised techniques to predict different clusters of students’ profiles (based on behaviour in the platform) and in the realization of heterogeneous groups selecting at least one student from each cluster [14].

The dataset was characterized by the selection of the learning analytics, extracted by the reports of Moodle, that allowed the detection of various features of the student learning process, such as the “presence”, “study” and “activity-interaction” [12]. These features permit the finding of student behaviour through clustering.

Specifically, the following data were selected: number of logins, last login, total time online, number of video tutorials, clicks for video tutorials seen, number of video experiments seen, clicks for video experiments seen, number of pdfs downloaded, number of exercises performed.

After the creation of the clusters, the software performs the algorithm that automatically and uniformly divides the students of various clusters in different heterogeneous groups.

$$student\_for\_het\_group = \frac{cluster\_lenght}{nr\_het\_groups}$$

Fig. 2. Number of the students belonged to the same cluster to be included in each heterogeneous group.

It first determines the number of groups to create, calculating the number of students to be included in the group, and then, it distributes group members equally assigning one or more students from each cluster (considering the lengths of each cluster) to each group, ensuring heterogeneity within. At the end of this step the list of the groups is displayed to the teacher.

2.4 Data collection and methodology

The results obtained from the quantitative analysis of the peer assessment process, on two different editions of the Genomics online laboratory, (2017/2018, using random groups; 2020/2021, using heterogeneous groups realized by the intelligent software), were compared to reply to research questions. It was chosen these two specific editions, because they included the same activities in the on-line course and the same number of the students involved, also in terms of international students.

In detail we analysed:

1. the improvements of the grade related to the works produced by the students after the peer assessment process (we compared the grades given by the teacher before and after peer assessment process);
2. the questionnaire on the perception of the students regarding the collaborative activity of the peer assessment.

Firstly, the score got by the students related to the task submitted before the peer assessment, was compared with the score of the final version of the task uploaded following the peers' feedback. The aim was to see the different impact in the improvement of learning outcomes in both editions respectively using random group approach (edition 2017/2018) and heterogeneous groups approach through Machine learning application (edition 2020/2021).

Then a final questionnaire based on similar already tested investigations related to the users' satisfaction about collaborative activities [17] was delivered anonymously at the end of the peer assessment. It was characterized by 21 questions ranked on a five-point Likert scale and 10 open ended questions, covering 5 main topics such as:

1. general opinion on peer assessment activity,
2. improve the final report before the submitting of the final draft,
3. improve critical thinking,
4. self-evaluation,
5. enhance the learning of the main concepts in Genomics.

The same questionnaire was delivered in both editions, to quantify the impact of the new machine learning compared to the previous approach not only in terms of performance but also in terms of perception.

2.5 Data analysis

The results of the research questions required some analysis that involved the comparison of the grades obtained by the students before and after the peer assessment process and the answers of the questionnaire related the perception of the students and their behaviour about the peer assessment.

The comparison between the grades was performed through the "t-test paired two sample for means" of MS Excel, a statistical method used to compare the means of two groups [18]. The T-test was applied to analyse the means of the grades obtained by the students before and after the peer assessment for each edition of the on-line courses. The goal was to discover if the p values in the both editions returned a significant difference between the grade obtained before and after the review process, and then comparing the means in the two on-line courses to detect if there were some differences in terms of effectiveness.

The analysis of the questionnaire was made using the software Excel, selecting the questions that define satisfaction and perception related to the peer assessment process, also in terms of improvement of soft skills and knowledge. In particular the questions ranked on a five point Likert scale were used for the analysis in order to compare the percentage of satisfaction between the two editions and if they register important differences.

3 Results

The results required an analysis of the students' behaviour, grades and perceptions, in order to satisfy the research questions:

1. Does peer assessment based on heterogeneous groups enhance the improvement of students' performance compared to the same activity based on random groups?
2. Does the use of the heterogeneous groups influence an improvement in students' perceptions compared to the same activity that required random groups?

3.1 Realization of heterogeneous group

Firstly, a dataset was created in order to execute the software (that include clustering techniques and the sorting algorithm) aimed at the creation of effective heterogeneous groups.

