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Effect of different grouping arrangements on students' achievement and experience in collaborative learning environment

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ABSTRACT

The study aims to investigate the effect of homogenous and heterogeneous grouping on students' achievement and experiences of learning in a collaborative environment. A collaborative learning environment has been used as a pedagogical tool for a long time now. However, there is no clarity on which grouping strategy to use. In this paper, we study the impact of grouping on students' performances. We aim to examine how different grouping arrangements, leading to different learning environments, affect students' academic achievement. Also, in most cases homogeneity or heterogeneity is decided on the basis of students' ability. For group learning, students were grouped into two different settings on the basis of their learning perspectives derived from class notes and their personality types. In the present study, we used a novel algorithm based on k modes clustering. Grouping indeed improved students' performance, particularly, the heterogeneous groups performed better than the homogenous groups. Students' experience with learning in the two different environments indicates that they were more satisfied with homogeneous group settings.

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Collaborative learning environments; homogeneous grouping; heterogeneous grouping

1. Introduction

Teaching-learning strategies widely acknowledge collaborative learning environments for the positive learning outcomes they lead to (Gillies, 2006; Johnson & Johnson, 2002). A collaborative learning environment is a setting in which individuals acquire and share knowledge through experience with one another (Argote et al., 2001). In other words, a group of students learn together and take advantage of each other's expertise and experiences to achieve a common goal. Learning in groups improves performance levels (Gregory & Thorley, 2013; Johnson & Johnson, 2009), enhances student achievement (Donovan et al., 2018) and makes the transfer of knowledge easy among the participants (Pfaff & Huddelston, 2003). Students who learn in groups also develop better social interaction skills (Johnson & Johnson, 1990). Apart from the academic and social benefits, collaborative learning (CL) benefits students psychologically (Laal & Ghodsi, 2012).

However, despite being a widely practiced teaching strategy, there is ambiguity on grouping methods in collaborative learning environments. Homogenous and heterogeneous grouping are the two major ways to group students in CL. In homogeneous grouping, students of similar characteristics learn together. Contrary to this, students of diverse characteristics and abilities learn together in heterogeneous grouping (Baer, 2003). The question of grouping "who with whom" is

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still unanswered (Saleh et al., 2005; Zamani, 2016) because of the conflicting evidence (Donovan et al., 2018). Several studies claim that homogenous grouping yields better learning outcomes (Baer, 2003; Kemper Patrick, 2020; Schullery & Schullery, 2006). On the other hand, some experiments suggest assigning students into heterogeneous groups enhances student learning and interdependence (Wilkinson et al., 2010). Studies with no overall difference between the impact of the two grouping strategies also exist (Hooper & Hannafin, 1988; Zamani, 2016). These variations may result from the basis of deciding homogeneity or heterogeneity.

In this paper, we study the effect of grouping on learning outcomes and the difference the two grouping strategies have on students' achievement and experiences. Groups are formed on the basis of learning perspectives and personality types of students in a class. To extract the unique learning perspectives, we use students' class notes and teacher's notes. The information extracted from class notes can be mapped to different learning perspectives. Additionally, claims of high chances of conflicts in heterogeneous grouping (Schullery & Schullery, 2006) inspire us also to consider personality types while grouping students. The difference in scores in post- and pre-test is taken as a measure of impact. Students' experiences with different learning environments are analyzed with a survey. The following are the contributions of the paper:

- We propose a novel grouping algorithm based on k modes clustering to group students homogeneously and heterogeneously.
- To group students, we consider the learning perspective of every student in the class.
- To minimize conflicts, we also take consider the personality type of every student.
- We study the effect of grouping by comparing the learning performances of students learning without any grouping with the one's learning in groups.
- Students' achievement and learning experiences are compared in homogenous and heterogeneous learning environments.

1.1. Research questions

The study specifically evaluates the impact of grouping methods in CL on undergraduate students. To examine how grouping methods relate to academic achievement, the following hypotheses are tested:

$H0_1$: There is no statistically significant difference in the academic achievement of students' learning in collaborative learning environments.

