

# Dynamic Group Formation in Mobile Computer Supported Collaborative Learning Environment

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**Abstract:** Forming suitable learning groups is one of the factors that determine the efficiency of collaborative learning activities. However, only a few studies were carried out to address this problem in the mobile learning environments. In this paper, we propose a new approach for an automatic, customized, and dynamic group formation in Mobile Computer Supported Collaborative Learning (MCSCL) contexts. The proposed solution is based on the combination of three types of grouping criteria: learner's personal characteristics, learner's behaviours, and context information. The instructors can freely select the type, the number, and the weight of grouping criteria, together with other settings such as the number, the size, and the type of learning groups (homogeneous or heterogeneous). Apart from a grouping mechanism, the proposed approach represents a flexible tool to control each learner, and to manage the learning processes from the beginning to the end of collaborative learning activities. In order to evaluate the quality of the implemented group formation algorithm, we compare its Average Intra-cluster Distance (AID) with the one of a random group formation method. The results show a higher effectiveness of the proposed algorithm in forming homogenous and heterogeneous groups compared to the random method.

## 1 INTRODUCTION

The rapid development of wireless communication and mobile technologies led to the emergence of Mobile Learning (M-Learning). This new form of learning allows people to learn anywhere and anytime thanks to mobility, individuality, accessibility, connectivity, and context sensitivity of mobile technologies (e.g. Smartphones, Tablets, PDA) (Looi et al., 2013). These features allow providing collaborative, contextualized, customized, and personalized learning (Baran, 2014).

On the other hand, Collaborative Learning is one of the important means to improve the communication skills of learners and to enhance their knowledge through the exchange of ideas and experiences. Combining M-Learning with collaborative learning areas enables the creation of natural mobile collaboration environments with face-to-face interactions termed Mobile Computer Supported Collaborative Learning (MCSCL) (Cortez et al., 2004). MCSCL allows people to construct their knowledge collaboratively anywhere, anytime,

and in any context using wireless and mobile technologies. Thus, many researchers find that MCSCL represents the next logical step for the development of collaborative learning field (Boticki et al., 2010; Caballé et al., 2010).

One of the requirements for an effective collaborative learning is the appropriate formation of learning groups. According to (Bekele, 2006), studies show that the unsuccessful outcomes of collaborative learning activities are generally due to failures of the learners grouping. Therefore, the instructors should pay a great attention to this issue, in order to provide the necessary conditions for a successful collaborative learning.

However, finding the appropriate group for each learner is a hard and time-consuming task that could not be well accomplished without computer support (Hubscher, 2010). In MCSCL environments, this task is more complicated. The grouping process should not consider only the diversity of learners' personal characteristics (age, gender, skills, cultures, religions, etc), but also the diversity of their learning behaviours (communication, preferences,

movement, etc), and the information related to the learning contexts. Therefore, our primary objective is to propose a new approach for forming the best possible learning groups in MCSCL environments.

In order to achieve this goal, this work identifies the following research questions:

- RQ1: What is the state of research on this topic?
- RQ2: What are the relevant grouping criteria?
- RQ3: What characteristics of grouping process contribute for its effectiveness ?

The paper is organised as follows: Section 2 presents the relevant studies with their limitations; Section 3 describes the proposed approach for group formation in MCSCL environment with the different considered grouping criteria; Section 4 presents the grouping mechanism with emphasis on its peculiarities; Section 5 describes the system design and implementation; Section 6 provides an evaluation of the proposed approach. Finally, Section 7 presents our conclusions and further work.

## 2 RELATED WORK

The following list of related works was defined, evaluated, and analysed using a systematic literature review (SLR) method (Kitchenham, 2007). We have presented a more exhaustive description of this SLR on another paper (Amara et al., 2015). Among more than 160 found papers that discuss the group formation problem in MCSCL environments, we

have been able to select only 10 studies that are considered, by SLR, as the most relevant to this research problem. These studies are labelled from S1 to S10 and shown in Table 1. The group formation criteria are classified in three sets: learner’s characteristics, learner’s behaviours, and context information.

Study S1 (Huang and Wu, 2011) introduces a method for collecting some kinds of learning behaviours and recording them in ubiquitous portfolios. Then, a systematic grouping mechanism transforms the collected data into a portfolio grid and creates a learner similarity matrix. Finally, a heterogeneous grouping algorithm forms learning groups using this matrix.

Study S2 (Zurita et al., 2005) presents a MCSCL environment that supports dynamic changes in the composition of groups. The authors found that the dynamic composition of groups contributes with significant qualitative and quantitative improvement in learning and social behaviours of learners (communication, interaction, help, negotiation, etc).