Different features were extracted by Moodle logs and organized in the dataset, selecting the data that better characterized the students' behaviour in the platform, based on their interaction in the on-line course during the first period of individual study. These features were included in the dataset:

1. login frequency;
2. total time online;
3. number of views of video experiments online;
4. frequency of viewing of video experiments online;
5. number of views of teaching materials;
6. frequency of viewing of teaching materials;
7. number of exercises performed.

The dataset was then processed by the K-means clustering algorithm, implemented in the software.

K-means is an unsupervised machine learning algorithm that attempts to partition the dataset into K predefined distinct and non-overlapping subgroups (clusters) [19].

Since this algorithm needs the number of clusters to be created as input, the elbow method was used to find the optimal number of clusters [20].

K-means returned 3 clusters of students (identified by ID). Students were then included automatically by the sorting algorithm in 8 heterogeneous groups, including in each group at list one member belonged to a different cluster.

These are the clusters returned:

1. Cluster 0: [0, 14, 16, 25, 26, 28, 32, 40];
2. Cluster 1: [2, 6, 9, 11, 12, 15, 17, 18, 20, 24, 29, 35];
3. Cluster 2: [1, 3, 4, 5, 7, 8, 10, 13, 19, 21, 22, 23, 27, 30, 31, 33, 34, 36, 37, 38, 39].

Based on the clusters obtained, the software creates 8 heterogeneous groups, paying attention to try to ensure the heterogeneity in each group:

1. Group 0 [0, 2, 1, 3, 4];
2. Group 1 [14, 6, 5, 7, 8];
3. Group 2 [16, 9, 10, 13, 19];
4. Group 3 [25, 11, 21, 22, 23];
5. Group 4 [26, 12, 27, 30, 31];
6. Group 5 [28, 15, 33, 34, 36];
7. Group 6 [32, 17, 37, 38, 39];
8. Group 7 [40, 18, 20, 24, 29, 35].

3.2 Results of peer assessment

Once created the groups, and after the first submission of the task at the end of the self-learning part, students were included in the peer assessment process.

In particular, two reports, written by peers belonging to the same group, were assigned to each student, who had to provide a total score (sum of the values assigned to each grid's criteria) and to write general feedback related to the reports aiming at improving the quality of the works.

At the end of the process the teacher assigned to each student two grades related to the task submitted, respectively to assess the task before and after the peer assessment. For each student a comparison between the scores obtained was made to check the effectiveness of the peer review process.

Does peer assessment based on heterogeneous groups enhance the improvement of students' performance compared to the same activity based on random groups? A new analysis was made to answer this research question, comparing the differences between the score obtained by students before and after the peer assessment process for the edition 2017/2018 and 2020/2021, determining if there were differences between them, and checking if the heterogeneous groups approach, based on Machine Learning, enhance the improvement performance compared to the random group approach.

Before defining the correct tool to use for the statistical analysis, the normality of the data was assessed using the Shapiro Wilk Test with R [21]. In all cases of the both editions of the course, the Shapiro Wilk test returned a not-significant p-value, (greater than the alpha value of 0,05). Because of the normal distribution of the grades, the paired t-test was selected for the comparison (the same elements were evaluated in different times, before and after the peer assessment). T-test returned p-values lower than the level of significance (alpha level) of 0,05 for both comparisons. These data confirmed a statistically significant difference between the pre-treatment condition and the post-treatment condition; the post-treatment average was higher in both years, therefore this difference is attributable to the efficacy of the peer assessment process (post treatment was higher than pre-treatment). Considering that the edition based on heterogeneous group with an increase of the grade (1,41) was greater than the edition based on random group (0,67), it can be assumed that the peer assessment process related to the new edition of the course statistically performs better than the previous edition (heterogeneous group edition p-value 0.0000000027 vs random group edition p-value 0.0000637). The figure 3 represents the grades obtained by students of the Genomics Laboratory 2017/2018, while the figure 4 the grades of students involved in the Genomics Laboratory 2020/2021. The figure shows an improvement of the performance after the collaborative activity in both the editions, even if the gaps between the grades obtained by the students involved in the peer assessment with heterogeneous groups are more evident compared with the other approach.