$H1_1$: There is a statistically significant difference in the academic performance of students' learning in collaborative learning environments.

$H0_2$: There is no significant difference in students' academic performance of homogenous and heterogeneous groups in collaborative learning environments.

$H1_2$: There is a difference in students' academic performance of homogenous and heterogeneous groups in collaborative learning environments.

Here, the learning environment in which the students learn is an independent variable. In other words, the grouping method is an independent variable, and academic achievement is a dependent variable. In addition to this, examining how was the collaborative environments provided on the basis of learning perspectives raised the following research question:

RQ1: How was students' learning experience in the two collaborative environments?

The paper is organized into four more sections. The next section of the paper elaborates on work on grouping strategies in the past. Section 3 gives details of the materials and methods used in performing the experiment. The results of the study are explained in section 4. In the end, the authors list some essential conclusions.

2. Related work

2.1. Homogeneous vs. heterogeneous grouping

Despite several pieces of evidence indicating the usefulness of collaborative learning environments, there is a lack of agreement among researchers as to which groping method is better. One of the largest studies compared the two methods of grouping over three consecutive semesters. Students were grouped homogeneously and heterogeneously on the basis of prior achievements. Here, a significant difference was observed in the performance of final exams, with homogeneously grouped students performing better (Baer, 2003). Schullery and Schullery (2006) also studied the variations in outcomes of two groups composed differently on the basis of personality. The experiment was performed on 394 undergraduate students who were asked to complete a project collaboratively. At the end of the project, it was noted that both the grouping strategies had positive impacts on certain sets of skills. However, students from homogenous groups achieved more academically. Ability-based grouping methods also claim the superiority of homogenous grouping over heterogeneous when performed on school students (Adodo & Agbayewa, 2011). Similar outcomes were observed on subjects like chemistry when students were grouped on the basis of gender (Adesoji et al., 2015).

Contrary to this, the heterogeneous grouping strategy also proves to be more beneficial in certain scenarios. For instance, the effect of the two methods of grouping was analyzed on students' discourse and comprehension. Here also, the students were grouped on the basis of ability. The authors found heterogeneous grouping much more beneficial than homogenous grouping (Murphy et al., 2017). However, it was a small experiment involving only a group discussion. With the increasing acceptability of e learning, the idea of collaborative environments was also applied in online scenarios. Sanz-Martínez et al. (2019) claim that CL improves the effectiveness of MOOCs. The authors grouped students on the basis of engagement levels. Rather than grouping with the two contrary strategies, they grouped all the students according to varying degrees of homogeneity. Task completion, satisfaction, peer interaction and overall experiences were better in groups with a higher degree of homogeneity. In a similar attempt, Wichmann et al. (2016, august) found heterogeneous groups slightly more productive than homogeneous groups in a massive online learning course.

2.2. Basis of deciding homogeneity and heterogeneity

The variation in outcomes is an indication that several other factors play a crucial role in determining the success or failure of grouping methods. The most common parameter for grouping used in the past is students' ability (Adodo & Agbayewa, 2011; Miller et al., 2012; Saleh et al., 2005). Studies have also considered race, culture (Shen, 2003), students' choice (Donovan et al., 2018) and gender (Adesoji et al., 2015) while forming different groups. For e-learning systems, students' engagement levels are considered for grouping (Sanz-Martínez et al., 2019). In an educational context, students can also be described by their unique cognitive style (Jovanovic et al., 2012). Cognitive abilities are a crucial determinant of note taking and memory for lecture content (Jansen et al., 2017). Taking notes in a class while the teacher is teaching is indeed cognitively effortful (Piolat et al., 2005). Apart from cognitive abilities making a difference, identifying the important and unimportant information also depends greatly on the student's perspective (Peverly et al., 2014). Hence, class notes represent a student's learning perspective that is unique due to cognitive differences and other such reasons.