Study S3 (Huang et al., 2010) proposes a mechanism for analysing the learners’ reading interests to create learning communities. The study uses the social platform Del.icio.us to collect the users’ behavioural data (library’s circulation records) and recommends partners with similar interests.

Study S4 (Messeguer et al., 2010) introduces an approach for group prediction in collaborative

Table 1: Used grouping criteria from the existing approaches.

Id	Personal characteristics	Learning behaviours	Context information
S1	✗	Observing/ Answering quiz/ Interacting/ Moving/ Losing/ Answering questions/ Referencing/ Completing tasks/ Taking note	Locations of learners and learning objects
S2	Preferences /Achievement / Sociability/ Interests	✗	✗
S3	✗	Past activities (read books)	✗
S4	✗	Learner’s preferences (place, partners, preferred subject) / Time spent for learning	Time / Place / Available neighborhoods
S5	Profile information	✗	Location/ Surrounding objects
S6	Personal background	Learner's interaction	Location
S7	Learning profile / Learning styles / Learning interests	✗	Location
S8	Learner’s interests	Learner’s actions: creating an account/ setting up the profile/ searching for learning groups/ creating learning groups	✗
S9	Gender / Age / Motivation / Previous knowledge	✗	✗
S10	✗	Helping history	✗

learning. The system uses some data of learner's behaviours (such as creating, joining, leaving and destroying groups) to train and test an intelligent system that could automatically estimate group membership.

In study S5 (El-Bishouty et al., 2010), the authors develop a model for finding the best matched peer helpers for certain tasks. The system uses RFID tags to detect meaningful surrounding objects, and create a social knowledge awareness map for the peer helper based on the detected objects.

Study S6 (Hsieh et al., 2010) presents a grouping method based on a mining social interaction. To evaluate the level of learner's interaction, wireless networks are used to measure the distance between two or more learners in a certain amount of time.

Study S7 (Tan et al., 2010) a dynamic location-based grouping mechanism is developed. The proposed process considers the learners' location together with other criteria such as learner's profile, learning style, and learning interests.

Study S8 (Giemza et al., 2013) presents an approach for creating informal learning groups. The used grouping data comes from the campus environments (personal profiles), location information, and several types of cloud services (e.g. Google drive, Brainstormer, and Doodle).

Study S9 (Mujkanovic et al., 2012) demonstrates the importance of creating groups that exhibit some desired behaviours. Authors assert that both individual characteristics and behaviours can be used to accomplish desired group behaviours.

Study S10 (Yin et al., 2012) presents an approach that evaluates the level of personal relationship between learners according to the frequency of peer helping. The system uses this evaluation to recommend the appropriate partners for each learner.

Although the presented studies offer useful solutions for enhancing the process of learning group formation, they show some limitations. As shown in Table 1, the majority of the studies pay a little attention to the learner's behaviours. Only S1 proposes an interesting approach for utilizing a set of behaviours to create learning groups. In addition, some kinds of learning behaviours are completely ignored (e.g. communication with instructors and interaction with learning objects).

Regarding the use of context information as grouping criteria, one can remark that the location is the most used criterion. Although the ability of context awareness offered by the mobile technologies, the majority of analysed approaches

ignore this type of criteria. Only studies S1, S4, S5, S6, and S7 proposed solutions to consider some kinds of context information (time, surrounding objects, available neighbours).

The dynamic formation of learning groups is very useful in real world contexts, since the MCSCL activities are generally exposed to many technical problems (disconnections, low memory of mobile devices, etc) and social problems (misunderstanding, disunion, etc). However, the majority of analysed studies do not support the dynamic composition of learning groups.

Another limitation is related to the configuration settings of the existing grouping processes. The majority of these processes lack a customized grouping mechanism. That means that instructors are unable to select their own grouping choices such as the nature of groups (homogeneous or heterogeneous), the number of learners in each group, and the grouping criteria that could be considered more appropriate for their learners, objectives, situations, etc.

### 3 PROPOSED GROUP FORMATION APPROACH

In light of the findings obtained from the analysis of existing approaches, we propose a new approach for creating suitable learning groups for MCSCL environments (see Figure 1). The main idea is to combine the three kinds of criteria (learner's personal characteristics, learner's behaviours and context information) in a single grouping process and allow the instructors to customize it according to different scenarios, activities, learners, needs, objectives, etc. The following subsections describe the considered group formation criteria.

#### 3.1 Personal Characteristics

In order to make the group formation process useful in different learning contexts, the greatest possible number of grouping criteria should be used. For that, different personal characteristics are considered (e.g., age, gender, languages, preferences, skills, hobbies).

