Dynamic Group Formation in Computer Supported Collaborative Learning

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A post graduate thesis submitted to the Department of software engineering as a partial fulfilment of the requirement for the award of degree of M.S (Software Engineering).

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Abstract

Computer-Supported Collaborative Learning (CSCL) emerges as an instrument of learning and training that can encourage the social nature of learning by adopting range of computer-mediated communication tools and pedagogical methods. These tools are used to facilitate the learning and instructional communication among students and learners in small groups. In this process, group formation becomes painstaking and challenging task. Various factors are involved affecting group formation that includes; personal characteristics, social, cultural, psychological and cognitive diversity. Although, this issue was addressed in various research studies yet an optimal solution for dynamic group formation is not discussed evidently. In dynamic groups, students work or collaborate on a short term tasks in a group that change frequently based on the performance of students. In this research study we have proposed a method for dynamic group formation and the impact of dynamic group formation in collaborative learning among peers is demonstrated by conducting an experiment. This experiment is conducted in two phases. In first phase of the experiment, learning styles are assigned to the students and their knowledge level is calculated. Whereas, in second phase of the experiment, the impact of dynamic grouping on collaborative learning of students is determined. Further, two algorithms are proposed, first is used for determining initial number of clusters and second algorithm is used for dynamic grouping after the completion of each permutation. Results of our experiment shows a positive impact of dynamic grouping on learning of students as the performance of collaborative learning among peers is better than individual performances.

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Chapter 1

Introduction

Collaborative learning is an area that has been under discussion for several years. It became prominent due to the support of the technologies and the internet. Collaborative learning is a pedagogical method in which students collaborate to learn and share their experiences while solving the problem [1]. In conventional learning, collaborative learning (CL) is used for group activities and projects. Mentors create groups manually, assign them tasks, students then collaborate and try to solve the assigned tasks mutually. Groups created manually by mentors are not of the same capability, some groups perform better while others are unable to perform the tasks. Such group formation affects the learning of students. The advent of computers and the internet empowered collaborative learning. Students are given scenarios and tasks, which they solve by using the computer supported shared resources e.g. shared whiteboard, a shared tool for creating diagrams or drawings, etc. [2].

The prime and most important task in CSCL is group formation [1]. Group formation is dividing students into different clusters and assigning them some sort of tasks. They collaborate and complete those tasks. They are clustered into groups based on some attributes like their knowledge level, behavior, learning styles, and interests. From literature, it is evident that there are 3 main ways of group formation [3]. 1. Random selection 2. Self-selection 3. Instructor selection. In random selection, any computer program or teacher swaps students randomly and create groups out of that, to get heterogeneous groups. Heterogeneous groups have students of different types e.g. different knowledge levels and different personality characteristics. On the other hand, in homogenous groups, all the students are of the same level and capacity. In [4], authors proved that heterogeneous groups perform better than homogenous groups. The self-selection method of group formation allows students to choose their group partners. This type of group formation produces better results but on the other hand, it has a consequence that most of the time students of the same capacity and level make groups, which results in almost all weak students in one group and almost all good students in another group. This type of group formation is also not based on the pedagogical grouping method, it is based on the personal friendship of empathy. So, unbalanced groups are achieved instead of good performing groups [3]. The third way of group formation is instructor-selection method, instructors are allowed to create groups. This is hectic for the instructor to judge and analyze every student's performance and characteristics, so, that he can arrange them in groups. In this method, the instructor can create heterogeneous or homogenous groups.

In previous studies, authors have used different attributes for group formation. A proper consensus among authors does not exist, that which attributes are playing a vital role in group formation. In our study, we have adapted the knowledge level as a prime attribute for group formation. Along with the knowledge level, we are also finding out the learning styles of each student and finding its impact on group formation. These learning styles are adapted from the study of Richard M. Felder [5], where they proposed learning styles for engineering education.

The first phase of the experiment of our study is designed based upon the questionnaire of learning styles proposed by Richard M. Felder [5]. Following are the learning styles we are using in this study.

- Sensory
- Intuitive
- Active
- Reflective
- Visual
- Verbal
- Global
- Sequential

Sensory and intuitive refers to the information perception of the students. Do students get information from the surroundings using 6 senses or he/she is getting the information from the intuition (internal) [5] ?

Visual/verbal is the mode of channel through which students get the information. Visual means students are getting information in the form of pictures and videos, while verbal means getting information in verbal form or textual form.

Active and reflective are the two terminologies which the author [5] has used for the processing of information. These terms (Active and reflective) specifies how students are processing the information he/she is receiving. They may actively process it by talking about it or practicing it. They may process it intuitively which is also called introspective processing of information. Introspectively processing the information is termed as reflective learning.

Then there comes other terms called global or sequential students. Global students learn by making large jumps, they learn with the abstract eye, while sequential students go in the depth of the information and try to understand each detail [5].

Problem Statement

In CSCL the prime task is the group formation where data is manually collected for group formation which was fed to traditional algorithms to create fixed groups. Students are not swapped among the groups based on their performance, which affects the learning experience of students and groups' performance.

The aims and objectives

The purpose of the current research work is to identify the characteristics and attributes of students and groups that are effective in group formation. This research will focus on designing a novel approach for dynamic group formation, where students will be swapped based on their performance, to improve student learning experience and groups‘ performance.

Research Questions

In this study our research objectives are

- How to create dynamic groups in CSCL?
- How to overcome the cold start i.e how to create initial groups?
- Can dynamic group formation enhance the group performance and student learning?

Contributions

The main contribution of this thesis can be summarized as follow

- We proposed an algorithm for dynamic group formation, which swaps students based on their performance after each activity.
- Solved the cold start problem of group formation. Groups are created without instructor intervention.
- Design an activity to find the learning style of students

Thesis Organization

The rest of the document is structured as follows:
Chapter 2 **Related Work:** in this chapter we will go through the literature that how much work has already been done in this area of dynamic group formation in computer supported collaborated learning. We had discussed about the different techniques used by different researchers to do group formation in CSCL and how these techniques are not fitting the dynamic group formation.
Chapter 3 **Methodology:-** goes through the methodology used in taking this research work. This chapter describes the outcome of the experimental planning phase, including data collection procedures, analysis procedure and evaluation of the validity.
Chapter 4 **Design and Experiment:-** describes each step in the production of the experiment, including the sample, preparation, data collection performed and validity procedure.
Chapter 5 **Analysis:-** in this chapter we have discussed and thoroughly analysed the results we got from the experiment and deducted whether our technique of dynamic group formation was effective in learning or not.

Chapter 6 **Conclusion and Remarks:-** This chapter interprets the findings from the analysis including an evaluation of results and implications, limitation of the study, inferences and lessons learned.

Chapter 2

Literature Review

Introduction

This chapter presents the history of collaborative learning, computer supported collaborative learning, and group formation in CSCL. In this chapter we will go through the literature and find out the importance of group formation in CSCL. Different research scientists have proposed different techniques for group formation to obtain the optimal solution for grouping, we have tried to go through all the techniques proposed in the literature and touch the boundary of existing knowledge.

Background

The Concept of student space was used by Rahel et al [2]. They defined the student space as the group of attributes like work attitude, interest for subject, self-confidence, shyness, etc. The values of these attributes were obtained from easily available indicators like expert opinion and discussion with colleagues. They have proposed a mathematical model where heterogeneity of the groups is calculated using the Euclidean distance. They implemented their mathematical model using ant colony optimization. Christodoulopoulos et al were using a fuzzy C-mean algorithm for Homogenous and heterogeneous group formation [6].

IHUCOFS (Integrated human coalition formation and scaffolding) framework is proposed by Soh et al [3]. They designed an algorithm called VALCAM as a preliminary implementation of iHUCOFS. VALCAM contains the system agents which were assigned to the human agents. System agents hold an auction and the user agents bid in the auction with the virtual currency they have earned from participating in the previous coalition. The VALCAM is based on certain rules.

The Semantic group formation framework is introduced by Ounnas et al [4]. Students were asked to enter their data like a list of friends and their preferences. The Authors created an ontology called semantic learner profile. When students submitted their data it was stored in the RDF file which was then processed using Jena. Their framework had a teacher interface that allows the teacher to select the constraint they care about the most. The authors were using the DLV solver for creating the group based on the constraints set by the instructor.

Ho et al have used particle swarm optimization for the heterogeneous group formation [7]. Their group formation was based on the competence, learning style, and interaction among the student. Neil Rubens et al have proposed a group formation method for informal collaborative learning [8]. They collected data from different sources like blogs, social media, and other databases. They created a mash of data and then used data mining to make groups.

Hubscher, R. created groups using the tabu search after the instructor set the preferences [9]. Yannibelli et al have worked on the group formation for the software engineering courses. Grouping criteria were based on the Belbin team roles. Students were divided into different groups, which were then decoded and evaluated using the fitness function. The fitness function evaluated the groups to obtain the optimization objective. The optimization objective was to generate the maximum number of balanced groups [10].

Abnar et al. have proposed a new method for group formation using the genetic algorithm [11]. Teachers were asked to set different attributes about the students and rate them. Teachers were then displayed with the graph showing the distance. The algorithm was then run to create different groups that were presented before the teacher for acceptance or rejection.

Brauer et al. have used the social network called diaspora for the research. Users/learners select the topic, potential candidates are then found on the network to form groups [12]. Moreno et al have used a genetic algorithm to make inter-homogenous groups. They encode the different attributes of the learners and creates a matrix out of it. Then they apply selection, crossover, and mutation to make groups [13].

Mujkanovic et al have worked on the group formation for the remote laboratories' access, where a student can access the laboratories and solve the lab manual in the group. The authors were using the regression analysis to make groups. Metadata of students were given to the algorithm, then group formation was done based on the rules set by the admin. The algorithm was learning from the student performance to update the rules [14].

Tien et al have proposed the concept of TOPSIS (Technique for order performance by similarity to ideal solution). The main steps of the technique were pre-categorization, encoding, initial population, fitness function and if the termination criteria were met then grouping results were shown otherwise selection, crossover, mutation, and elitism were performed to calculate the fitness function again [15].

Ivan Srba et al. used and developed an application called popCorm, in which they experimented with the dynamic short term group formation for the online environment. They used the Group technology approach for dynamic grouping. This is the technique used in manufacturing and engineering to find similarities among the products. Input to the method was 2 clusters. The cluster of characteristics and the cluster of assignments were used as input. Data for the input matrix were gathered from questionnaires and external sources. The result of the technique is homogeneous groups. [16].

Zhilin Zheng et al used the discrete particle swarm optimization for the composition of groups using the gender and the MBTI personality as attributes. They also compared the DPSO with the competing method and the random method and according to them, DPSO performs better [17]. Ullmann et al used particle swarm optimization to form groups using the MOOCs platform. Their group formation was based on the knowledge level and interests [18].

YR Chen et al have proposed a method for group formation, in which they have used the edX platform for experimentation. Teachers assign a task to the student. Students solve the task and do a discussion on the discussion board. The system fetches the information of interaction on the discussion board and fetches the grades of the students and display the group's list [19].

Hamid Sadeghi et al used the undirected weighted graph to model the online e-learning platform. In the graph learners are a node and the relation between them shows the similarity of their interest. They have used the questionnaire to collect data about the students‘ interests. The similarity was measured by taking a mean of their absolute interest. The graph was also shown in the form of the asymmetric adjacency matrix. The binary integer programming model is introduced to assign students to their respective groups based on their interests [20].