In this paper, we aim to evaluate the learning perspectives of students on the basis of class notes taken while the teacher is teaching in class. Homogenous and heterogeneous groups are formed on the basis of learning perspectives. In addition to learning perspectives derived from class notes, personality types also determine people's compatibility in a group (Schullery & Schullery, 2006; Stapleton, 2007). Personality type in a group influences the learning outcomes and group cohesion (Tett & Murphy, 2002). For personality type-based grouping, MBTI is a commonly used tool for assigning a personality type to each student (Schullery & Schullery, 2006; Stapleton, 2007). Considering this, we also use MBTI to extract various personality traits of students.

3. Materials and methods

3.1. Participants

One hundred ninety-four undergraduate students from the seventh semester of the computer engineering department at an engineering college participated in the study. The experiment was carried out in the spring semester of 2020–2021. Group learning was facilitated in the class of Agile software development. Following the accepted ethical practice, the participants were assured that their identities would be kept anonymous.

3.2. Design

The study follows a quasi-experimental design since it involved a pre-test at the beginning of the session followed by treatment and a post-test at the end. The same teacher taught all the students and evaluated the papers of pre-test and post-test. Students' achievement measured by test scores was the dependent variable of the present study. The type of grouping and personality of students were the two independent variables. Overall, three groups were participating in the study, with one control group and two experimental groups. The control group learned individually without any grouping. The heterogeneous experimental group consisted of students with different learning perspectives and different personality types, and homogenous groups comprised students with similar learning perspectives.

3.3. Procedure

In all three groups, at the beginning of the semester, the teacher taught in a traditional setting without any collaboration. After two weeks of traditional teaching, the teacher took a pre-assessment test to evaluate the performance of each student. The test consisted of four open-ended questions on the introduction and basics of agile software development. Each question carries 5 points, making the pre-assessment test of 20 points. While the control group continued to learn traditionally, the students from the two experimental groups had to give some tests. The students passed a personality assessment test that assigned them to an appropriate MBTI personality type. MBTI classifies people into 16 different personality types based on their lifestyle, attitude towards life, method of perception and judging. Every personality is a combination of four-letter from: E/I; S/N; T/F and J/P where, E – extravert, I – introvert, S – sensing, N – intuition, T – thinking, F – feeling, J – judgment and P – perception (Smith, 1989).

Students from the experimental groups were also asked to submit their class notes of their first lecture on "Scrum and Adaptive Software development". The students were made familiar with the aim of the course and the benefits of CL. They were also made aware of their partners for the entire course duration. However, the basis of grouping was not disclosed. Each class in the semester was followed by discussions on the topics taught in class. During the discussion, the teacher walked into the class and among the pairs to observe the participation of the learners. At the end of the course, the teacher took a post-test of 20 marks involving all the students from experimental and control group. Similar to pre-test, it also had 4 open-ended questions of 5 marks each. This evaluated each student's performance individually. A survey was also conducted to judge the differences in experiences with the two learning environments. The research flow is depicted in Figure 1.

3.4. Instruments

We used two major instruments in the present study: academic achievement and class notes. First, the teacher took a pre-test to analyze the current abilities of students. The purpose of the pre-test was to measure the change in academic achievement before and after the treatment in the experimental group. Having administered the pre-test, the participants were asked to submit the class notes to the teacher for further processing. The class notes are used to homogenize and heterogenize the students on the basis of learning perspectives. Experience with the collaborative learning environments based on the learning perspectives was estimated with a survey.