To motivate the learners in their learning, the proposed system enables them to define the lists of their preferred partners. And in order to avoid hindering the learning activities, the system allows the learners to set the lists of their disliked partners. The existence of these lists does not necessary mean

that they will be used. The instructors can or not consider them.

The proposed approach considers also the learner's learning styles. Analysing each learner's learning style helps the system to know whether a learner is: active or reflective, sensing or intuitive, visual or verbal, sequential or global. To identify the learning style pattern, each learner has to fill out a Silverman's index of learning styles questionnaire (Felder and Silverman, 1988).

Another characteristic considered by the system is the learner's health state. The system could classify the learners into healthy or disabled learners.

The values of personal characteristics criteria are generally static, and each learner introduces them to her/his profile only once. However, some data such as skills and background knowledge are evaluated by the system during the learning process.

## 3.2 Learning Behaviours

Learning behaviours are those actions related to learning process such as self-motivation, interaction, communication and satisfaction with the learning (Dillon et al., 2007).

To ensure a dynamic grouping, the learning behaviours should be regularly updated. The following subsections show the list of learning behaviours used as grouping criteria.

### 3.2.1 Communication with Partners

In order to evaluate the level of communication between two learners, two metrics are used: the time spent in communication and the number of direct and remote contacts between them. The fact that two learners are in communication doesn't mean that both are active; the system should know which one of them has initiated the communication.

Based on the evaluation of learner-learner communication level, the system classifies the learners into social or introvert.

### 3.2.2 Communication with Instructor

Similar to the learner-learner communication, the system should know whether it was the learner who initiated the communication or the instructor.

The evaluation of learner-instructor communication level allows the system to classify the learners based on their autonomy. If a learner does successfully his tasks with minimum communication with the instructor, he/she can have a high level of autonomy.

### 3.2.3 Interaction with Learning Objects

Learning objects are classified into smart and non-smart objects. In order to make the non-smart objects detectable by the mobile devices and allow the system to control their interaction with the users, some technologies such as Radio-Frequency Identification (RFID), or Quick Response (QR) codes are used to tag them. To measure the level of interaction between a learner and learning objects, the system evaluates the number of interactions, and the time spent in interaction between each learner and learning object.

### 3.2.4 Learner's Movement

The system defines the movement pattern of the learners by identifying and memorising the different places they have visited and the learning objects with which they have interacted. The system could then classify the learners according to their movements into moving or passive learners.

### 3.2.5 Learner's Preferences

Based on the analysis of learners' past activities, the system evaluates and updates continuously the preferences list of each learner. This list contains the preferred partners, instructors, activities, learning objects, places, and times of learning.

### 3.2.6 Tasks Completion Rate

The instructors ask sometimes their learners to do some activities (develop projects, study phenomena, solve problems, etc). In our approach, we assume that each learning activity is composed of one or more tasks, and each task could be completed in a predefined period of time. The learners could be then classified based on the level of completion of their past tasks. To enable the system know whether a learner (or a group) completed a task or not, learners have to submit their works, pass some tests, or answer some learning related quizzes. For certain tasks, the system is unable to evaluate each learner. In such a case, the evaluation is done manually by the instructor. At the end of each task, the level of tasks completion of each learner should be updated.

## 3.3 Context Information

With the arrival of new wireless and mobile technologies, the task of collecting and evaluating the context information becomes possible. However, the usage of this kind of information to improve the



process of group formation is rarely proposed. Hence, we propose in this approach the use of four types of context information.

### 3.3.1 Location of Learners and Surrounding Learning Objects

MCSCL activities are generally carried out in informal environments, where learners move freely, and are not obliged to stay at a given place. Controlling the learners in such environments is a hard task or even impossible in some situations. Nevertheless, the use of mobile technologies enables tracking the learners and collecting instantaneous information about them. In our approach, a context service is used to provide the system with the current geographical location of the learners and the surrounding learning objects. The location information is used also as a way to evaluate some learners' behaviours. For instance, to measure the level of communication between two learners, the system analyses periodically their geographical locations. If they stay together in the same place for a given amount of time, the system considers that they are in communication and updates their learner-learner communication level.

### 3.3.2 Learner and Learning Object Availability

At a given moment, a learner can be busy, available, or awaiting for a learning object. Similarly, the learning objects can be available or in use by learners. The system must be aware of this context information (current availability state of the learners and of the learning objects) in order to avoid assigning busy learners to new groups, or forming groups that need to work with already allocated learning objects.