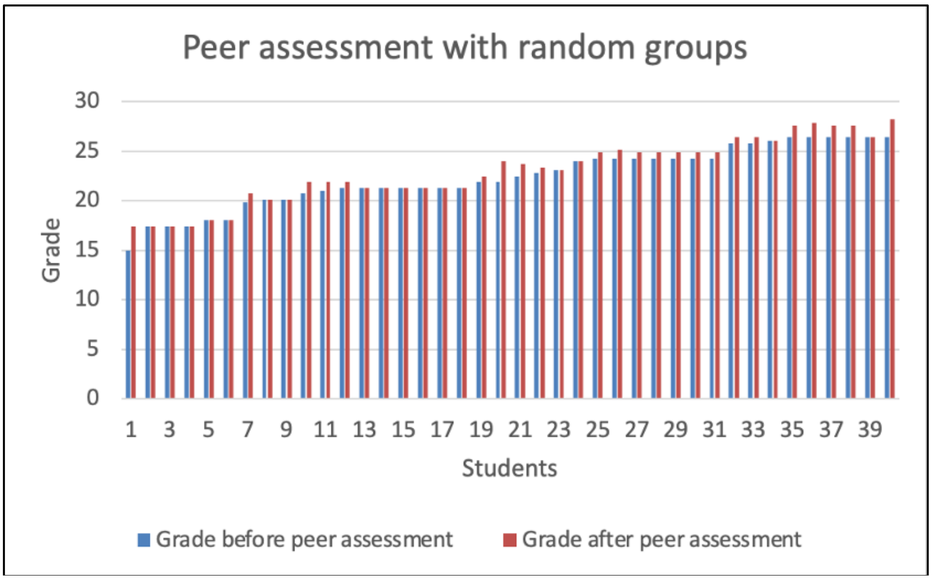

Fig. 3. Comparison between the grade obtained by students before and after the peer assessment with Random Groups.

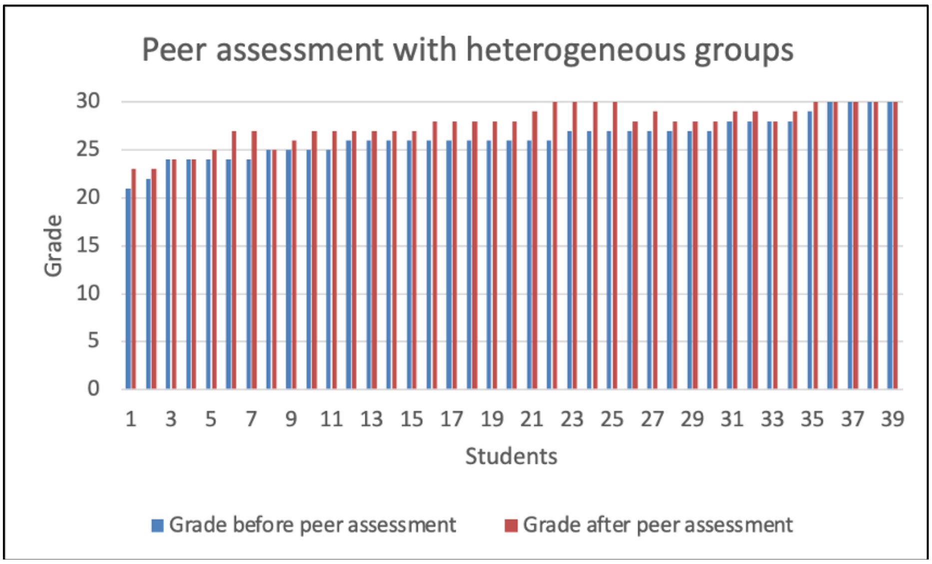

Fig. 4. Comparison between the grade obtained by students before and after the peer assessment with Heterogeneous Groups.

This trend is also confirmed by the results returned by the data analysis because the heterogeneous group approach returns the 41% of students that achieved a grade with an increment >=2 and only 20% of students that didn't improve their grade, compared to the random group approach where only 7,5% of the students achieved a grade with an increment >=2 and instead the 42,5% of students didn't improve their grade after the peer assessment. It's necessary to specify that, as the histogram in figure 4 shows, four people already achieved the maximum score before the peer assessment, and this fact means that the percentage of students who didn't improve their grade could be lower.