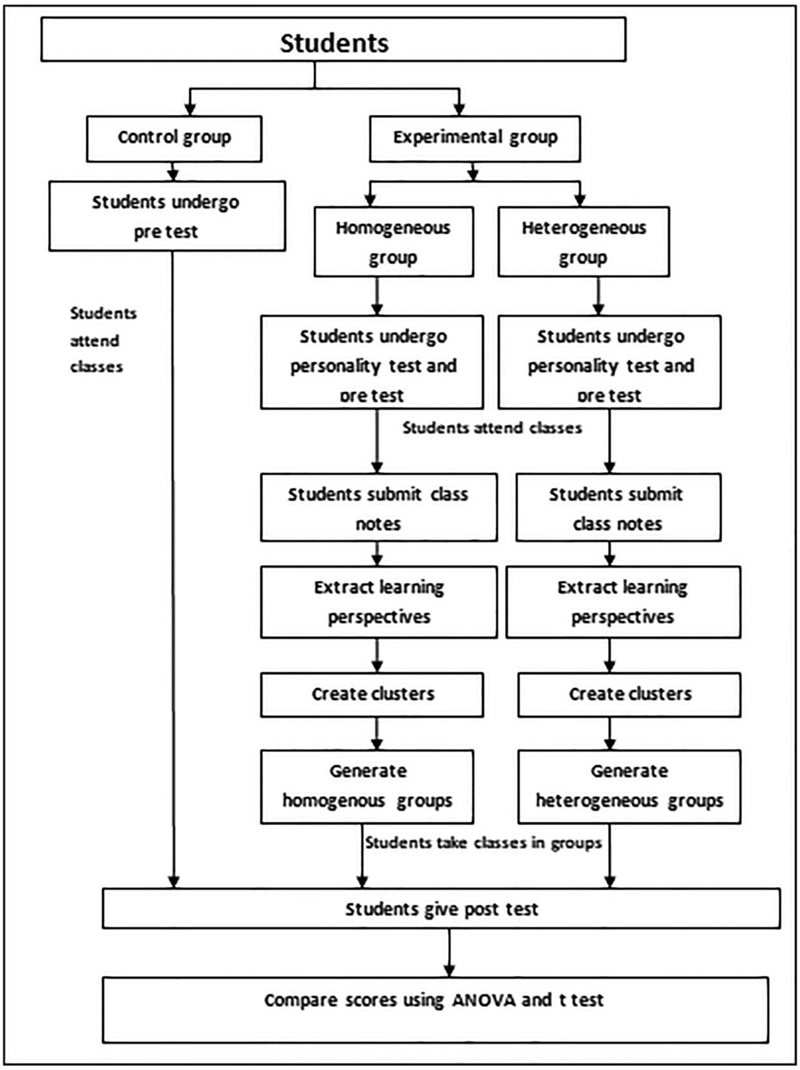

Figure 1. Flowchart depicting research flow.

3.4.1. Academic achievement

The control group took classes and completed assignments individually with no grouping. Both the experimental groups were given the assignment to complete collaboratively. The participants were assessed for independent knowledge gains. A pre-test and a post-test were used to evaluate students' independent knowledge gains in all three groups. A score was given out of 20 points to each individual and groups.

3.4.2. Experience of collaborative learning environment

Students' experience with the CL provided through different types of grouping in the experimental groups was assessed by measuring their satisfaction. Satisfaction was evaluated using the following questions given by Peeters et al. (2006):

i "If I ever have to participate in a similar project, I would like to do it with this group."
ii "Overall, I was satisfied with the composition of our group."
iii "In general, the proceedings of the group were done in a pleasant atmosphere."

These questions assess satisfaction as a measure of the perceived effectiveness of grouping. For every question the participants had to rate their agreement on a 5-point Likert-type scale, ranging from 1 (strongly disagree) to 5 (strongly agree).

3.5. Grouping

Class notes of each student are given as input to an Optical Character Recognition (OCR) system. The data are first pre-processed, corrected for spelling errors and the part-of-speech tagging is applied. The system then selects all nouns and nouns followed by adjectives as keywords. The keywords are converted into concepts using the index of an e-book corresponding to the subject (First author et al., 2019).

Let $T_C = \{\text{concepts extracted from teacher's notes}\}$.