C Yin et al have proposed a model called GFS. They were clustering the students into groups based on gender, major, reading pages, reading time, attendance, and content. They were using the educational log and data from Moodle for their research. The teacher had to set the attributes for group formation, the algorithm then makes and display groups created [21]. Y Zheng et al used a genetic algorithm for group formation [22]. Bhardwaj et al have used a test-based approach called DISC for the compatibility of employees working in an organization. They divide employees into four type

- Dominant
- Influence
- Steady
- Compliance

Further, they divide them into two categories called active and passive. They created a matrix where they put values of different attributes of personalities of employees. Based on those values Euclidean distance is calculated if the Euclidean distance is less than the cutoff distance then the compatibility is 1 vice versa [23].

D Jagadish has used the KNN algorithm for grouping. They have used moodle for experimentation [24]. Maina et al have worked on group formation. They have used the means and EM clustering algorithms. Group formation was based on the log data of the discussion forum of moodle. Their log file contained several posts, user id, number of replies, and forum ratings. Authors have proposed the method where they get data from the log file and create clusters out of that. Groups were then created based on the cluster formed. Members from each cluster were assigned to the groups based on the high competence level [25].

Yu-Chen Kuo et al. performed collaborative learning experiments on students of the English language who study English as a foreign language. The authors performed experiments on three different types of groups. The first form of the group was generated randomly. Kolb's learning styles were used to generate the second and third types of groups. The second group was homogeneously containing students having the same learning styles and thirds group was heterogeneous which had students with different learning styles [26]. Cícero et al. generated groups randomly for collaborative activities. Evaluation of group collaborations is carried out using linear regression. Variables for linear regression were self-esteem, and self-efficacy, which were extracted from the student self reports [27].

Jigsaw group formation was carried out by Ishari et al. Where tasks were assigned to each student, then groups were created in the form of the jigsaw. For example, if there were 5 tasks and 20 students then these tasks are distributed among the 20 students. Groups were created in a way that each group would have 5 students with a different type of questions, each group would have exactly one representation of each task [28]. Ivica at al. Worked on the content independent collaborative learning. They experimented with the 37 school students. Students were given a choice to choose their groups for collaborative learning based upon their needs [29].

The behavior of penguins is mimicked by zedadra et al as they proposed an algorithm based on the natural phenomenon of penguins. They performed dynamic group formation in CSCL by proposing this new approach. Initially, learners used the LMS system where their profile traces are collected which means their profiles are learned by the system. Based on the traces of the profile, learners are grouped randomly in homogeneous groups. Groups are updated regularly using their dynamic grouping algorithm which is mimicking the natural behavior of penguins [30].

Another approach for dynamic group formation was proposed where students were given individual tasks and based on their performance evaluation, they were placed in different groups which the author called pots. Groups were created with equal participation from each pot and were being updated regularly based on the students' performance. The drawback of this method was that it was not taking into account the negative effect of students' swapping from one group to another group, that degrade group performance. For example, if one student from group A is swapped to group B, the performance of group B may increase but the performance of group A may drop. Swapping should only happen if it does not affect the performance of the previous group [31].

Critical Analysis

Author	Publication Year	GF Attributes	Technique
Sabine et al [2]	2006	Personality trait Performance	Ant colony optimization
Christodoulopoet al [6]	2007	Knowledge Learning style	K-means and FCM
Soh et al [3]	2007		VALCAM algorithm based on multi agents.
Ounnas et al [4]	2008	Team work Learning style Belbin team roles	Semantic web DLV solver (implementation of disjunctive login programming)
Ho et al [7]	2009	Learning style Competence Interactions	Particle swarm optimization
Neil Rubens et al [8]	2009	Student knowledge Goals (wants to learn)	Mash up Technique Data mining
Hubscher, R. [9]	2010		Tabu search
Yannibelli et al [10]	2011	Belbin team roles	Knowledge based Evolutionary algorithm
Abnar et al [11]	2012	Online profiles Personality type Learning style	Genetic algorithm Greedy algorithm
Brauer et al [12]	2012	Learning style Knowledge Availability	Semantic web Breadth first search Random walk search Best connected search
Moreno et al [13]	2012	Various	Genetic algorithm
Mujkanovic et al [14]	2012	Personality traits	Unsupervised learning Regression analysis
Tien et al [15]	2013	Various	Genetic algorithm
Ivan Srba et al [16]	2015	Knowledge Compatibility	Clustering using the group technology
Zhilin Zheng et al [17]	2014	MBTI Personality and gender	Discrete particle swarm optimization
MRD Ullmann et al [18]	2015	Level of knowledge and interest	Particle swarm optimization
YR Chen et al [19]	2015	Academic results, Social network	
S Amara et al [28]	2016		SLR
Hamid Sadeghi et al [20]	2016	Interests	Binary integer programming model
C Yin et al [21]	2017	Gender Major Reading pages Reading time Attendance Content	Group formation system (GFS)

Author	Publication Year	GF Attributes	Technique
Simone Borges et al [1]	2017	Various	SLR
Y Zheng et al [22]	2018	Student preferences and programming skill	Genetic algorithm
Bhardwaj et al [23]	2017	Personality	DISC theory and neural network
D Jagadish [24]	2014	Knowledge	KNN
EM Maina et al [25]	2017	Competence level	SKmeans and EM

Chapter 3

Research Design

Introduction

This chapter explains the research methodology and its design. Purpose of this research is to find out the impact of dynamic group formation on student's learning. Initially, we have conducted an experiment with students to find out their learning style then dynamic group formation is carried out using our custom algorithm for that. We first collected data from the experiments and then the results of which is presented and analysed in the later chapters. The study was conducted in December 2019.

Research Design

In this section, we have discussed our proposed framework. The block diagram in figure 1 represents the proposed framework. This framework comprises the following blocks.

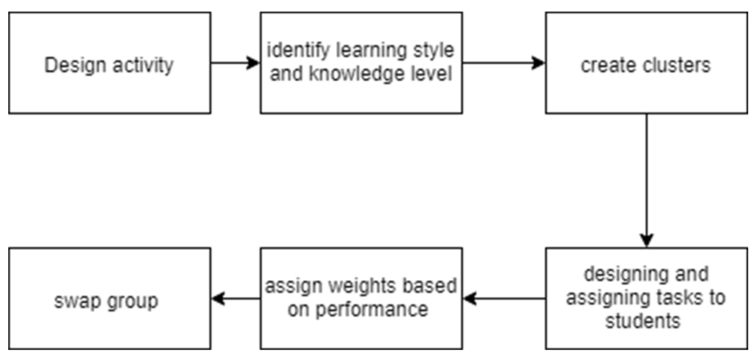

Figure 1: Block Diagram of Research Design

- Designing of activity to find out the leaning style and knowledge level of students.
- Creating clusters of students using our custom algorithm
- Designing and assigning tasks to students.
- Assigning scores according to performance and swapping groups.

Our methodology is evident from literature [32][26], most of the researchers used the same methodology to verify their proposed technique for collaborative learning. We proposed our custom algorithm for dynamic grouping in our experimentation instead of using the predefined algorithms because we could not find an algorithm that can be used for dynamic grouping.

Detail Overview of the Experiment Conducted

The experiment was conducted in two phases. In first phase of experiment we identified the learning style and knowledge level of the students. In second phase, based on the data received from the phase 1, we created initial clusters and then carried out the dynamic group formation.

Experiment Platform

In order to conduct our experiments we designed web based application. This application is developed using Laravel (PHP framework). MySQL data base is used to store the data of the application.

Participants

We performed a controlled experiment under the supervision of an instructor. For experimentation purposes, we chose 19 students of the Object-Oriented Programming course as participants for post-test, who belonged to the second semester (Fall 2019) of their degree program and had only taken the programming fundamentals course for beginners in their first semester. They were only able to do structural and procedural programming in C++ using the basic construct of programmings such as variables, loops, decisions, arrays, and structures. They knew each other socially for 6 months. That was a positive point for our successful collaborative learning. They were willing to work in groups and help each other. The activities involved in the experiment were also considered as their regular class assignments, for which they were to be evaluated accordingly. Therefore, they had to take all the tasks seriously and work hard to score well. They were encouraged to participate in group learning and 5 bonus marks were also announced to be given to the best-performing groups. In this way, they were given an extrinsic motivation as performance-contingent rewards to improve motivation and performance [33].

Experiment Phase 1

The purpose of this phase of the experiment is to identify the learning styles of students how one student loves to learn and what are his/her personality traits towards learning. Our second purpose of the experiment is to calculate the knowledge level of students. This first phase of the experiment is comprised of certain steps, in each step students perform certain activities, based on those activities, learning styles, and knowledge level of students is identified and calculated. In step 1 of the first phase of the experiment, students are presented with the application where they have to create their accounts. After registering on the system they log in to the system using their email and password.

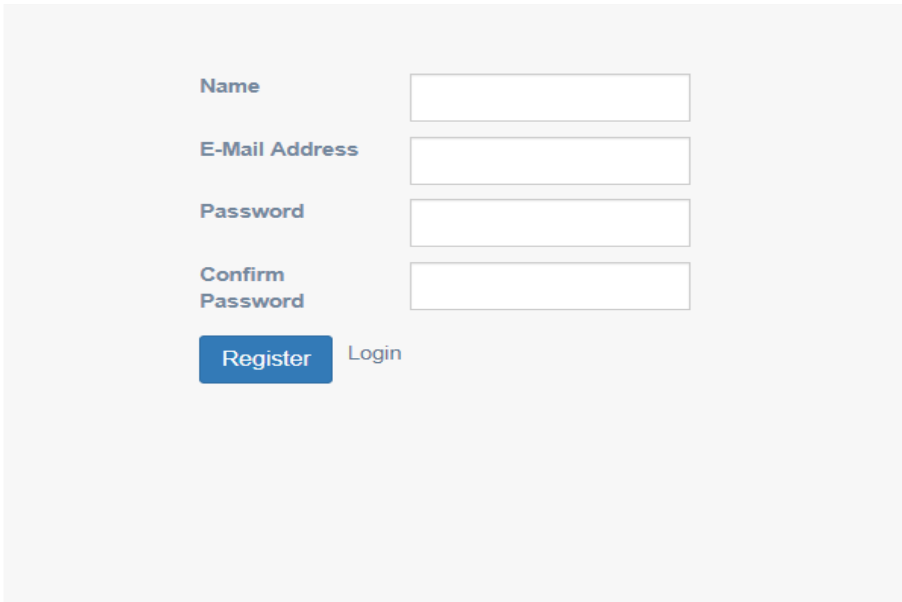

Figure 2: Registration Screen

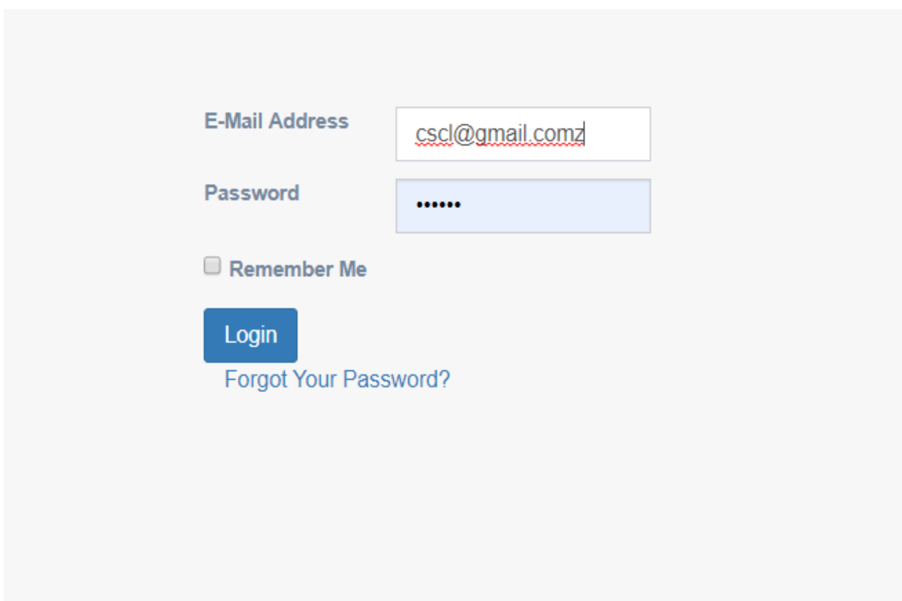

Figure 3: Login Screen

In the 2nd step of phase 1, students are presented with the interface as shown in figure 4. Where students have to select the type of content they want to learn from. After selecting the content type (videos, text file or presentation slides) they will be presented with content/lessons in that format based on their selection.

