Forming Suitable Groups in MCSCL Environments

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ABSTRACT

Given the peculiarities of mobile computer-supported collaborative learning (MCSCL) environments, forming suitable groups in such learning environments represents a hard and time-consuming task. This is because many conditions related to mobile learners, devices, and environment should be considered. Unlike the existing solutions, the present paper shows a grouping approach that allows a customizable formation of (1) homogeneous groups, (2) heterogeneous groups, and (3) mixed groups. The proposed solution does not only help instructors to dynamically form appropriate MCSCL groups, but it also allows to continually control the learners' learning, psychological, and social developments. To assess the effectiveness of the proposed solution, three metrics were used: (1) comparison between the characteristics of the existing group formation tools, (2) average intra-cluster distance of each grouping algorithm, and (3) an experimental evaluation in a real world environment. The obtained results show a great superiority of the proposed solution compared to the existing ones.

KEYWORDS

Collaborative Learning, Group Formation, Grouping Algorithms, MCSCL, Mobile Learning

INTRODUCTION

Collaborative learning (CL) is a process in which two or more learners work together to achieve certain common learning objectives. For instance, to obtain, construct, or share new knowledge; to resolve some problems; to develop some projects, etc. CL could effectively help learners to develop their personal and social skills that could not be achieved individually, such as “making ideas explicit, communicating with others, reasoning, arguing and negotiating” (Carro, 2008, p. 3). Many other researchers have demonstrated the importance of CL (Dillenbourg, 1999; Johnson & Johnson 1994; Roger & Johnson, 1994; Yadegaridehkordi et al., 2019; Zurita et al., 2005).

The development of information and communication technologies (ICT) has led to the emergence of “E-learning”, which is based on the use of ICT to facilitate the tasks of constructing and sharing knowledge. The educators began then to search how to benefit from the rapid evolution of ICT to improve the CL pedagogy. As result, since the late 1990s, a new branch of learning called Computer

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Supported Collaborative Learning (CSCL) has emerged (Lai, 2011). CSCL represents a pedagogical approach that aims to promote the collaboration between learners by helping them to construct their knowledge using computers and networks as their principal means of communication.

As part of ICT, the use of mobile communication technologies in last years has greatly expanded. According to the 2018's annual data and statistics report published by the International Telecommunication Union agency (ITU), the rate of mobile-cellular telephone subscriptions has been increased from 15% in 2001 to 107% in 2018 (ITU, 2018) (see Figure 1). According to the same report, the penetration of mobile broadband in the world reaches 69.3% in 2018. This value has increased 12 times since 2007. This explosive growth in the usage of mobile technologies has led to the appearance of mobile learning (M-learning). In such a learning model, learners use only mobile devices (e.g., Smartphones, tablets, PDA) to learn anywhere and anytime.

Combining the two learning paradigms (CL and M-learning) in one process permitted the appearance of a new learning domain called Mobile Computer Supported Collaborative Learning (MCSCCL). MCSCCL allows mobile learners to collaboratively obtain, construct and share their knowledge without the constraints of place and time.

As demonstrated by many researchers, a successful CL is the one that is based principally on the formation of effective learning groups (Dillenbourg, 1999; Huang & Wu, 2011; Webb et al., 1998). However, having such successful groups requires a lot of efforts and time, especially when the number of learners is considerable. Compared to traditional learning environments, the group formation issue in MCSCCL context represents more hard and time-consuming task. Instructors should not consider only the personality traits of learners (age, gender, cultures, skills, etc), but also their various learning behaviours (communication, movements, preferences, learning styles, etc), and information that are related to learning contexts (location, time, availability, etc). Therefore, the main challenge of this study is to provide the MCSCCL community with a new automatic, dynamic, and customizable group formation solution that could enhance the learning, psychological, and social development of learners. To well achieve this objective, the following research questions should be clearly answered:

- Question 1: Which grouping criteria could affect the learning quality of created groups?
- Question 2: How a grouping algorithm should be developed in MCSCCL environments?
- Question 3: How to evaluate the effectiveness of the proposed group formation solution?

The rest of paper is organized as follows: section 2 presents some interesting related works. Section 3 describes the proposed group formation approach. Section 4 shows the proposed grouping algorithms. Section 5 describes the evaluation of the proposed approach. Section 6 presents the limitations of the study. Finally, conclusions and recommendation for future works are provided in section 7.