3.5.1. Clustering students with similar learning perspectives

To cluster students with similar learning perspectives together, we use the K-Modes algorithm. The K-Modes algorithm gives considerably good results when applied to real-world categorical data. This algorithm replaces the means of clusters with modes and minimizes the cost function using a frequency-based method (Huang, 1998). The algorithm takes as input a matrix M representing the distribution of concepts among students with respect to the concepts the teacher taught in class. For this, we compare concepts extracted from notes of every student with that of teacher's notes. The following is the conversion of data into matrix M:

$M := (a_{i,j})_{m*n}$, for all $1 \le i \le m$ and $1 \le j \le n$, where m is the total number of students and n is the keywords present.

$a_{i,j} = 0$ if a concept from T_C is not present in the student's notes.

$a_{i,j} = 1$ if a concept from T_C is present in the student's notes.

The K-Modes algorithm treats every row in M as the feature vector for a particular student. While clustering using the K-Modes algorithm, we also specify the optimum number of clusters. The aim is to choose the number of clusters so that adding a new cluster doesn't create much difference. To get this number, we use the elbow method and Within Cluster Sum of Squares (WCSS). WCSS is an indicator of the closeness of each point in the cluster with the center of the cluster (Hartigan & Wong, 1979).

3.5.2. Homogeneous grouping

Once we have clustered students according to their learning perspectives, now the clusters can be further divided into smaller groups. Group size is the minimum or maximum number of learners who learn collaboratively. Although the clusters already have students with a similar perspective, studies are indicating the preference of students to smaller group sizes (Kooloos et al., 2011). Also, small-sized groups are better from the viewpoint of productivity (Putnam, 1978), performance and social interactions (Saqr et al., 2019, september). Hence, the system divides the clusters into smaller sizes of 3–5. Rather than randomly picking up students and grouping together, the system consider the personality type of each student. Several studies state the benefits of diverse personalities in a group (Clinebell & Stecher, 2003; Sfetsos et al., 2006, june). Following a similar line of thought, we group students of a cluster with different personality characteristics. The stepwise details are given in the algorithm depicted in Figure 2.

3.5.3. Heterogeneous grouping

Since hamming distance in the matrix M represents the dissimilarities between rows/students' concepts, we use this as a base to group students heterogeneously. If a row differs from another row, the two students representing the rows are considered to have different learning perspectives. Hence they can be grouped provided they have different personality types. So, in a heterogeneous grouping, we group students of varying personality types and different learning perspectives. The detailed procedure for heterogeneous grouping is given in Figure 3.

4. Results

In the beginning, we randomly initialize the k modes algorithm. Using these random values, the calculated WCSS is plotted against corresponding k values (Hartigan & Wong, 1979). The elbow of the curve is highlighted in Figure 4. Following the method, 9 comes out to be an optimum number of clusters.

Input: CL (clusters of students), **Ps** (personality types of all students)
Step 1: Let CL is a list of lists where, CL[i] is the list of students
belonging to the ith cluster obtained from algorithm 1.
Step 2: For all clusters in CL, let N is the size of cluster,
2.1 For N <=4
Compare personality types of each student in the cluster.
If at least one student has different personality type, make the cluster a group.
Else, merge the cluster with nearest cluster.
2.2 For N >4, find the number of groups N_G:
Case 1: N_G = (N/3), if 3 divides N
Case 2: Else, N_G = ((N/3) + solve (3, N%3))
2.3 Size of each group= 3 for case 1
2.4 Size of all groups 3 except last group= 3+ remainder for case 2
Step 3: In each cluster,
If no. of students with identical personality types=< N_G
3.1 Assign students in different groups.
3.2 Fill all groups to their size by randomly selecting students from the cluster
Else if: No. of identical personalities> N_G,
&& no. of distinct personalities>= N_G,
3.3 Assign one student from students with distinct personalities to each group.
3.4 Fill all other groups randomly with remaining students
Else Make preferable group size 2 by replacing 3 with 2 in step 2.
3.5 Repeat step 3 till all the students is grouped.
Step 4: Skip step 3 and group students randomly from each cluster on the
basis of group size obtained from step 2.3 and 2.4 if the algorithm
reaches step 3.4 with preferable group size 2.
Output: Homogenous groups of students

Figure 2. Algorithm for homogenous grouping.