### 3.3.3 Learning Progress Level

In order to ensure a dynamic grouping, the collaborative work of each group should be periodically controlled. Based on the progress status, the instructor decides whether a formation of new groups is or not required.

### 3.3.4 Time of Learning Activity

Since some learning activities are not similar at different points in time, this context information could affect the learning process. Therefore, the system should be aware about this information before the formation of learning groups. The time

information is classified into: times of the day (morning, afternoon, evening, night) and types of days (weekend, working days, holidays).

## 4 GROUPING MECHANISM

When a new learner subscribes to the platform, she/he should use the learner interface to introduce her/his personal characteristics that are stored in the learner's personal profile database (see Figure 1).

In order to continuously collect the learners' behaviours during the collaborative activities, a data collection application is installed in the device of each learner. This application stores frequently the behaviours data in a set of log files. At the end of each activity, the system (through the module *data extraction*) analyses the log files, extracts the relevant behavioural information and stores it in the active database.

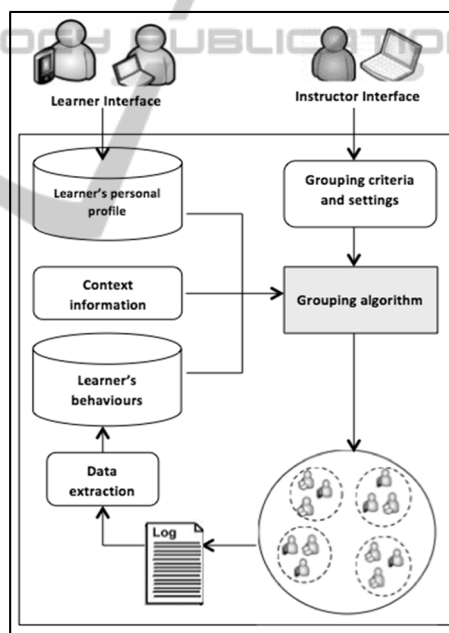


Figure 1: Proposed grouping mechanism.

To obtain different context information such as time of learning and location of learners, the system uses some mobile technologies such as *Global Positioning System (GPS)*, *Bluetooth*, *Radio-Frequency Identification (RFID)*.

Before starting any collaborative activity, the instructor, through the module *Grouping criteria and settings*, selects the types of criteria (learner's personal characteristics, or/and behaviours, or/and context information). According to the chosen types

of criteria, the system shows a list of grouping criteria. The instructor selects then the criteria and gives a weight for each criterion. In addition, she/he should define the nature of groups (homogeneous or heterogeneous), the number of groups, or the number of learners in each group.

Finally, the grouping algorithm receives the list of grouping criteria selected by the instructor. It accesses to the requested databases and interact, if necessary, with the *Context service* in order to get some context information. After obtaining all the values of necessary grouping criteria, the algorithm finds the most appropriate learning groups. Instructor and learners receive then the list of created groups through their mobile interfaces.

The following subsections describe the main characteristics of the proposed approach.

#### 4.1 Customized Grouping

The proposed approach gives the instructors a full freedom to select the type, the number, and the weight of grouping criteria. In addition, they could define to the nature of groups (homogenous or heterogeneous), the number of groups, or the number of learners per group. Instructors have the choice between three type of grouping criteria: learners' personal characteristics, learners' behaviours, and context information. They can choose a single type of them, two, or all together, depending on the different kinds of learners, activities, needs, etc. Additionally, the instructors could specify a weight for each used criteria, which allows them to give more or less importance to the various criteria involved in the formation of groups.

This customization in forming groups makes the grouping mechanism fairly global. It could be used for any type of learners (young students, secondary school students, researchers, etc), any type of activities (developing projects, resolving problems, etc), and in any learning place (schools, universities, gardens, museums, campuses, etc).

#### 4.2 Dynamic Grouping

Dynamic grouping means the ability to create learning groups and change their members at any moment (Zurita et al., 2005). This ability requires a continuous update of all the used grouping criteria.

The dynamism of group composition is very useful in MCSCL environments. Apart from its ability to change the groups' members during or after the end of each learning stage or activity, it helps the instructors to evaluate the different

learning strategies by using the different grouping methods in different times and places. In addition, the dynamic grouping could help a newly arrived learner to find easily an appropriate learning group. Furthermore, The majority of MCSCL activities occur in wide and natural places (gardens, forests, museums, etc), so, they are generally exposed to a number of obstacles that could hinder the good running of the different activities. in certain situations, these obstacles led to stop the collaborative activities and destroy the learning groups. The dynamic grouping represents in those cases the best solution to quickly restart the activities with new learning groups.