RELEVANT RESEARCH

Many solutions have been proposed in literature to deal with the problem of learning group formation in MCSCCL environments. Among the most relevant studies, there is the solution proposed by (Huang & Wu, 2011), that developed a systematic grouping method that records learners' behaviors data in learning portfolios, and forms heterogeneous groups based on the stored data. (Mujkanovic et al., 2012) demonstrated that using some specific grouping criteria (learners' characteristics) could help to obtain desired outcomes. (Yin et al., 2012), (Tan et al, 2010), (Yamamoto & Uchida, 2018), and (Zurita et al, 2005) implemented collaborative learning environments to support dynamic grouping of learners in real-time. (El-Bishouty et al., 2010), (Hsieh et al., 2010), and (Huang et al., 2010) proposed grouping systems that use the level of social interaction between learners as grouping criteria. (Messeguer et al., 2010) developed an intelligent system that uses contextual information

Figure 1. Evolution of technology usage (ITU, 2018), Source: (ITU, 2018)

from students' devices to estimate group membership. (Mballo, et al., 2017) proposed a grouping method based on the level of learners mobility.

The learning groups in MCSCL environments can be created according to three types of grouping criteria: (a) the learner's personal characteristics, (b) the learner's behaviours, and (c) the learning context information (Amara et al, 2016). However, all the proposed studies use only few grouping criteria, and there is no solution that considers the three kinds of grouping criteria in one grouping process.

In many learning situations, instructors need to introduce their specific requirements, such as the grouping criteria, the nature of groups, the size of groups, etc. However, the majority of proposed solutions does not allow instructors to customize the grouping process.

Furthermore, the majority of existing studies is unable to provide a possibility to re-build learning groups in real time. Such a dynamic regrouping is very useful for reaching the benefits of CL.

THE PROPOSED GROUP FORMATION APPROACH

In light of the literature review findings, the researchers propose a new approach for dynamically build heterogeneous, homogeneous and mixed groups of mobile learners. The proposed approach takes into consideration the combination of the three types of criteria in one grouping process. Such a combination makes the proposed solution more adaptable for different situations. Moreover, the proposed solution gives instructors a flexible mean to control the developments of their learners through the continuous storage of different types of data (learners' capacities, learners' achievement, learning outcomes, etc).

Unlike the existing studies, which handicap instructors to choose the relevant grouping criteria, the proposed solution gives them the possibility to customize the group formation process. That means that instructors are able to chose between many available grouping criteria. The proposed solution is based on the idea that a useful grouping mechanism should not be specific for a particular type of learners or situations; it should not be related to a particular criterion; and it should not provide only one type of grouping (homogeneous or heterogeneous groups). To achieve this objective, the proposed

Table 1. Used group formation criteria

Personal characteristics	Learning behaviours	Context information
<ul style="list-style-type: none"> · Age · Gender · Mother languages · Mastered languages · Academic performance 	<ul style="list-style-type: none"> · Communication with partners · Communication with instructor · Interaction with learning objects · Learning style 	<ul style="list-style-type: none"> · Locations of learners · Location of learning objects · Time of learning · Learner availability · Learning objects availability

approach allows instructors to customize the task of forming groups according to different scenarios, activities, learners, needs, objectives, etc. Table 1 shows the set of grouping criteria considered for this study. Some of those criteria are selected from the literature review study conducted by (Amara et al, 2016).

Dynamic Grouping

A suitable group formation mechanism should not be specific for certain types of learners or learning, but it should be useful for different learning objectives, needs, and scenarios. To reach this goal, the proposed tool is developed to be used in different situations. Among the possible situations is when a new learner comes late and searches for a learning group; Or when a learner finds difficulties (social, learning, cultural, etc) with his/her partners and wants to change the group; Or when a learner lost contact with his/her group mates due to technical or geographical barriers. In all of those cases, dynamic group formation process helps learners to quickly find new appropriate groups according to the updated values of their learning, social, and personal information.