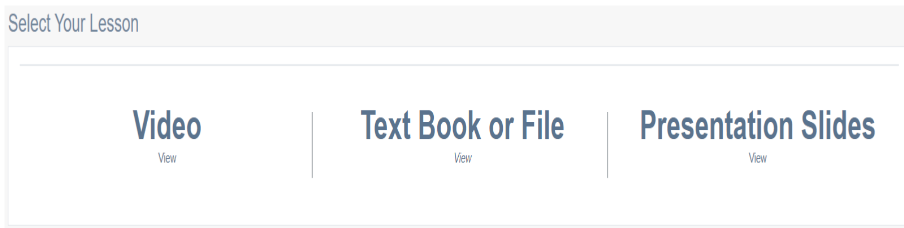

Figure 4: Select Type of Content

Once, students select the type of content they are migrated to another interface where they see lessons as shown in figure 5.

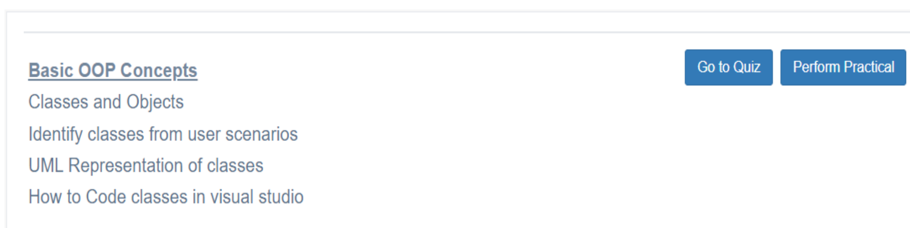

Figure 5: Content Interface

Students can also see the "go-to quiz" option and "perform practical" option. If a student clicks on the "perform practical" button they are redirected to some external resources for practice. This link of practice is set by the instructor while designing the activity. But, if student choose to click on the "go-to quiz" option then they are redirected to another interface where they solve the quiz as shown in figure 6.

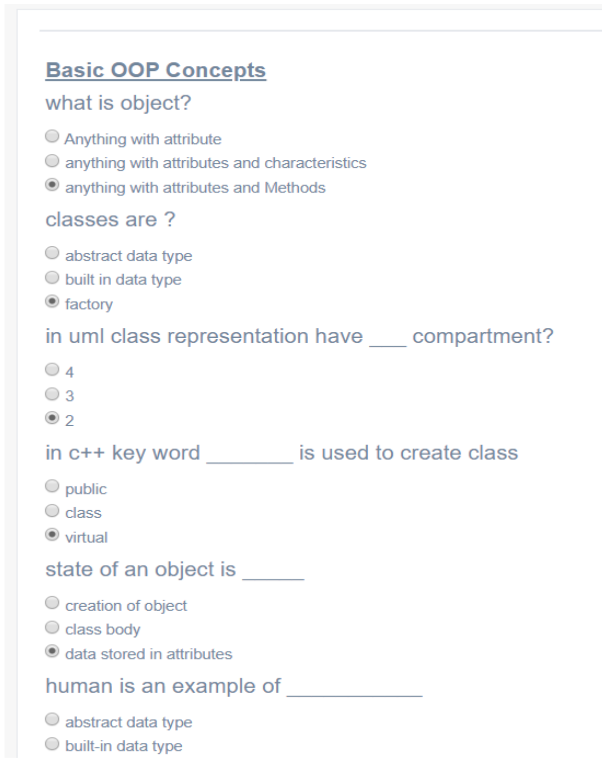

Figure 6: Quiz

After they submit a quiz, they are displayed with an image as shown in figure 7. Students have to name all the objects they see in the picture to find out whether they are sensory or intuitive.

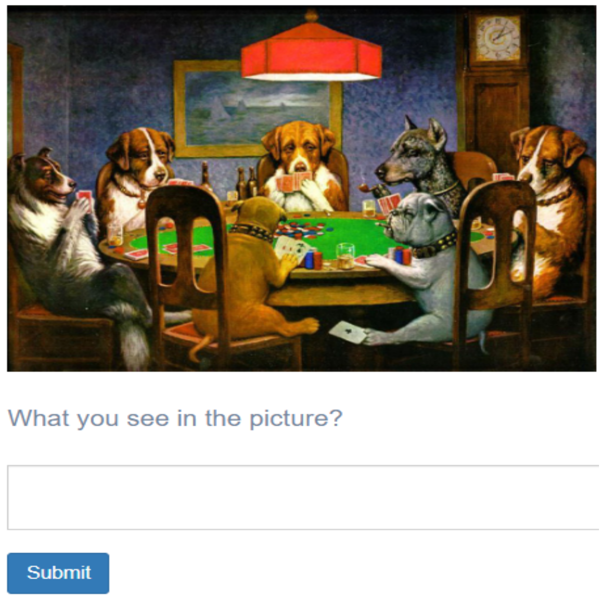

Figure 7: Activity for Finding Sensory or Intuitive

Identify Learning style and calculate Knowledge level

M. Felder's learning styles [5] are adopted in this study . Following are the list of attributes, values of which are extracted in experiment phase I. 0 or 1 is set to these attributes against each student.

- Visual
- Verbal
- Sensory
- Intuitive
- Active
- Reflective
- Global
- Sequential

In step 2, if student selects video or presentation slides then its visual is set to true. But if he/she selects the text files/books then its verbal is set to true. In step 3, if student clicks on all the content link one by one then its sequential attribute is set to true otherwise global is set to true. Similarly in step 3, if student selects "perform practical" option then its active is set to true otherwise

Name	Sensory	Intuitive	Visual	Verbal	Active	Reflective	Global	Sequential	Knowledge
student 1	0	1	1	0	0	1	0	1	71%
student 2	0	1	1	0	0	1	0	1	71%
Student 3	1	0	1	0	1	0	1	0	100%
Student 4	0	1	1	0	1	0	0	1	57%
Student 5	1	0	1	0	0	1	0	1	85%
Student 6	1	0	1	0	0	1	0	1	71%
Student 7	0	1	1	0	0	1	0	1	100%
Student 8	0	1	0	1	0	1	1	0	57%
Student 9	0	1	1	0	1	0	0	1	71%
Student 10	1	0	1	0	0	1	0	1	71%
Student 11	1	0	1	0	0	1	0	1	100%
Student 12	0	1	1	0	1	0	0	1	100%
Student 13	0	1	0	1	0	1	1	0	100%
Student 14	0	1	1	0	0	1	1	0	100%
Student 15	0	1	1	0	0	1	1	0	100%
Student 16	0	1	0	1	0	1	1	0	100%
Student 17	1	0	1	0	1	0	0	1	100%
Student 18	1	0	1	0	1	0	0	1	100%
Student 19	0	1	1	0	0	1	0	0	57%

Figure 8: Knowledge Level and Learning Styles of Students

its reflective attribute is set to true. Now in step 4, student are shown picture with scenario, they have to name each object in the picture. If they reach the count of keywords set by instructor their sensory is set to true otherwise intuitive is set to true. The table above in figure 8 represents the learning styles of 19 students.

Experiment Phase 2

In the second phase of the experiment, initial groups are created using our proposed algorithm 1. These groups are created from the data collected from phase I of the experiment. Initial group formation algorithm is very simple, we get the knowledge level of each student and calculate the mean. Students with the knowledge level value less than the mean are placed in one cluster and students with knowledge level value greater than the mean are placed in another cluster. Detailed working of algorithm is shown in figure 9.

Algorithm 1 Initial Group Formation

```
studentData ← getDataFromDataBase()
for studentData do
    total ← calculateKnowledgeLevel(student[i])
end for
mean ← total/counter
cluster1[]
cluster2[]
for data do
    if studentData[i]->KnowledgeLevel() < mean then
        cluster1 ← studentData[i]
    else
        cluster2 ← studentData[i]
    end if
end for
totalGroups ← 5
for cluster1 do
    Assign group number to students
end for
for cluster2 do
    Assign group number to students
end for
```

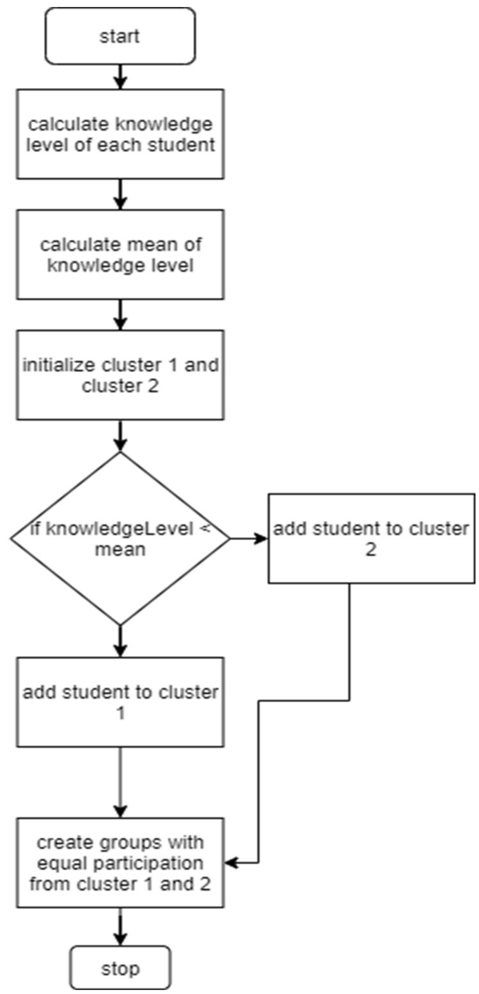

Figure 9: Initial Group Formation Algorithm Working

Implementation Details of Initial Group Formation Algorithm

```
public function clusterMakeLinkCommit(Request $request)
 {
$data =  User::where('type','s')->
whereDate('created_at','=',$request->date)->get();
$arrayName = array();
 $total = 0;
 $counter = 0;
$large = $data[0]->calculateKnowledge($data[0]->id);
$small = $data[0]->calculateKnowledge($data[0]->id);
    foreach ($data as $key => $value) {

$arrayName[] = array('id'=>$value->id,"knowledge"=>
$value->calculateKnowledge($value->id));
//calculated mean
 $total += $value->calculateKnowledge($value->id);
$counter += 1;
//calculate large value
 if($value->calculateKnowledge($value->id) > $large){
$large = $value->calculateKnowledge($value->id);
 }

//find small
if($value->calculateKnowledge($value->id) < $small){
 $small = $value->calculateKnowledge($value->id);
 }
}
 $mean = $total/$counter;

    //make clusters
 $cluster1 = array();
 $cluster2 = array();

 foreach ($data as $key => $value) {

 if($value->calculateKnowledge($value->id) < $mean){
  $cluster1[] = array("id"=>$value->id,"knowledge"=>
  $value->calculateKnowledge($value->id));
  }else{
  $cluster2[] = array("id"=>$value->id,"knowledge"=>
  $value->calculateKnowledge($value->id));
}
```

```
}

$total_grp =  ceil(@count($data)/5);
 $counter = 1;
 $grp = $start;
 foreach ($cluster1 as $key => $value) {
   echo $grp."<br>";
 if($counter == $total_grp){
 $counter = 1;
 $grp = $start;
  }
 $user = User::find($value['id']);
  $user->grp = $grp;
 $user->update();
 $grp++;

$counter++;
 }

 $counter = 1;
 $grp = $start;
 foreach ($cluster2 as $key => $value) {
  echo $grp."<br>";
  if($counter == $total_grp){
      $counter = 1;
      $grp = $start;

      }
    $user = User::find($value['id']);
 $user->grp = $grp;
  $user->update();
  $grp++;

   $counter++;

   }

  return redirect()->back();

    }
```