Input: $M_{i,j}$, P_s(personality types of students)
Step 1: If i is divisible by 3
No. of groups (N_G) = (i/3) and size of each group= 3
Else, N_G= ((i/3) + solve (3, i%3))
Size of each group= 3 and last group=3+ remainder from step 1.
Step 2: Cluster students with 0 hamming distance from $M_{i,j}$ in C_h.
Step 3: If size of C_h <= N_G, assign one student from C_h to each group.
Step 4: For remaining students
If no. of students with identical personality types=< N_G
4.1 Assign these students to different groups.
4.2 Fill all groups to their size by randomly selecting students from the cluster.
Else if: No. of identical personalities> N_G,
&& no. of distinct personalities>= N_G
4.3 Assign one student from students with distinct personalities to each group.
4.4 Fill all other groups randomly with remaining students
Else Make preferable group size 2 by replacing 3 with 2 in step 1.
4.5 Repeat step 2 till all the students are grouped.
Step 5: If size of C_h > N_G, try to make groups of size two by replacing 3 with 2 in step 1.
Step 6: If distinct personality types are still low in number to provide heterogeneity, group randomly after step 3.
Output: Heterogeneous groups

Figure 3. Algorithm for heterogeneous grouping.

Figure 5 depicts the number of students in each cluster. After clustering and grouping using algorithms for heterogeneous and homogenous grouping discussed in Section 3, the students attended classes in groups. At the end of the course, they were assessed for academic achievement.

4.1. Academic achievement

The mean scores of pre-test and post-test for the control group are 15.23 and 15.27, respectively. The mean scores of the same for the homogenous group are 15.14 and 15.30. As given in Table 1, the mean scores of the two tests for heterogeneously grouped students were 15.77.and 16.51. The variations in mean scores of students from homogeneous and heterogeneous groups are depicted in Figure 6. The graph shows that students in heterogeneous and homogeneous groups at the post-test improved. The achievement gain for the students of the control group was 0.04, for the homogeneous group, it was 0.16 and it was 0.74 for heterogeneously grouped students.

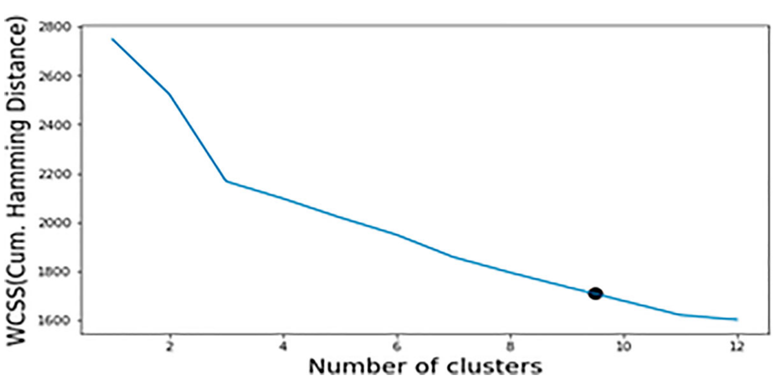

Figure 4. The elbow method for finding the optimum cluster number.

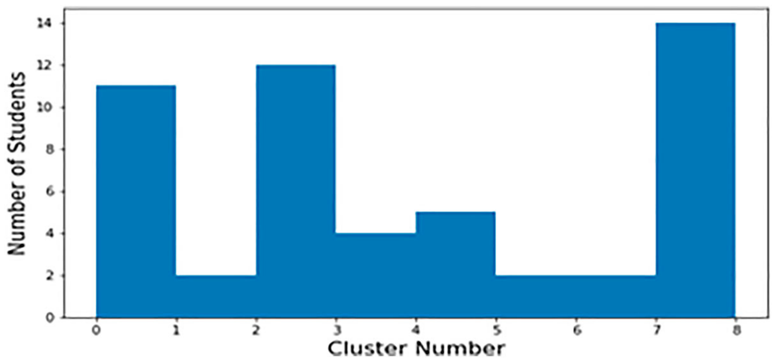

Figure 5. Number of clusters and students in each cluster.