Customizable Process

There are no specific grouping criteria that could be considered as optimal for any CL activity. The choice of the best criteria should depend on the type of target populations, the nature of the collaborative activities, the needs, the objectives, the place and time of learning. Indeed, an effective group formation process should help instructors to easily customize the grouping mechanism. Thus, one of the objectives of the proposed solution is to provide instructors with a flexible tool with a greatest possible number of grouping criteria, in order to allow them to select the criteria that could adapt the different situations.

Continuous Monitoring of Learners Development

The proposed solution allows instructors to continuously control the learning and social developments of their learners. To reach this goal, the proposed system stores the learning information of learners (marks, levels, competences, etc); and also their psychological and social information (preferences, communication with others, etc). Furthermore, the system saves more information related to MCSCL environments such as preferred places, preferred devices, preferred applications, etc.

Group formation algorithm

As previously described, one of the advantages of the proposed group formation solution resides in its capacity to provide instructors with a customizable tool, which could be used for different learning situations. To achieve this objective, the authors considered the three possible kinds of grouping: (a) homogeneous grouping, (b) heterogeneous grouping, (c) mixed grouping.

The Learner Space

To have a clear comparison between learners' attributes, the researchers applied the concept of vector space model, where each learner is represented by a vector in a multidimensional space. The number

and the type of the used dimensions are given by instructors according to different learning situations. For instance, if instructor considers three grouping criteria; age, gender and level of communication with partners; then each learner should be represented as a vector $L(C_1, C_2, C_3)$, where C_1 represents the age of this learner, C_2 represents his/her gender, and C_3 represents his/her communication level with partners.

Another important step before executing the grouping algorithm is related to the data normalization problem, because the attributes of learners are represented in different measurement scales. For example, the age values are between 14 to 20, the gender values are between 0 (female) to 1 (male), the communication level values are between 0 to 5, etc. Therefore, the researchers added a normalization process that serves to bring all the considered attributes to the same scale. To accomplish the desired normalization, the researchers adopted the min-max normalization method proposed by (Jain & Bhandare, 2011). The developed normalization process turns a given vector $L(C_1, C_2, \dots, C_n)$ into a new vector $L'(C'_1, C'_2, \dots, C'_n)$. The value d' of each new attribute C' is calculated using the formula (1).

$$d' = \frac{d - \min(C)}{\max(C) - \min(C)} \quad (1)$$

Where d represents the old value of the attribute, $\min(C)$ represents the minimum value between all the data of the attribute C , $\max(C)$ represents the maximum value between all the data of the attribute C . For example, let the ages data of learners is: $C = \{15, 14, 18, 20, 16\}$. The minimum value in this example is $\min(C) = 14$, and the maximum value is $\max(C) = 20$. Then the normalized data is:

$$C'_1 = \left\{ \frac{15-14}{20-14}, \frac{14-14}{20-14}, \frac{18-14}{20-14}, \frac{20-14}{20-14}, \frac{16-14}{20-14} \right\} = \{0.16, 0, 0.66, 1, 0.33\}.$$

Homogeneous Grouping Algorithm

The proposed grouping algorithms are principally based on the calculation of Euclidian distances between learners' attributes. The Euclidian distance between two learners L_1 and L_2 is presented with formula (2).

$$D(L_1, L_2) = D(L_2, L_1) = \sqrt{\sum_{i=1}^n (C_{i,1} - C_{i,2})^2} \quad (2)$$

Where $C_{i,1}$ represents the value of the i th attribute of learner L_1 , and $C_{i,2}$ represents the value of the i th attribute of learner L_2 . And n represents the number of the considered attributes.

Homogeneous grouping algorithm serves to form groups of learners with the most similar features. To achieve this objective the algorithm follows the following phases:

Phase A: The algorithm receives the grouping settings from the instructor's device, such as: the number of groups, the list of grouping criteria, and the type of groups.

Phase B: According to the number of groups given by instructor, the algorithm selects randomly some learners to be the centroids of clusters (groups), and uses the attributes' values (criteria) of the selected learners as the initial clusters means.

Phase C: The algorithm examines the data related to every learner, calculates the Euclidean distances between him/her and all the clusters' centroids, and allocates him/her to the closer cluster.

Phase D: after each allocation of any learner to a new cluster, the algorithm recalculates the new centroid vector of the last and the new cluster of this learner.