Does the use of the heterogeneous groups influence an improvement in students' perceptions compared to the same activity that required random groups?

Table 1 and table 2 summarize the answers to the questions related to the peer assessment, selected by the questionnaires filled by students that participate in both editions of Genomics Course, in order to determine if the realization of groups of students using Machine Learning techniques gave benefits to students, affecting their satisfaction in the study. Analysing the answers released by students in the two surveys, the edition 2020/2021 returned very good results that reflect an improvement in terms of satisfaction compare to the other edition, as reported by the following results related to the answer of students involved in heterogeneous groups, realized by the application of Machine Learning: 83% agree (A) or strongly agreed (SA) in the use of the feedback to revise their tasks, 72% (A+SA) believe that peers are qualified to provide qualitative feedback/comment about the exercises, 74% improved their knowledge on the course topic being an assessors and providing critical feedback, 74% (A+ SA) think that the quality of the final work improved because of the peer-assessment process, and 91% (A+ SA) think that the peer-assessment process was a valuable learning experience.

Table 1. Results of the 5 questions selected by the questionnaire related to the on-line Genomics Laboratory 2017/2018, characterized by peer assessment based on random groups. SD=Strongly Disagree; D=Disagree; N=Neutral; A=Agree; SA=Strongly Agree.

Questions	SD	D	N	A	SA
I used feedback/comments provided by peers to revise the first draft of my task.	1%	21%	24%	47%	7%
I believe my peers are qualified to provide qualitative feedback about my exercises.	4%	21%	39%	35%	1%
My understanding and knowledge of the topic improved by being an assessor and providing feedback.	0%	7%	26%	54%	13%
The quality of my final work improved because of the peer-assessment process.	2%	20%	23%	40%	15%
I think that the peer-assessment process was a valuable learning experience.	2%	7%	10%	50%	31%

Table 2. Results of the 5 questions selected by the questionnaire related to the on-line Genomics Laboratory 2020/2021, characterized by peer assessment based on heterogeneous groups. SD=Strongly Disagree; D=Disagree; N=Neutral; A=Agree; SA=Strongly Agree.

Questions	**SD**	**D**	**N**	**A**	**SA**
I used feedback/comments provided by peers to revise the first draft of my task.	0%	0%	17%	49%	34%
I believe my peers are qualified to provide qualitative feedback about my exercises.	1%	1%	23%	66%	6%
My knowledge of the topic improved by being an assessor and providing feedback.	0%	3%	23%	54%	20%
The quality of my final work improved because of the peer-assessment process.	0%	5%	20%	54%	20%
I think that the peer-assessment process was a valuable learning experience.	0%	0%	9%	54%	37%

The perception of the students, that included very low percentage of the strongly disagree and disagree responses (at maximum 5%), confirmed the effectiveness of the artificial intelligence approach in the composition of the groups that provide benefits for the students for enhancing their learning experience.

4 Conclusions and future perspective

This work proposed a new Machine Learning Approach able to create effective heterogeneous groups of students to be involved in the online peer assessment process, in order to enhance learning outcomes and satisfaction in the students. The use of this tool overcomes the limitations of the standard Moodle activities, applying machine learning techniques by analysing the students' data extracted by the Moodle analytics.

The course "Genomics Laboratory " of the University of Camerino was delivered on-line in different academic years, where the peer-review activity was based on random groups, but it highlighted some gaps:

1. Random groups didn't ensure that each group was composed of heterogeneous students.
2. Because of random groups, some students could have a bad perception of the peer review activity, negatively affecting their engagement and motivation.

By exploiting the method here implemented, the use of heterogeneous groups helped the teacher in the creation of effective groups of students expected to work in the peer assessment process, increasing the probability to have a good review for each member of the group. In this way, each student was able to enhance its learning experience, performance, knowledge, and satisfaction, contributing to the achievement of high-quality learning outcomes.

Future development will consist of realizing new additional applications of the Machine Learning software used in this work, applying new functionalities that can improve the heterogeneity in each group and testing the software in a new on-line course in order to confirm its effectiveness.

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