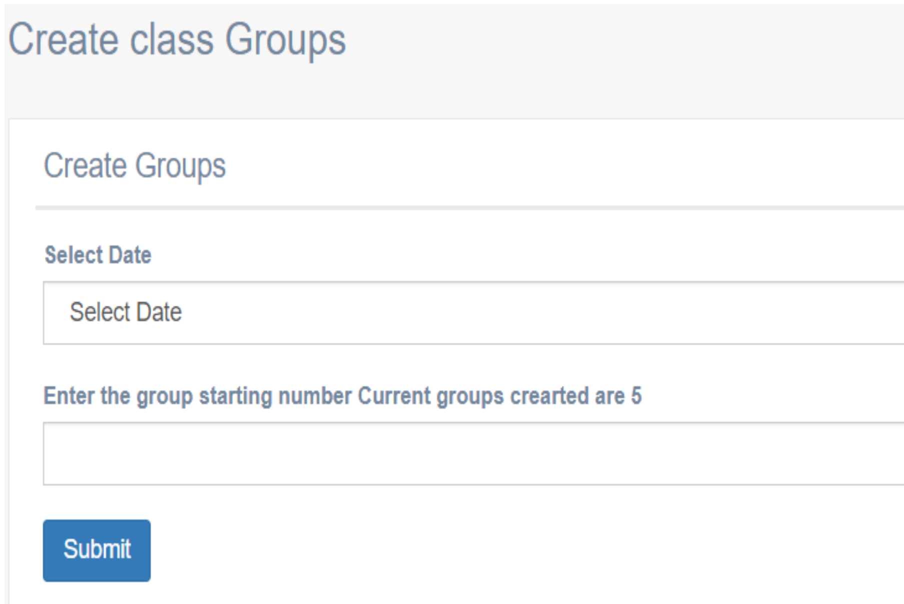

Figure 10: Interface of instructor for group creation

Figure 10 is showing the interface for setting the number of groups that is generated using our proposed algorithm. This is basically threshold set by instructor for number of groups need to be generated.

After the initial groups are created. Activities are assigned to each student, which they solve individually. After tracking the individual performance of each student, they are assigned activities in the form of groups. Prior to assigning tasks, instructors have to create activities. In the following section we will go through the process of creating activities.

Figure 11: Create Activity form

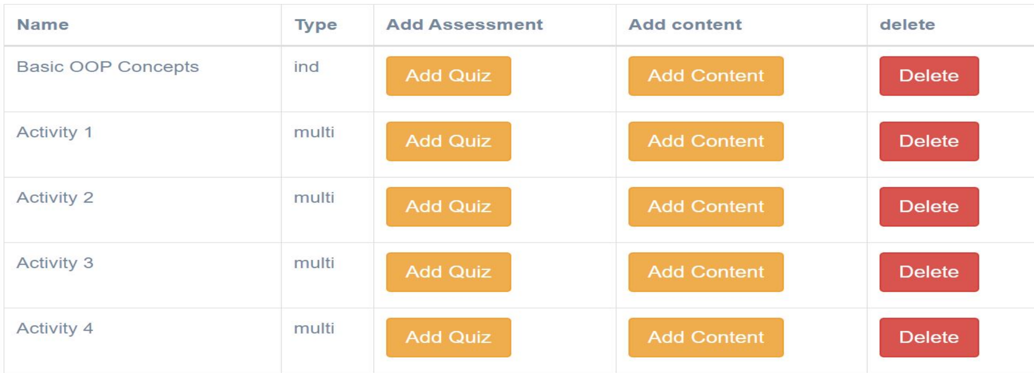

Figure 12: View all activities interface

Figure 11 is form for instructors to create the activity. Once the activity is created instructor then adds content and quiz to the activity. Figure 12 shows the interface where instructor selects to add quiz to the activity or he/she can add content to the activity. In case of adding quiz, instructor has the option to enter the questions of quiz and then add options to quiz as shown in the figure 13 and figure 14. Instructor can choose the type of content of the quiz's question. It can be an image or textual form. Instructor can add any number of quizzes to the activity. If instructor chooses to add content then a new interface is displayed to the instructor as shown in the figure 15. In content section instructor can add video, presentation slide or textual file.

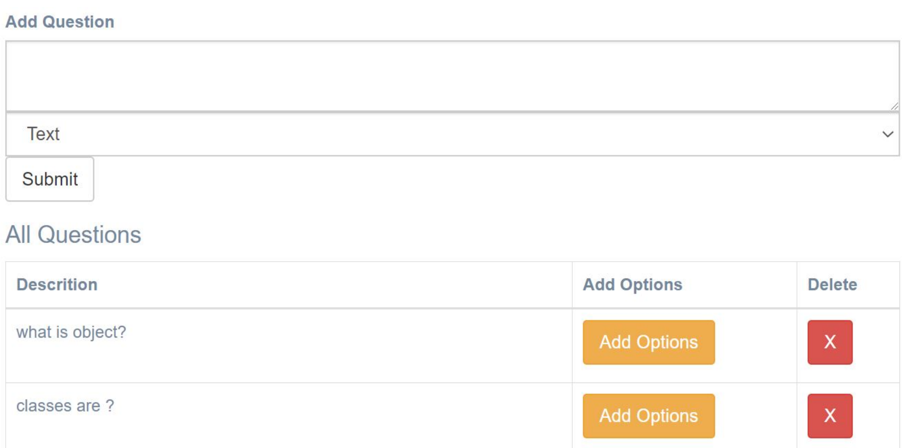

Figure 13: Add Quiz Activity

Figure 14: Add Option Activity

Figure 15: Add Content Activity

Above we discussed the whole process of activity creation. Now, we will go through the last part of the experiment. In the last part of the experiment students are given the activities which they solve. These activities are designed by the instructors. 6 activities are designed, each has 5 MCQs as shown in figure 16.

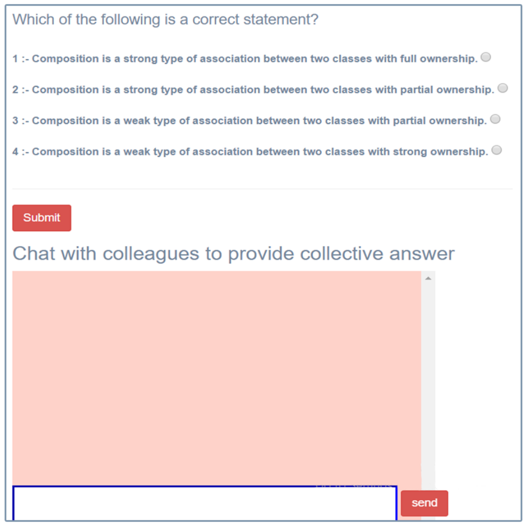

Figure 16: Collaborative learning activity

Students can chat with each other to build consensus on the common answer and submit a collective answer. We ran 6 permutations, each time student‘s groups are swapped using our proposed algorithm for dynamic grouping 2.

In a dynamic group formation algorithm, each group's points are calculated. Then we calculate the mean value of the points of groups. Two clusters are created, one called as smallPoints cluster where groups with smallPoints are saved and another is called as greaterPoints cluster where groups with greaterPoints are saved. This categorization that takes place is based on the mean value, if the points are less than the mean then it is saved in smallPoints group and vice versa. Now, smallPoints cluster is sorted in ascending order and greaterPoints cluster is sorted in descending order. After the sorting, students of both the clusters are swapped in such a way that weak students become the part of good performing groups and average or the student who is the second-best performing in the good performing groups are swapped to the low-performance group to improve their performance. This swapping takes place keeping in view that the performance of the previous group is not affected. Detail working of dynamic group formation algorithm is shown in figure 17.

Algorithm 2 Dynamic Grouping Algorithm

```
groupPoint ← getGroupPoints
mean ← calculateMean(groupPoint)
greaterGroupPoint[]
smallerGroupPoint[]
for groupPoint do
  if groupPoint->point < mean then
    smallerGroupPoint ← groupPoint
  else
    greaterPointGroup ← groupPoint
  end if
end for
smallerSorted ← AssendingSort(smallerPointGroup)
largeSort ← descendingSort(greaterPointGroup)
toBeSwapped[]
while smallerSorted do
  smallStudent ← smallerSorted[i]− > getStudents()
  smallStudent ← descendingSort()
  for smallStudent do
    toBeSwapped ← smallStudent
  end for
end while
toBeSwappedWith
while largeSort do
  LargeStudent ← largeSort[i]− > getStudents()
  largeStudent ← AscendingSort()
  for largeStudent do
    toBeSwappedWith ← largeStudent
  end for
end while
```