Phase E: after the allocation of all learners to their clusters, the algorithm verifies if every learner was assigned to his appropriate group using the Euclidean distance. If not, the algorithm should repeat the phases B, C, and D, until no change appears in the groups' members.

Phase F: sometimes it's possible that the algorithm cannot find the best solution (no stop in repetition of phases B, C, and D). In this case, the execution of the algorithm should be stopped after a predefined number of iterations.

Heterogeneous Grouping Algorithm

Heterogeneous grouping algorithm aims to form groups of learners with the most different features. The developed algorithm follows the following phases:

- **Phase A:** The algorithm receives the grouping settings from the instructor's device, such as: the number of groups, the list of grouping criteria, and the type of grouping.
- **Phase B:** By calculating the distances between all the participated learners (using formula 2), the grouping algorithm creates a similarity matrix that is represented as a table of n rows and n columns, where n is the number of learners.
- **Phase C:** To form a heterogeneous group, the algorithm selects from the similarity matrix the two learners with the greatest distance value. Then it calculates the mean vector of this group using the attributes' values of the two selected learners, and removes them from the similarity matrix.
- **Phase D:** In this phase the algorithm:
 1. Calculates the distances between the mean vector of the created group and the rest of learners;
 2. Finds the learner that had the greatest distance value with the mean vector;
 3. Adds the selected learner to the created group;
 4. Removes the selected learner from the similarity matrix;
 5. Calculates the new mean vector of the formed group.
- **Phase E:** The phase D is repeated until reaching the requested number of learners in the group.
- **Phase F:** The phases C, D, E are repeated until removing all learners from the similarity matrix.

Mixed Grouping Algorithm

While all the grouping methods existing in literature permit the formation of only one type of learning groups (homogeneous or heterogeneous learning groups), the method proposed in this study allows the formation of mixed groups. That means that the grouping algorithm could form groups that are homogeneous in terms of certain criteria and heterogeneous for other ones. For instance, forming groups that are homogenous in terms of gender (only males or females in a same group) and heterogeneous in terms of learning styles (learners with different learning styles in a same group).

The mixed grouping algorithm aims to classify learners in a set of hierarchical steps. In each step, a given criterion is used, and a given grouping method is followed. For instance, first the algorithm classifies learners based on their geographical locations in a set of main groups. Then, each created group would be divided in a set of subgroups based on the learners' gender. Then each created subgroup would be divided in small groups based on the learners' interaction level, and so on.

Using such a grouping mechanism, instructors would be able to select the grouping criteria in a priority manner. He/she could first classify learners using the highest priority criteria (the criteria that he/she finds them most important according to a given need or situation). Then he/she uses successively the rest of criteria according to their priority to create new groups from the existing ones.

The proposed mixed grouping algorithm follows the following phases:

1. The algorithm receives the grouping settings from the instructor's device, such as: the number of groups or the maximum number of learners in each group; the list of grouping criteria in a priority manner; and the type of grouping for each criterion (homogeneous or heterogeneous).
2. The algorithm creates a set of main groups of learners, using the criterion of the high priority, and the type of grouping related to this criterion.
3. After the creation of the main groups, the algorithm divides each one of them to a set of subgroups, according to the criterion provided by instructor.
4. Each created subgroup can be also divided in a set of small groups using another criterion.

To form the groups in steps 2, 3 and 4, the homogeneous and heterogeneous algorithms are followed.

EVALUATION

Evaluation Based on The Characteristics of Group Formation Tools

Table 2 shows a general comparison between the existing group formation solutions. This comparative study was principally conducted by (Amara et al, 2016), and the researchers added two new approaches that are recently proposed by (Mballo, et al., 2017) and (Yamamoto & Uchida, 2018).

First, one can see that all the existing solutions can form only one type of groups (Heterogeneous or Homogeneous groups). The proposed study is the only one that allows instructors to chose between the formations of heterogeneous, homogeneous, or mixed groups according to different learning situations.

Regarding the grouping criteria, one can remark that the existing approaches have never considered the three types of grouping criteria (learners' personal characteristics, learners' learning behaviours, and context information) in one tool. The proposed solution is the only one that allows such a combination.