For testing the first hypothesis, $H0_1$ stating that there is no difference in the academic achievement of students learning in collaborative learning environments, we apply paired *t*-test on the scores of pre-test and post-test of the control group and experimental groups. The difference in the mean scores of post-test and pre-test is 0.53 for experimental groups. On the other hand, the difference of mean scores in the case of the control group is 0.04. The results of *t*-test on pre-test and post-test scores of students indicate an improvement on the post-test with a mean difference significant at $t\ (127) = 4.06$, $p < .001$. The analysis of pre-test and post-test difference of the control group leads to no significant improvement with $t\ (66) = 0.19$, $p < .001$.

In addition to this, we also tested the post-test scores of the control group, heterogeneous group and homogeneous group for any significant difference using ANOVA. The results at $p < .05$ and f ratio 12.46 indicate a significant difference in the performance of the three groups with $p < .001$. A pairwise comparison suggests that the mean scores of students of the control group and the students of the experimental group with homogeneous grouping did not differ significantly. However, on comparing the scores of students from the experimental group with heterogeneous grouping with the other two groups, a significant difference was recorded. The statistical details are given in Table 1. Table 2 depicts the test results.

So, on the basis of this, the null hypothesis $H0_1$ is rejected. And according to the acceptance of $H1_1$, we can conclude that collaborative learning environments indeed improve the learning environments. However, it is still not clear which grouping strategy is better.

To test the null hypothesis $H0_2$ of the research claiming that there is no significant difference in academic performance of students of homogenous and heterogeneous groups in collaborative learning environments, we check for statistically significant differences between the gains of the two groups. The descriptive statistics is given in Table 3.

By looking at the descriptive statistics, we can say there is a clear improvement in the performance of students of heterogeneous groups, and the mean score of homogeneously grouped students also improved slightly. However, to find out whether the differences between the means were statistically significant or not, paired t-tests were applied. The results of $t\ (61) = 1.89$, $p < .01$ indicate no significant difference in the mean scores of the homogeneous group on the pre-test and post-test.

Table 1. Statistical data for ANOVA on the control group and experimental groups.

Variables	Control group	Homogeneous group	Heterogeneous group
Number of students	66	62	66
$\sum X$	1008	959	1090
Mean	15.27	15.46	16.51
Std. deviation	1.55	1.74	1.27

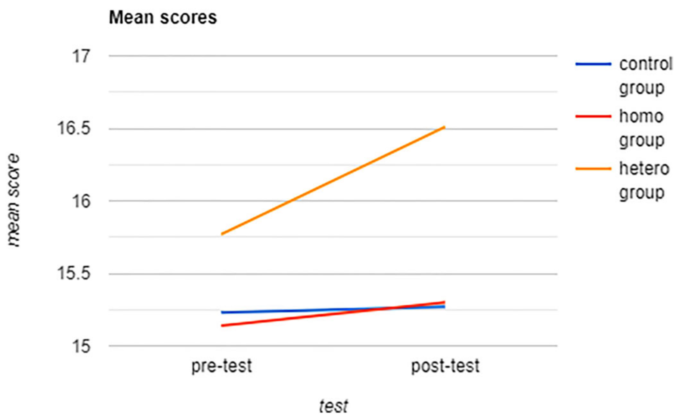

Figure 6. Improvement in mean scores of control group, heterogeneous and homogenous group.

The results on heterogeneously grouped students show an improvement on the post-test with a mean difference significant at t (65) = 3.72, $p < .01$. It is concluded that students from the heterogeneous groups improved in the post-test. Therefore, the null hypothesis $H0_{2,}$ which said there is no significant difference between students' academic achievement working in homogenous and heterogeneous groups, is rejected. The scores of heterogeneous groups improved significantly. On the other hand, no significant improvement was seen in the scores of homogenous groups.