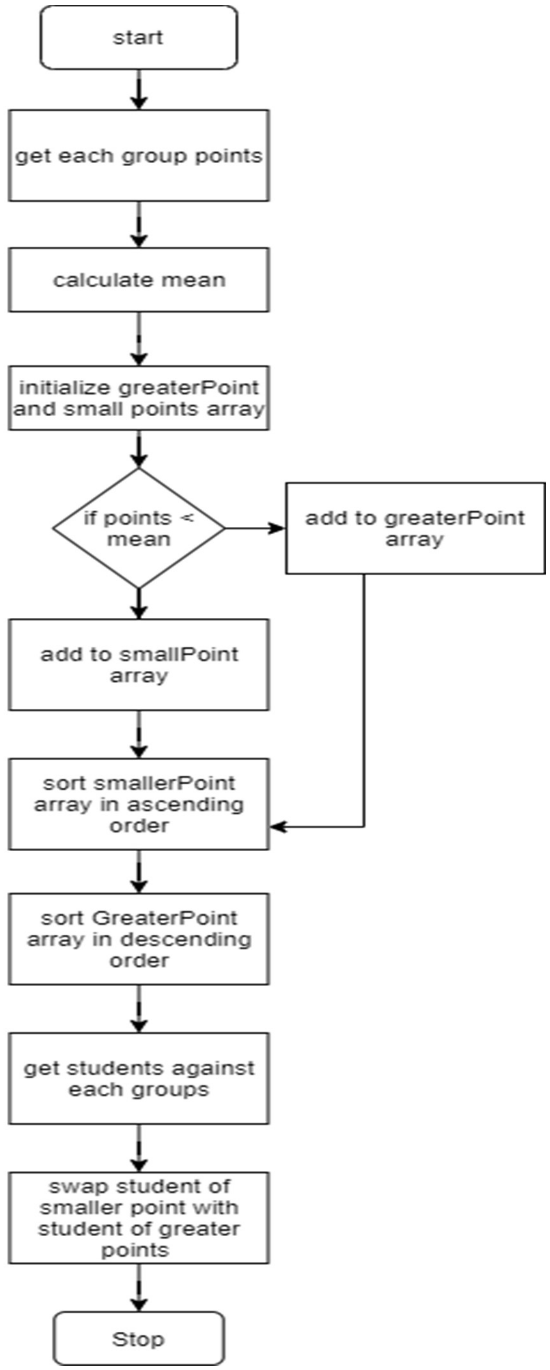

Figure 17: Dynamic Group Formation Working

Implementation Details of Dynamic Group Formation Algorithm

```
public function swap($activity)
{
$groups = grpPoint::where(['activity'=>$activity, 'status'=>0])->get();
 if(@count($groups) > 0){
 //calculate mean of the group
$mean = $this->calculateMean($groups);
 //create clusters based on the mean calculated
$greaterPointsGroup = array();
$smallerPointsGroup = array();
foreach ($groups as $key => $value) {
if($value->point < $mean){
 $smallerPointsGroup[] = $value;
 }else{
  $greaterPointsGroup[] = $value;
}
 }
//sort the groups-- smaller in acsending order
 $Smallersorted = $this->Asort($smallerPointsGroup);
 //and larger in descending order
  $largeSorted = $this->Dsort($greaterPointsGroup);
//perform swaping //getting smaller marks students to be swapped
 $toBeSwapped = array();
 for($i = 0;$i<@count($Smallersorted); $i++) {
 $Smallstudents = $Smallersorted[$i]->getStudents($Smallersorted[$i]->grp);
$Smallstudents = $this->DStudentsort($Smallstudents);
 for ($j=0; $j < @count($Smallstudents); $j++) {
 if($j <= 1){
 $toBeSwapped[] = array("id"=>$Smallstudents[$j]->student);
 }

 }
}
//perform swaping //getting larger marks students to be swapped with
 $toBeSwappedWith = array();
 for($i = 0;$i<@count($largeSorted); $i++) {
 $Largestudents = $largeSorted[$i]->getStudents($largeSorted[$i]->grp);
$Largestudents = $this->AStudentsort($Largestudents);
 if(@count($Largestudents) <= 2){

 $toBeSwappedWith[] = array("id"=>$Largestudents[1]->student);
// $toBeSwappedWith[] = array("id"=>$Largestudents[2]->student);
 // $toBeSwappedWith[] = array("id"=>$Largestudents[3]->student);
```

```
}else{
$toBeSwappedWith[] = array("id"=>$Largestudents[1]->student);
$toBeSwappedWith[] = array("id"=>$Largestudents[2]->student);
 // $toBeSwappedWith[] = array("id"=>$Largestudents[3]->student);
}

}
 //perform the real swapping here
if(@count($toBeSwappedWith) > 0){
 for($i =0; $i<@count($toBeSwapped);$i++) {
  if(!empty($toBeSwappedWith[$i])){
 $temp_group_of_smaller = User::find($toBeSwapped[$i]['id'])->grp;
 $updateSmaller = User::find($toBeSwapped[$i]['id']);
 $updateSmaller->grp = User::find($toBeSwappedWith[$i]['id'])->grp;
$updateSmaller->update();

$updateLarger = User::find($toBeSwappedWith[$i]['id']);
$updateLarger->grp = $temp_group_of_smaller;
$updateLarger->update();
 }

 }

}
 //update the status of activity after swaping
 $lock  = lockAnswers::where('activity',$activity)->update(['status'=>1]);
$groupointUpdate  = grpPoint::where(['activity'=>$activity])
->update(['status'=>1]);
 }
 }

public function calculateMean($array)
    {
        $avg = 0;
         foreach ($array as $key => $value){
            $avg = $avg + $value->point;
            }
             $avg = $avg/@count($array);

        return $avg;
    }

public function Asort($greaterPointsGroup)
{
for ($i=0; $i < @count($greaterPointsGroup); $i++) {
```

```
$min = $i;

for ($j=0; $j < @count($greaterPointsGroup); $j++) {

if($greaterPointsGroup[$j]->point > $greaterPointsGroup[$min]->point){
$min = $j;
$temp = $greaterPointsGroup[$i];

$greaterPointsGroup[$i] = $greaterPointsGroup[$min];
$greaterPointsGroup[$min] = $temp;

}
}

}

return $greaterPointsGroup;

}

public function Dsort($greaterPointsGroup)
    {
for ($i=0; $i < @count($greaterPointsGroup); $i++) {
$min = $i;

 for ($j=0; $j < @count($greaterPointsGroup); $j++) {

if($greaterPointsGroup[$j]->point < $greaterPointsGroup[$min]->point){
$min = $j;
 $temp = $greaterPointsGroup[$i];

$greaterPointsGroup[$i] = $greaterPointsGroup[$min];
$greaterPointsGroup[$min] = $temp;

 }


}

}

 return $greaterPointsGroup;

}
```

```
public function DStudentsort($greaterPointsGroup)
    {
 for ($i=0; $i < @count($greaterPointsGroup); $i++) {
  $min = $i;

 for ($j=0; $j < @count($greaterPointsGroup); $j++) {

  if($greaterPointsGroup[$j]->points > $greaterPointsGroup[$min]->points){
 $min = $j;
 $temp = $greaterPointsGroup[$i];
 $greaterPointsGroup[$i] = $greaterPointsGroup[$min];
 $greaterPointsGroup[$min] = $temp;

  }


}

  }

  return $greaterPointsGroup;

}

public function AStudentsort($greaterPointsGroup)
    {
 for ($i=0; $i < @count($greaterPointsGroup); $i++) {
   $min = $i;

  for ($j=0; $j < @count($greaterPointsGroup); $j++) {
  if($greaterPointsGroup[$j]->points < $greaterPointsGroup[$min]->points){
     $min = $j;
 $temp = $greaterPointsGroup[$i];

 $greaterPointsGroup[$i] = $greaterPointsGroup[$min];
    $greaterPointsGroup[$min] = $temp;

   }


  }

        }

 return $greaterPointsGroup;
```

```
    }

public function calculateMean($array)
    {
        $avg = 0;
         foreach ($array as $key => $value){
            $avg = $avg + $value->point;
            }
             $avg = $avg/@count($array);

        return $avg;
    }
```

Summary

In this chapter we explained in detail the whole methodology of our research work and experiment that we conducted on over 19 students of object oriented programming. Experiment was held in two phases, first phase was about discovering students' learning style and knowledge level and in the second phase we performed initial groupings and group swapping.

Chapter 4

Experiment Evaluation

Introduction

This chapter describes the analysis of results we got from the experiment performed on the 19 students of Object oriented programming course. Data we got from the experiment helped us find out the impact of group study on student‘s learning. In this chapter we compare individual and group performances of students. We presented and analysed the impact of dynamic group formation on student‘s learning.

Student Individual Performance Analysis

As described in chapter 3, we designed the experiment in such a way that students have to perform the activity individually and then in the groups. The aim of solving activities individually was to track the performance of the students when they are not in a group. Each activity of our experiment has 5 questions, each question carries 2 points. Results we derived from our experiment indicate the fluctuation of points between 0 to 10 against maximum students. Figure 18, 19, 20, 21, 22, 23 shows the graph of points of individual activities 1,2,3,4,5 and 6.

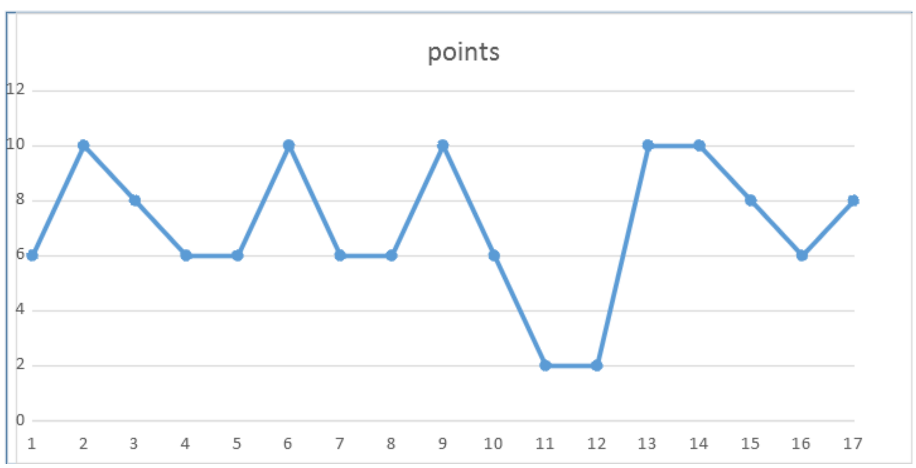

Figure 18: Individual Points Graph of Activity 1

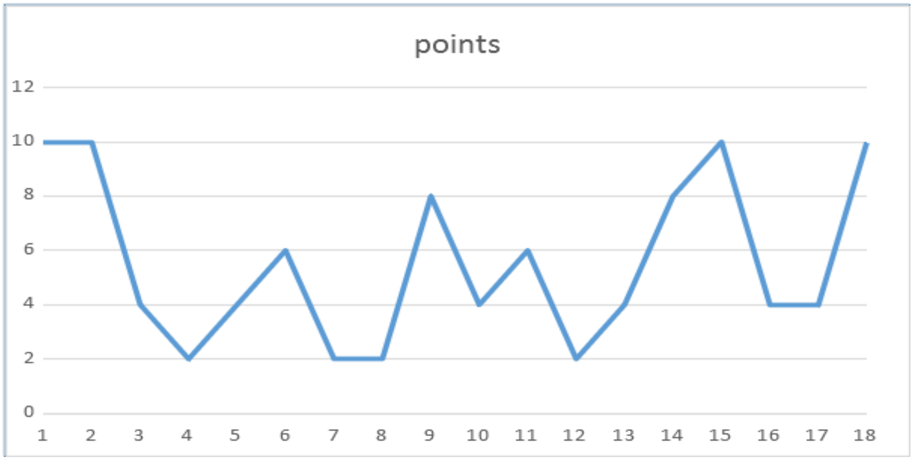

Figure 19: Individual Points Graph of Activity 2

Above graph is indicating the points of students in activity 2. Some of the students have scored maximum points up to 10 and some large number of students had scored low points.