Regarding the characteristics of the existing approaches, one can see that the proposed solution is among the few ones that permit the customization of the grouping process. It gives instructors the possibility to manage the formation of groups according to different situations, objectives, needs, etc.

Another characteristic is the dynamic formation of groups. The proposed solution is among the few approaches that provide the possibility to re-create the learning groups at real time. With such a grouping mechanism, mobile learners could change their learning groups at any moment they want. One of the characteristics that is completely ignored by the existing solution is the continuous control of learners' developments. By storing the different information of learners, the proposed approach allows to control the learning, social, and psychological progress of learners.

Average Intra-Cluster Distance (AID) of The Grouping Algorithm

In order to make an initial assessment of the group formation solution, a comparison between the effectiveness of the proposed grouping algorithm with other grouping methods has been made with the use of Average Intra-cluster Distance (AID) parameter. AID is used to indicate how much the created groups of a given algorithm are homogeneous or heterogeneous. A high value of AID indicates a high level of heterogeneity, and a low value of AID indicates a high level of homogeneity. To calculate the AID of a grouping algorithm the following steps should be followed:

- (1) For each created group we calculate the sum (S) of total distances between each learner and the other members one by one. The value of S is calculated with formula (3);
- (2) We calculate the AID_i of each created group G_i by following formula (4);
- (3) We calculate the global AID of the grouping algorithm by dividing the sum of the calculated AID_i of each group i on the total number of created groups; such is shown in formula (5).

Table 2. Comparison of the proposed group formation approach with the existing approaches

Study	Grouping type			Group formation criteria			Group formation characteristics		
	Heterogeneous	Homogeneous	Mixed groups	Personal characteristics	Learning behaviours	Context information	Customizable	Dynamic	Continuous Control of learners
(Huang & Wu, 2011)	✓	×	×	×	✓	✓	✓	×	✓
(Zurita et al., 2005)	✓	×	×	✓	×	×	✓	✓	×
(Huang et al., 2010)	×	✓	×	×	✓	×	×	×	×
(Messeguer et al., 2010)	×	×	×	×	✓	✓	×	×	×
(El-Bishouty et al., 2010)	×	×	×	✓	×	✓	×	×	×
(Hsieh et al., 2010)	✓	×	×	✓	✓	✓	×	×	×
(Tan et al., 2010)	×	✓	×	✓	×	✓	×	✓	×
(Giemza et al., 2013)	×	✓	×	✓	✓	×	×	×	×
(Mujkanovic et al., 2012)	×	×	×	✓	×	×	×	×	×
(Yin et al., 2012)	×	✓	×	×	✓	×	×	×	×
(Mballo, et al., 2017)	×	✓	×	✓	✓	×	×	×	×
(Yamamoto & Uchida, 2018)	×	✓	×	✓	×	×	×	✓	×
Proposed approach	✓	✓	✓	✓	✓	✓	✓	✓	✓

$$s = \sum_{i=1}^{g-1} \sum_{k=i+1}^g D(L_i, L_k) \quad (3)$$

Where g represents the number of learners in the group, and $D(L_i, L_k)$ represents the distance between learner i and learner k .

$$AID_i = \frac{S_i}{\frac{G_i!}{2!(G_i - 2)!}} \quad (4)$$

Where S_i represents the sum of total distances between learners of group i , which is calculated using formula (3). G_i represents the number of learners of group i .

Figure 2. AID's values of groups created by the proposed homogeneous grouping algorithm compared to random grouping

$$AID = \frac{\sum_{i=1}^n AID_i}{n} \quad (5)$$

AID_i represents the value of the average intra-cluster distance of group i . And n represents the total number of created groups.

Figure 2 (A) shows a comparison between the AID values of groups created by the proposed homogeneous grouping algorithm, with the AID values of groups that are randomly created. In this evaluation step only one grouping criterion was used for both grouping methods. One can remark that the proposed algorithm forms always groups with very low values of AID, whatever the number of learners.

Figure 2 (B) shows a same comparison but with multiple grouping criteria. The obtained results affirm that even with a large number of grouping criteria the proposed algorithm forms always groups with a very high level of homogeneity. There is also a very slight rise in the values of AID related to the proposed algorithm. This is due to use of multiple grouping criteria. Because the more we use a big number of grouping criteria, the more we grow the possibility to increase the distances between learners.