Hence, hypothesis $H1_2$, stating that the two grouping methods create a difference in students' academic achievements, is accepted with heterogeneous groups performing better. A summary of paired t-tests for learners in different collaborative environments is given in Table 4.

4.2. The difference in experiences with the two learning environments

The control group received no treatment; hence, we compare the experiences of the two experimental groups. A survey was conducted to assess the experiences of students' learning in different collaborative environments. The same questions were asked to all the students, and they had responses to choose from ranging from 5 to 1. The first question assesses the compatibility of grouping using learning perspectives and personality types. With the mode and median and mode at 4, homogenous and heterogeneous groups varied slightly in the mean values. The mean of responses of heterogeneously grouped students was 3.57, while that of homogenous grouping was 3.83. Similarly, on summarizing the responses to question measuring satisfaction, the mean of heterogeneously grouped students was 3.8, and the mean for homogeneously grouped students' responses was 4.04. Even in the third question of the survey analyzing the learning atmosphere, the mean of responses from the homogenous group was 3.95, while for the heterogeneous group it was 3.8. Although the responses from both types of learning environments were quite positive, comparatively, we can say that students from homogeneous groups had better learning experiences than heterogeneous groups.

Table 2. Results of ANOVA.

Source	SS (sum of squares)	Df (degrees of freedom)	MS (mean square)
Between groups	58.60	2	29.30
Within groups	449.01	191	2.35
Total	507.61	193	

Table 3. Data for pre-test and post-test in control, homogeneous and heterogeneous groups.

Group	Mean	Std. deviation	Std. error mean
Control group	15.23, 15.27	1.62, 1.55	0.20, 0.19
Homogeneous pre, post	15.14, 15.30	1.36, 2.17	0.17, 0.27
Heterogeneous pre, post	15.77, 16.51	2.22, 1.27	0.27, 0.15

Table 4. *t*-Test for homogeneous and heterogeneous groups.

	Paired differences				
Group	Mean	Std. deviation	Std mean error	*t*	Df and significance (2-tailed)
Homogenous	0.32	1.34	0.17	1.89	61, insignificant at .01
Heterogeneous	0.74	1.61	0.2	3.72	65, significant at .01

5. Conclusion

In the present study, we tried to see the impact of collaboration on students' achievements. We also aimed at seeking the superiority of one collaborative learning environment over the other. For this purpose, we used the learning perspectives of students and their personality types as the basis for group formation. The teacher also conducted a pre-test and post-test to track the improvement. The experiences with the learning environments were assessed with a survey comprising three simple questions. On the basis of the scores of pre-test and post-test, it was clear that collaboration influences the academic achievement of students positively. We compared the scores of the students studying in two different collaborative environments for significant differences.

It was observed that heterogeneously grouped students performed better than homogeneously grouped students. So, it can be concluded that although collaboration improves the academic achievement of students, heterogeneous grouping is found to have a greater influence on students' performance. The authors also analyzed whether the idea of grouping students on the basis of learning perspectives and personality types leads to compatible groups or not. For this, students' responses to questions assessing the satisfaction and perception for the learning environment were considered. The results indicated that the blend of learning perspectives and personality types lead to favorable group compositions. However, in this case, the responses from students who learned in homogenous groups had a better learning experience and satisfaction than the heterogeneously grouped students.

The study finds a collaborative environment with heterogeneous grouping superior over an environment comprising homogenous students in terms of academic achievement. Contrary to this, in terms of learning experience, homogenous learning environment was better. Hence, it can be concluded that the superiority of the type of collaborative learning environment depends on the results you want. However, in the future we would work on the optimization of group composition in such a way that the students have a better learning experience and at the same time improve their skills. This may be a blend of the two grouping techniques or a foolproof grouping strategy considering various factors such as gender, attitude and skill levels apart from learning perspectives.

Acknowledgements

The study was conducted in a technical university where no institutional ethics committee oversees study with human subjects. It is ensured that no subject is disadvantaged in any way under any circumstances. Responses and analyses were gathered through unique identifiers rather than actual identities. The dataset used in the experiment is anonymous.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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