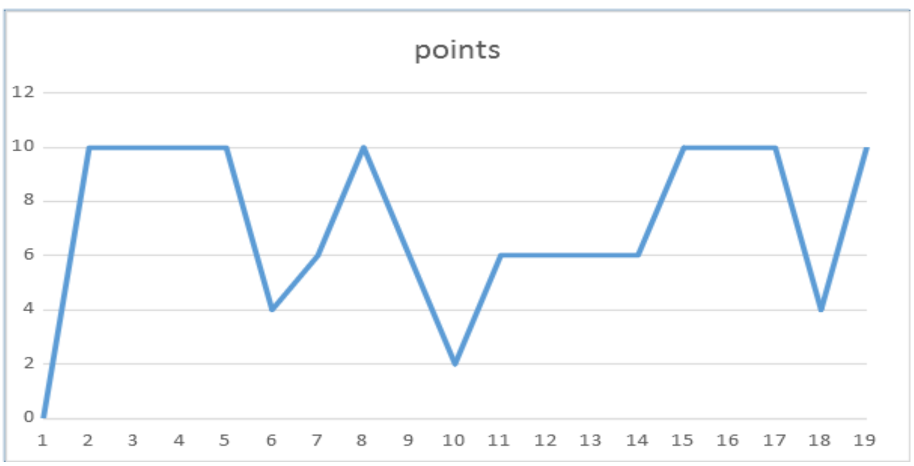

Figure 20: Individual Points Graph of Activity 3

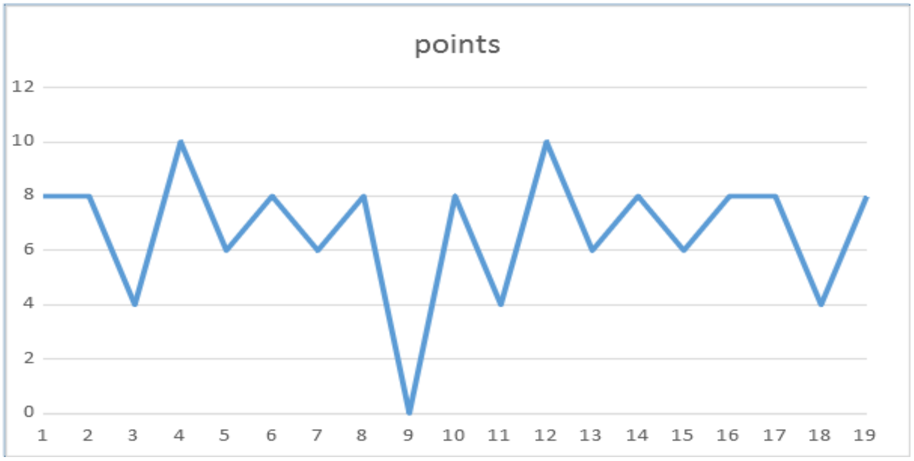

Figure 21: Individual Points Graph of Activity 4

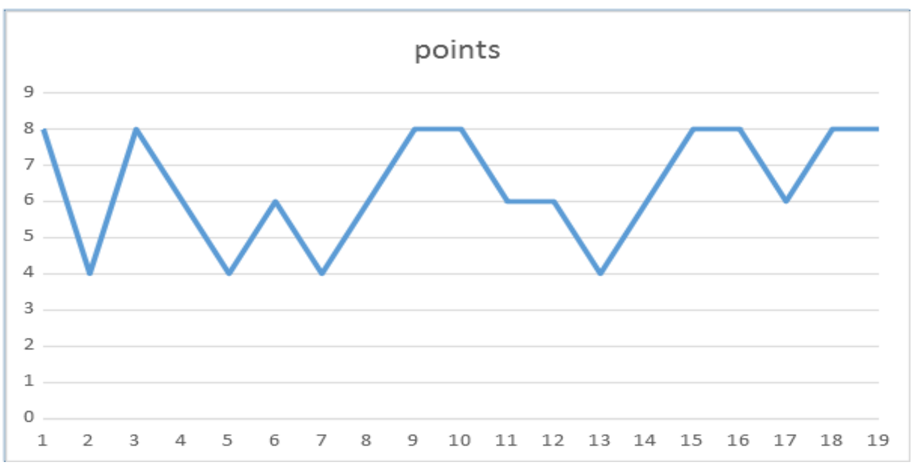

Figure 22: Individual Points Graph of Activity 5

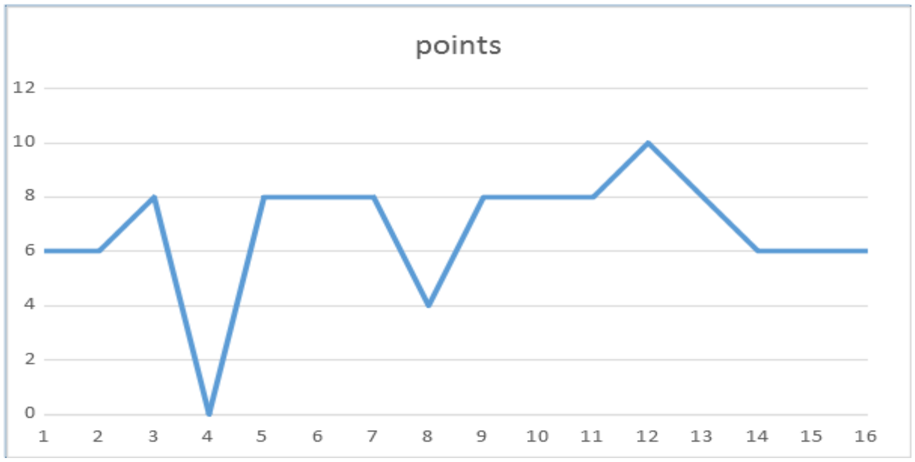

Figure 23: Individual Points Graph of Activity 6

Similarly graphs of figure 22 and 23 are also representing the fluctuation of points. Some students are performing well individually and some are not.

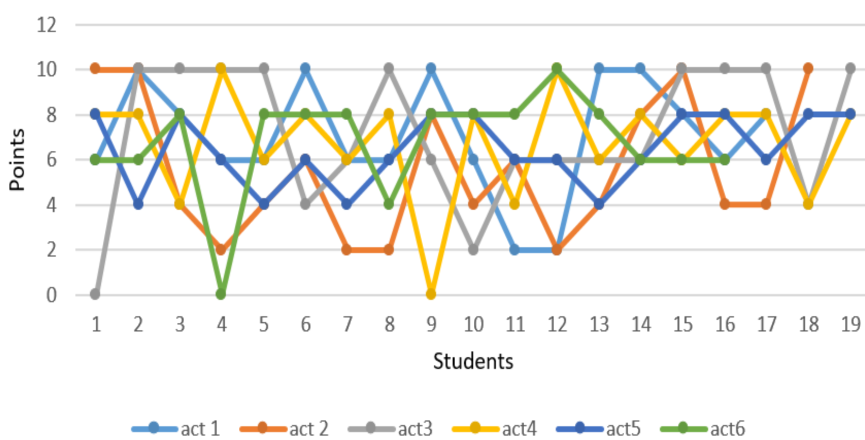

Figure 24: Comparison of Individual Students of all Activities

Figure 24 is the comparison of individual points of every student in all activities. We can see that out of 19 students, 3 have scored 0 points and 7 students have scored 2 points. Similarly huge number of point scoring is between the 6 and 8. So, if we conclude the analysis, we can say that there is huge number of fluctuation of points of every student in each activity.

Students Group Performance Analysis

In previous section of this chapter we discussed the performance of students when they were working individually on an activity. In this section of the chapter, we will discuss the performance of the students as a group.