Figure 3 (A) shows a comparison between the AID's values of groups created by the proposed heterogeneous grouping algorithm with those of a grouping solution proposed by (Zurita et al., 2005), considering a unique criterion. The obtained results affirm that when we consider a unique grouping criterion the learning groups created by the proposed algorithm show always a higher level of AID. That means that the proposed algorithm creates always the most possible heterogeneous groups.

Figure 3 (B) represents a comparison between the AID's values of groups created by the proposed heterogeneous algorithm with those of grouping solution proposed by (Huang & Wu, 2011) using multiple grouping criteria. The obtained results confirm the effectiveness of the proposed algorithm for creating heterogeneous groups. Although the number of grouping criteria is increased, the proposed algorithm forms always groups with the highest values of AID.

Figure 3. AID's values of groups created by the proposed heterogeneous grouping algorithm compared with the grouping solution proposed by other researchers

Experimental Evaluation

To confirm the results shown above, the researchers conducted an experimental study in which 54 students from a private secondary school were voluntarily participated. The participants consisted of 31 females and 23 males, aged between 16 to 17 years. The material chosen for this experiment was the French language, since the teachers of this material organize many interesting CL activities. Among the proposed works, the researchers chose a CL activity that asks students to make a reportage that presents a given city. The students of each group should search for the interesting information about the chosen city, visit it, obtain more information about it, and finally make a reportage that presents the visited city.

The experiment was lasted for two trimesters. During the first one, the researchers were working for collecting the different students' information, such as their biographic information, their learning styles, and their learning behaviors. Several techniques were used to obtain and save such information, like felling questionnaires, controlling collaborative activities, and testing individual competences. During this period, students were randomly assigned to small learning groups of three learners, in order to help them to be familiar with the MCSCL activities. The second trimester was dedicated for assessing the proposed group formation tool. To achieve this objective, two kinds of groups were created:

- (a) 9 control groups of 3 students were created by instructor;
- (b) 9 experiment groups of 3 students were automatically created by the proposed tool.

Even if the experiment groups were automatically created by the proposed grouping tool, but they were personalized by the instructor that introduced his grouping preferences (shown in table 3).

After forming the different learning groups, and before starting CL activities, students from control and experiment groups were asked to accomplish a pre-test of thirteen minutes, which will be compared with a post-test at the end of this experiment.

For both (control and experiment) groups, each participated learner was asked to complete with his/her colleagues several CL tasks, in different times and different places (in the classroom, and out of the classroom). First, learners of each group were asked to choose one city and to search the

Table 3. Instructor's choices for forming learning groups

Grouping type	Heterogeneous grouping
Grouping criteria	- Academic performance - Communication with partners
Group size	3 members

interesting information about the historical places and the important points of interest of this city. Then, learners have to visit together the city, to use their mobile devices for finding more interesting places, to communicate with his/her group mates, and to take some photos and videos that can be add to their work. After the end of this activity, each learner should individually prepare his/her own reportage, and then the instructor evaluates the personal work of each learner. Then, the members of each group meet again and accomplish together the final reportage of the group and present it to their classmates. Three evaluation metrics were used by instructors to assess the presented works: (1) The language quality of the presented work, (2) The quality of the reportages in terms of the presented information, (3) The level of communication during the preparation and the presentation of the work.

Table 4 shows a comparison between the learning results of control and experimental groups. During the pre-assessment phase, one can remark that both groups have almost the same mean (9.62 / 20 for control group, and 9.29 / 20 for experimental group). This means that students of control groups have the same prerequisites for developing collaboratively reportage in French language as students of experimental groups. The low mean value of both groups (less than ten out of twenty) indicates a lack of students' cognitive skills and knowledge on the topic of reportages.

As for the Standard deviation results of pre assessment phase, one can remark that experimental groups have a greater value of standard deviation (2.93) compared to control groups (1.59), meaning that experimental groups show more dispersion, and therefore these groups are more heterogeneous.

Regarding the post-assessment phase, one can remark that both groups have seen an increase in the mean values. But the rate of increase for experimental groups ($13.55 - 9.29 = 4.26$ as difference) was greater than that for control groups (1.72 as difference). This confirms that the proposed group formation solution had a significant impact on the learning achievement of learners. Therefore, one can say that the groups created by the proposed tool are more successful than the control groups.

Finally, one can remark from the shown results a valuable decrease in the value of standard deviation of experimental groups between the pre-assessment and post assessment phases (from 2.93 to 1.18), and no significant change for control groups (small increase from 1.59 to 1.99). This

Table 4. Mean and Standard deviation of pre and post assessment of control and experimental groups

	Control groups		Experimental groups	
	Mean	Standard deviation	Mean	Standard deviation
Pre-assessment	9.62	1.59	9.29	2.93
Post-assessment	11.34	1.99	13.55	1.18

Table 5. Effect size when comparing control with experimental groups using Cohen's d and Hedges' g measures

	Cohen's D	Hedges' G
Pre-assessment	0.139	0.137
Post-assessment	1.35	1.331

means that learning results from experimental groups have decreased the level of dispersion, and thus a reduction in the level of heterogeneity between the group's members, which represents the main goal of CL.

For well analyzing the obtained results, the researchers have followed an "Effect size" measurement technique. It is a statistical method for measuring the magnitude of difference between the results of two groups (Kelley & Preacher, 2012). In the case of this study, effect size helps researchers to know how much the learning outcomes of experimental groups are similar /different to those of the control groups.

As shown in table 5, the researchers have used two methods for measuring the effect size, Cohen's D and Hedges' G measures. (Cohen, 2013) suggested the following measures of similarity between groups:

- If ($D < 0.2$) then the effect size is non significant. - If ($0.2 \leq D < 0.5$) then the effect size is small.
- If ($0.5 \leq D < 0.8$) then the effect size is medium. - If ($D \geq 0.8$) then the effect size is large.

By applying Cohen's D measures on these experiments, one can see that during the pre assessment period there was no significant effect size ($0.139 < 0.2$). This means that students from both groups have similar prerequisites for learning. Conversely, during the post assessment period, there was a large effect size ($1.35 > 0.8$). This indicates that there is a great superiority of the groups created automatically over the control groups in terms of learners' achievement.

In order to confirm the results obtained above, the researchers added another effect size evaluation method, which is Hedges' G measure. As same as Cohen's D, the Hedges' G values 0.2, 0.5, 0.8 indicate respectively small, medium, and large effect size. As shown in table 5, there is no great difference between (D) and (G) obtained results (0.137 for pre-assessment, and 1.331 for post-assessment). Meaning that control and experimental groups have started their CL with similar prerequisites, but experimental groups finished their learning activities with large superiority than those of control groups. Thus, these results validate the effectiveness of the proposed group formation solution for creating successful groups.

LIMITATION

The main limitation encountered during the preparation of this study was related to the evaluation and comparison of the proposed solution with the existing ones. Because, only 2% of the existing studies has provided the source code of their group formation algorithms (Cruz & Isotani 2014). Fortunately, the researchers of this study were able to obtain the algorithm's code sources, as well as, detailed information about the assessment process of the solutions proposed by (Huang & Wu, 2011) and (Zurita et al., 2005), which are considered as the two most important approaches existing in literature (Amara et al, 2016).

CONCLUSION

This paper shows a suitable group formation method that helps instructors to dynamically create learning groups in mobile computer supported collaborative learning (MCSCL) environments.

With this work, the authors provide the MCSCL's community with a valuable solution to form homogeneous, heterogeneous, and mixed learning groups, with the possibility to customize the grouping process according the learning's contexts, objectives, and needs.

Different evaluation techniques were used for assessing the proposed solution. For technical side, the proposed algorithm has demonstrated its efficiency in forming homogeneous and heterogeneous groups, whatever the size of groups and the used grouping criteria. For educational side, results have

shown that experiment groups ensure always the best learning achievement compared with control groups.

Beside its benefits for learners, the proposed grouping solution represents a useful tool for instructors to continually evaluate and control their learners' development. It helps them to have detailed information about the personal, cognitive, social, and psychological progresses of learners. Furthermore, the proposed solution allows instructors to manage the learning groups whatever the place and time of learning.

Future research could address the integration of the proposed group formation process in the field of serious games. For instance, users could receive recommendations for players that share the same interests, which could help them to form gaming teams, or to discover new gaming communities.

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