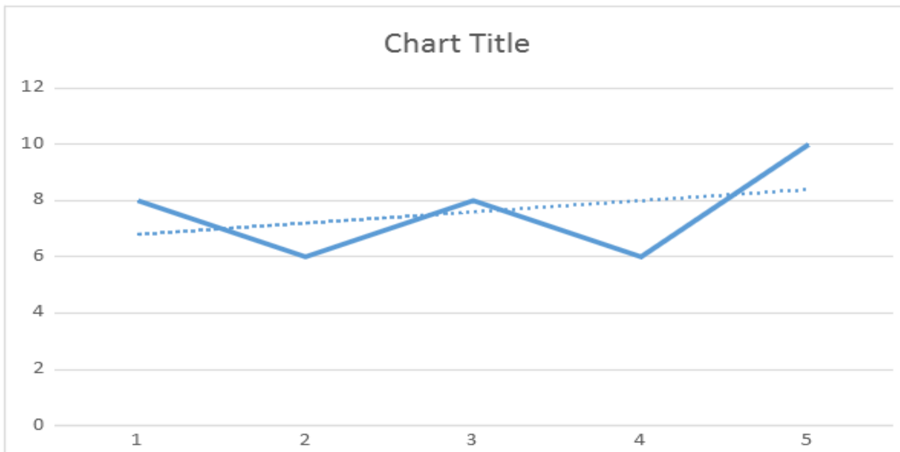

Figure 25: Group Performance Graph of Activity 1

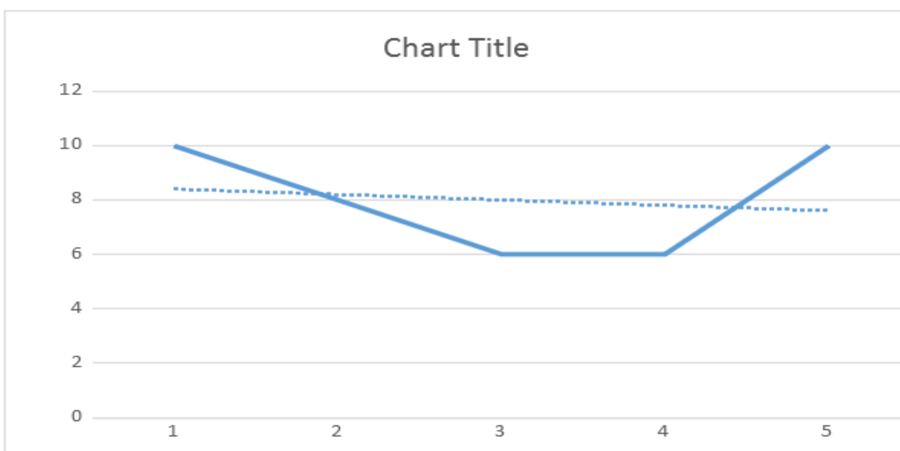

Figure 26: Group Performance Graph of Activity 2

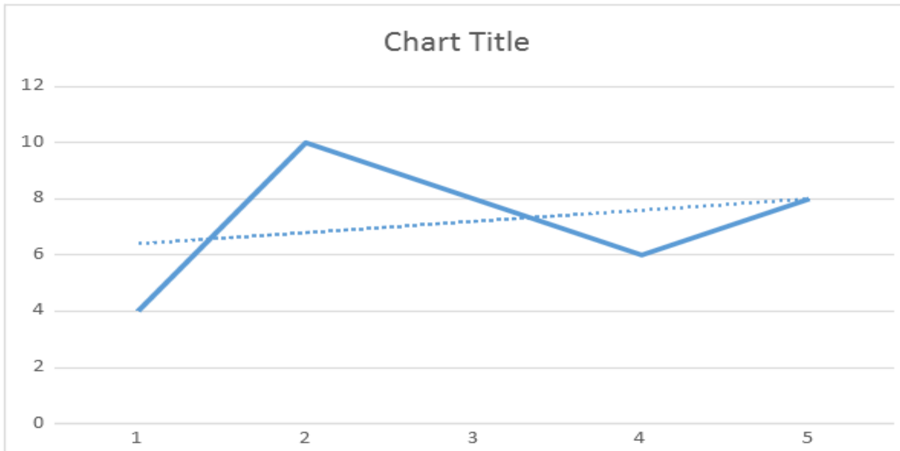

Figure 27: Group Performance Graph of Activity 3

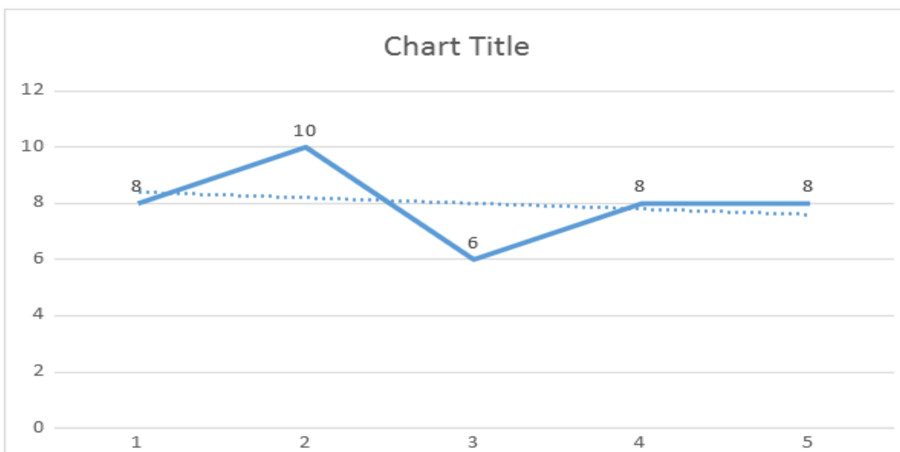

Figure 28: Group Performance Graph of Activity 4

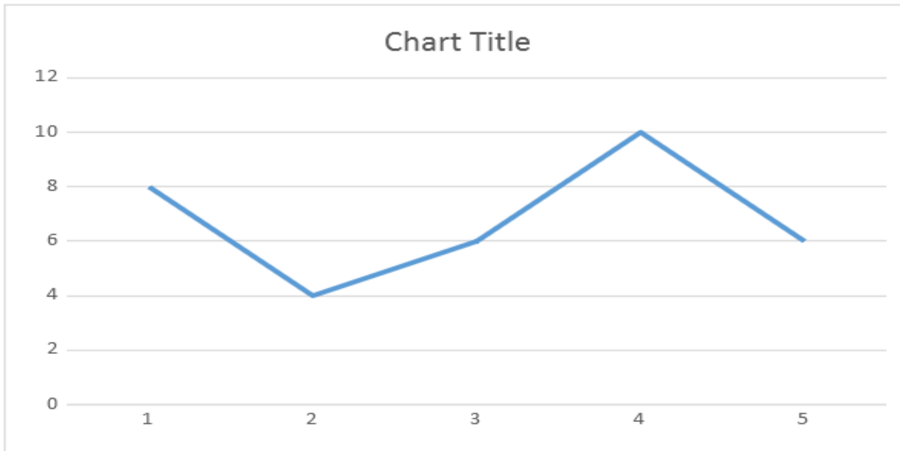

Figure 29: Group Performance Graph of Activity 5

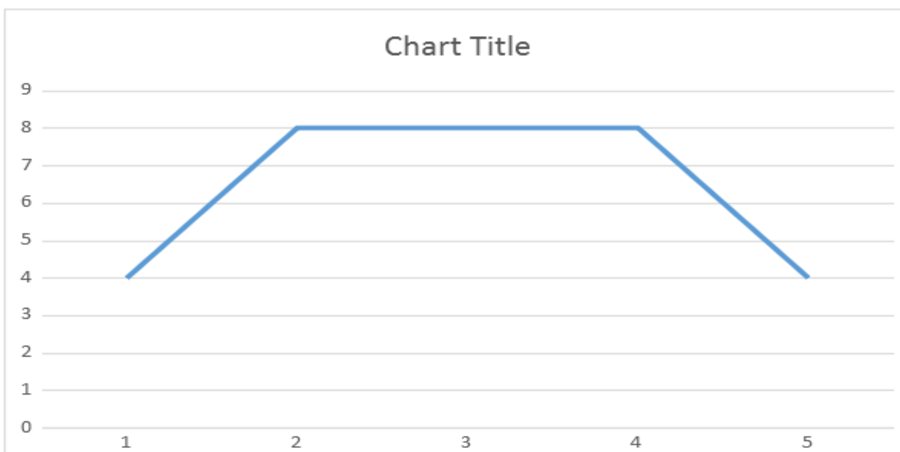

Figure 30: Group Performance Graph of Activity 6

If we look at the graphs in the figure 25, 26, 27, 28, 29 and 30 we can see that student performances in groups are good. Every group has scored points around 6 to 10.

Effect of dynamic grouping on students learning

Main purpose of our research study was to find out the impact of dynamic groupings on the learning of students. We executed an experiment on 19 students. We created their groups and assign them activities, after each activity their groups were swapped based on their performance. 19 students are divided into 5 groups. Groups for activity 1 are shown in the table 1.

Table 1: Activity 1 groups

Group 1	Group2	Group 3	Group 4	Group 5
Student 6	Student 18	Student 12	Student 10	Student 14
Student 1	Student 8	Student 5	Student 16	Student 4
Student 17	Student 15	Student 9	Student 13	Student 19
Student 3	Student 11	Student 2	Student 7	

After the first activity is executed with the groups shown above in the table 1, students are swapped based on the performance of their groups. Below table 2 shows changed groups for activity 2.

Table 2: Activity 2 groups

Group 1	Group2	Group 3	Group 4	Group 5
student 13	**student 9**	student 12	**student 6**	student 4
student 3	student 15	student 2	student 10	**student 5**
student 1	student 18	**student 19**	student 16	student 14
Student 7	student 11	**student 8**	**student 17**	

In the table above students marked bold are swapped students. Swapping took place between group 1 and group 4. Students of group 2 were swapped with group 6. Similarly, students of group 5 were swapped with group 6. For the next permutation of activity 3, group formation is given below in the table 3. We can see that the group swapping took place between group 3 and group 2. Similarly, students were also swapped among group 4 and group 5.

Table 3: Activity 3 groups

Group 1	Group2	Group 3	Group 4	Group 5
student 1	student 11	student 8	student 6	**student 16**
student 3	student 15	student 19	student 17	**student 10**
student 7	student 18	student 2	**student 14**	student 5
student 13	**student 12**		**student 4**	
	student 9			

Group formation for the permutation 4 is shown in the table 4.

Table 4: Activity 4 groups

Group 1	Group2	Group 3	Group 4	Group 5
student 3	student 18	student 8	student 14	student 10
student 13	student 15	student 19	student 4	student 5
student 7	student 9	**student 1**	student 17	student 16
student 11	student 12	student 2	student 6	

In the above table we can see that little swapping took place between the groups. There is only one student swap between group 1 and group 2 and similarly, group 1 and group 3. For the second last activity of our experiment, we get the following set of groups from our system/tool.

Table 5: Activity 5 groups

Group 1	Group2	Group 3	Group 4	Group 5
student 6	student 18	student 8	**student 3**	student 5
student 10	student 15	student 19	student 14	student 16
student 13	student 9	student 1	student 4	**student 7**
student 11	student 12	student 2	student 17	

Again very little students swapping was happened. Group 1 students are swapped with group 5. Similarly, group 1 student were also swapped with group 4. Now, last group formation for activity 6 is shown below in the table 6. We can see that no swapping took place at all.

Table 6: Activity 6 groups

Group 1	Group2	Group 3	Group 4	Group 5
student 6	student 18	student 8	student 3	student 5
student 10	student 15	student 19	student 14	student 16
student 13	student 9	student 1	student 4	student 7
student 11	student 12	student 2	student 17	

All the tables in this section are indicating the different group format for the upcoming next activities. These groups formation took place because of the performance of groups in the last activities. If we look closer at the swapping of groups and discuss their points than we can see that after the 1st activity, swapping between group 4 and group 1 took place because, group 4 has 6 points and group 1 has 8 points in the last activity that‘s why student exchange took place among them. Similarly after the completion of activity 2, swapping took place between group 2, group 3, group 4 and group 5 because of their 4, 8, 10, 6 points respectively in the last activity. So, the logic behind each swapping is same. Student’s swaps take place between high scoring groups and low scoring groups.

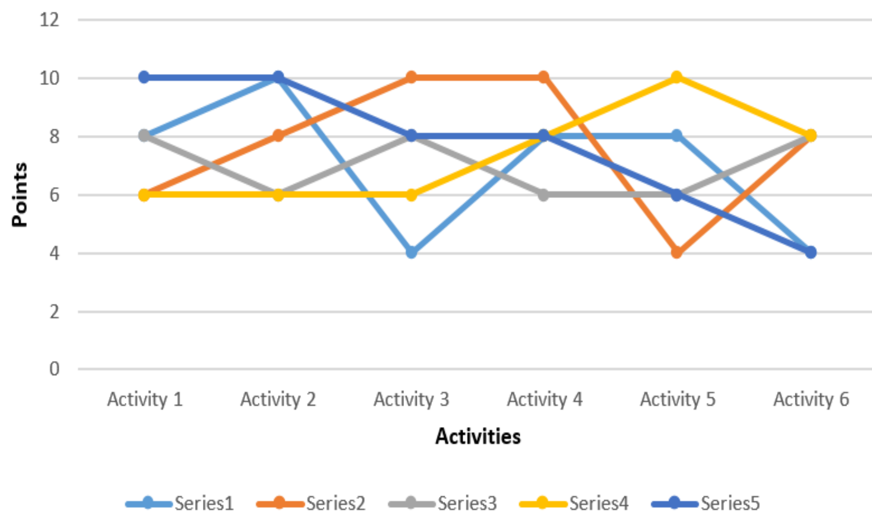

Figure 31: Group Activities Performance Graph

Graph in figure 32 shows points comparison of each group in all activities. We can see that performance of 3 groups out of 5 has improved. They are scoring same points. Remaining 2 group's performance is not bad, but they were unable to score points like the rest of the other 3 groups because of 1 disrupting student in each of these 2 groups, who were effecting the performance of overall group. Result of the above graph is a good gesture and its indicating that dynamic group formation has positive impact on the student's learning.

Research Findings

Research Questions Re-visited

Q1. How to create dynamic groups in CSCL?

We have discussed in previous chapter 3 about dynamic group formation in CSCL. Complete details of algorithm have been discussed there in the previous chapter 3.

Q2. How to overcome the cold start i.e. how to create initial groups?

Initial group formation is very challenging. We solved this problem by letting student solve the first activity of our experiment phase 1 individually. Once, students solved the activity, we then calculated their knowledge level and based on their knowledge we created clusters of average and best students. After the creation of clusters, groups are created with equal participation from each cluster of average and best students.

Q3. Can dynamic group formation enhance the group performance and student learning?

Yes, dynamic group formation enhances the learning of students. If we look at the graph again we can see that 3 out of 5 groups have performed better. So, we can conclude that dynamic grouping enhances the learning of students.

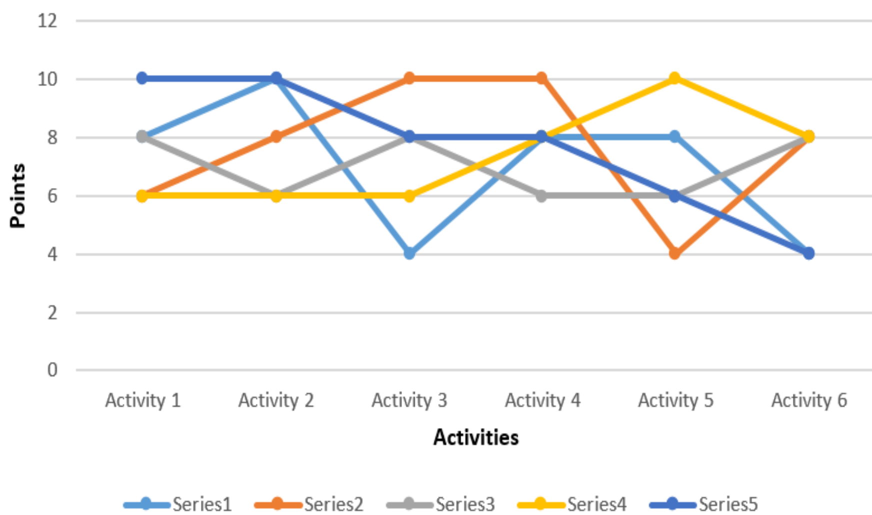

Figure 32: Group Activities Performance Graph

Validation

We conducted the verification of the efficiency of the algorithm using statistical comparison with the result of the pre-test conducted based on the random grouping and K-mean clustering. Random grouping and k-means clustering are widely used in the literature for group formation [32] [26]. We experimented with the other 19 students for the pre-test. All the participants in the pre-test were also from the Object Programming Course and they were all from the second semester (Spring 2020). Same questions were used with the same difficulty level in the pre-test as well. Summary of our verification is:

- Dynamic groups generated using our proposed algorithm performed better then the groups generated randomly and k-mean clustering.
- Groups generated using k-mean clustering performs better than the groups generated randomly.

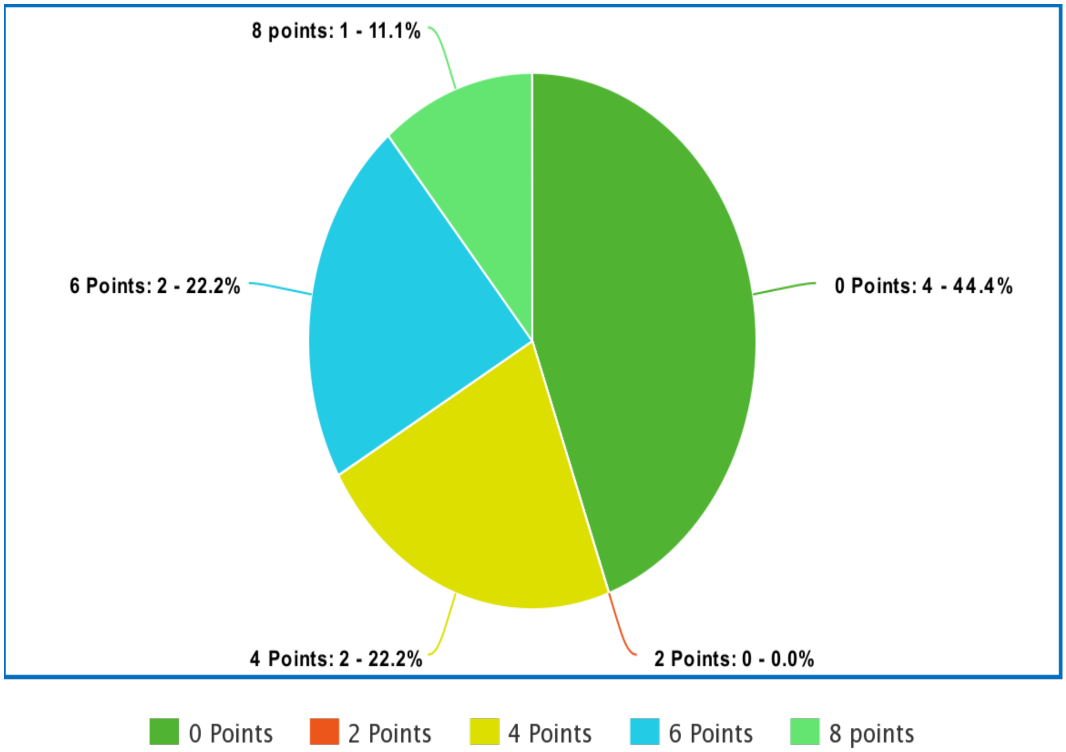

Figure 33: Results of Groups Generated Randomly

As it can be seen in figure 33, four groups scored 0 points in different activities, which is 44% of the whole result. Only one group scored the highest point.

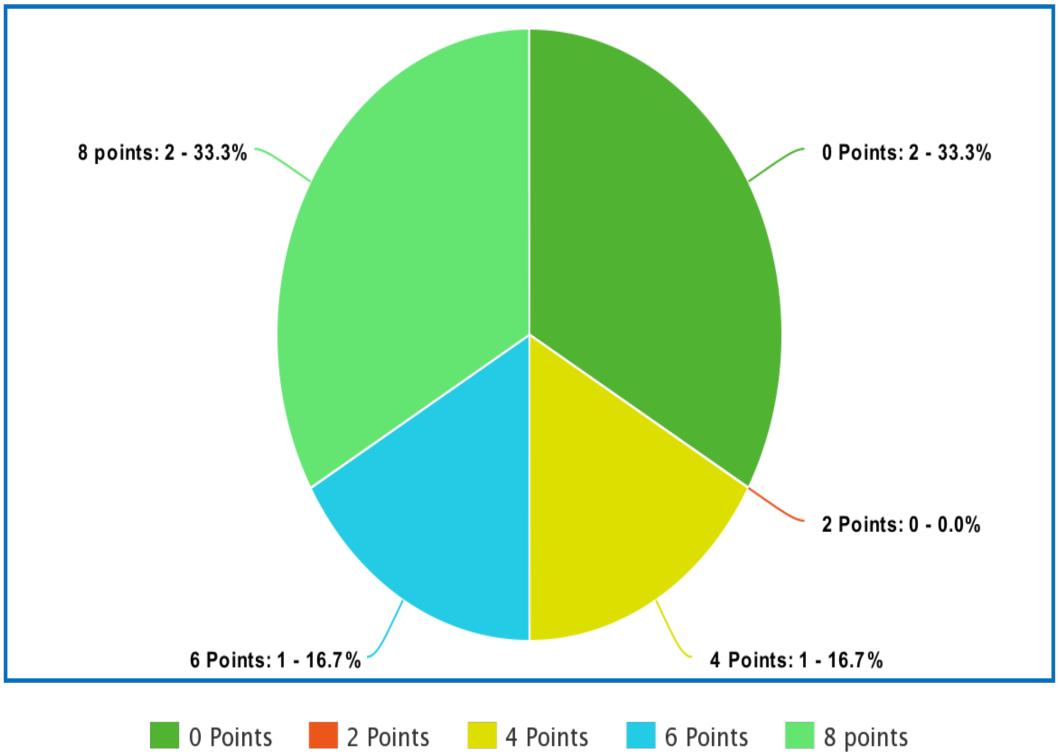

Figure 34: Result of groups generated using K-mean Clustering

Figure 34 above shows that two groups scored 0 points in different activities, which is 33% of the whole result. Two groups have reached the highest points. The result of the k-means clustering is better than the result of randomly generated groups.

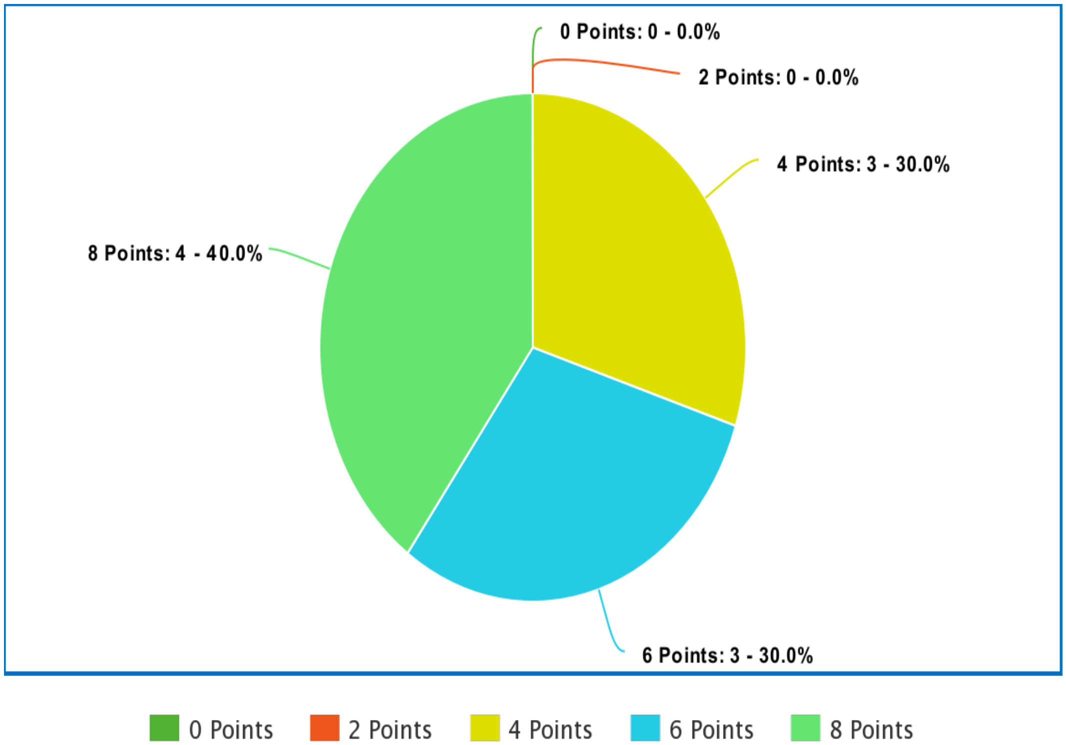

Figure 35: Result of groups generated using our proposed algorithms

Group performance has increased in the case of dynamic group formation using our proposed algorithm. Four groups reached the highest points and none of the groups scored 0 points in any activity as it can be seen in the pie chart in figure 35.

Group performance has increased in the case of dynamic group formation using our proposed algorithm. Four groups reached the highest points and none of the groups scored 0 points in any activity as it can be seen in the pie chart in figure 35.

The group formation is an essential part of collaborative learning. In literature, many researcher have proposed different techniques for group formation. We came up with our hypothesis that dynamic group formation can enhance the learning of students. Dynamic group means groups that are frequently changing based upon the performance. We experimented with pre and post-tests. Our methodology is evident from literature [32] [26]. In pre-test, we created groups using random grouping technique and k-mean clustering [32] [26]. In post-test, we used our proposed technique and we get the following results.

- In randomly generated groups 11% of students were able to get to the highest marks and 44% scored 0 marks.

- In groups created using k-mean based on the learning styles of students 33% student scored the highest marks and 33% scored 0 marks.

- Groups created using our technique 40% students scored highest marks, 30% scored 4 marks and 30% scored 6 marks.

Our results are supported by literature also as it states that heterogeneous groups perform better than homogeneous groups [4]. K-Means clustering create homogeneous groups while we are creating heterogeneous groups using our dynamic group formation method.

To further validate our result and make it trust able, we applied t-student test (statistical test). We have applied t-test because the sample size is less than 30. In order to apply t-student test we need null hypothesis. In our case null hypothesis is;

H0: dynamic group formation have no effect on the performance of groups in CSCL.

Data used in the pre-test is the result of activities performed by groups generated using k-means and for post-test we are using the result of activities performed by the groups generated using our algorithm. We are applying the t-test on the results of the groups so n = 5. Where n is the total number of groups generated during pre and post-test. These results are calculated with the confidence level of 95% ($\alpha = 0.05$). Degree of freedom is n-1 which is 5-1 = 4. It is mentioned in the student's distribution table that the value of t, when degree of freedom is 4 and confidence is 95%, is 2.7764. The t score we calculated for our pre and post test is 3.5. Therefore, value of t score is greater than the value of t 0.05, which means that our null hypothesis is rejected and the other hypothesis is correct that states dynamic group formation have positive impact on the performance of groups.

	N	Mean	SD	*t* score
Pre-test	5	3.6	10.24	3.5
Post-test	5	6.4	3.84	

Figure 36: t-student test analysis table

Chapter 5

Conclusion

We aimed to find out the impact of dynamic grouping on student‘s learning. In this paper, we have focused on three objectives (1) how to create dynamic groups? (2) How to make initial groups? (3) what is the impact of dynamic group formation on student‘s learning? To achieve our objective we experimented with two phases. In the first phase, initial group formation is carried out, that was quite a challenging task and we solved this problem by letting students solve the first activity of our experiment phase 1 individually. Once, students solved the activity, their knowledge level is calculated, and based on their knowledge level clusters of average and best students are created using our proposed algorithm 1. After the creation of initial clusters, groups are created with equal participation from each cluster of average and best students using our proposed algorithm 2. Activities are assigned to these groups, which they solve in collaboration. After the completion of each activity, groups swapping took place. Our experimental results show that dynamic group formation has a positive impact on student learning. Student‘s performance is better when groups are balanced.

In the real time class environment, instructors evaluates students based on the individual assessments and group projects. This research study will help instructors create balanced groups based on the individual assessments. During the project based assessment dynamic groups will enhance the learning and performance of students.

The potential limitation of our study is that it is only feasible in a controlled environment like collaborative activities of classrooms. Therefore, the validity of this research can be improved in the following ways:

- Extend this study for the e-learning platforms
- In this study we are not measuring the interaction of each students, so we can extend this study to propose a method for measuring the participation of each students and their interaction with each other.
- Include open ended questions in our experiment and use Natural Language Processing (NLP to find out the impact of dynamic group formation in CSCL.
- Use NLP to find out the group leader of the group from chat history of students.
- Integrate this research study with ITS (intelligent tutoring system). So, that ITS can handle multiple students.
- we can add gamification in collaborative learning where students can be rewarded with points and ranks badges on their profile [34].

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