## 5 SYSTEM IMPLEMENTATION

For the implementation of the proposed system, we have used a *client-server* architecture whose components are grouped in client, middle and database tiers (see Figure 2).

### 5.1 Client Tier

In this tier, users (learners or instructors) use smartphones or tablets equipped with a web browser (where the grouping tool should be displayed) and a set of interface applications (such as *GPS*, camera, *RFID* reader, etc), and some communication tools (such as *Viber* and *Skype*).

The learner's behaviours (communication level, visited places, preferred partners, etc) are collected from specific mobile applications installed on the user's device. These applications collect frequently the data related to the learner' activities and store them on a set of log files. At the end of each collaborative activity, the system through the module *Log analysis* analyses these log files to extract and store the relevant information.

### 5.2 Middle Tier

This tier represents the application server of the system. We have chosen *Apache Tomcat* as a web server because it is the most flexible, fast and secure. In this tier two sub tiers are found: *presentation* and *business* tiers. *Presentation tier* contains *Servlets* and *Java Server Pages (JSP)*, which communicate with each other using the *Hypertext Transfer Protocol (HTTP)*. The clients (learner or instructor) view the *JSP* pages through the mobile browser.

The *business tier* is composed of a set of modular components (*Java* classes) that ensure the

good running of the system. The *Log analysis* module serves to analyse the log files installed on the device of each learner as so to extract the behavioural values and store them in the active database. The log files are formatted in a way that facilitates the process of data extraction. Each event logged in those files mentions the user identifier, the current location, the current time, and other information related to the current activity (communication with partner, interaction with learning objects, etc).

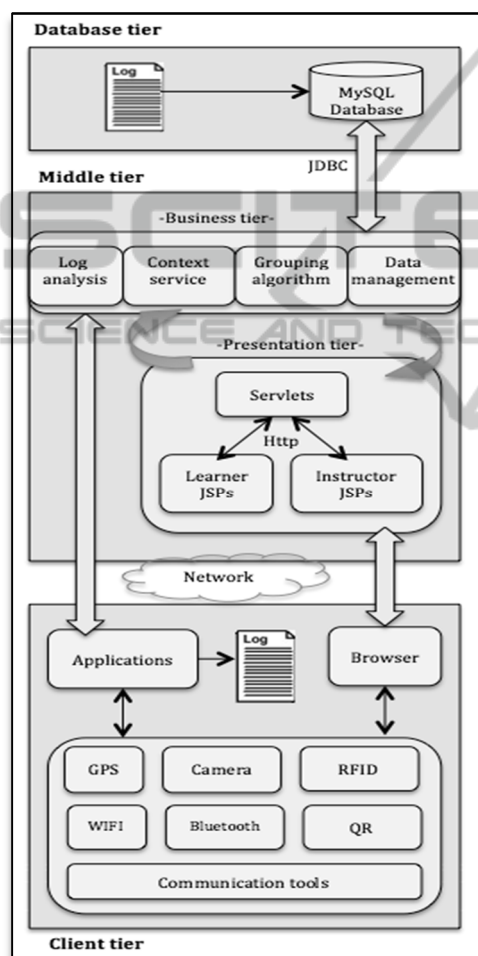


Figure 2: System architecture.

The *Context service* module provides the grouping system with the needed context information (current time, current locations of learners, location of learning objects, etc) before starting the grouping process.

The *Data management* module manages the data flow between the client tier and the application server, and between the application server and the database tier. This module serves also to normalize

the data to be used by the grouping algorithm. Additionally, this module allows the users to create new accounts, to consult and update their data, and to delete existing accounts.

The *Grouping algorithm* module receives the grouping criteria and settings from the instructor’s browser, obtains the learner’s characteristics and behaviours from the active database (*MySQL* database), and gets the context information from the context service. The grouping algorithm is implemented to support both heterogeneous and homogenous grouping. To form homogeneous groups, the principle of K-means is used: choosing K learners as the first members of K groups, and assigning successively the other learners to closest groups using the Euclidean distance. To form heterogeneous groups, the grouping algorithm searches to maximize the distances within the learning groups. It creates a similarity matrix between all the learners, and from this matrix, it successively searches the farthest pairs of learners to assign them to the same learning groups. After the initial formation of a given number of groups, the algorithm calculates the distance between each learner and all the created groups in order to assign him/her to the farthest group.

### 5.3 Database Tier

This tier serves to store all the data used for learning processes and the grouping mechanism. The component of the business tier uses a Java Database Connectivity Protocol (*JDBC*) to communicate with the database. Two kinds of databases are found in this tier: a main active database (*MySQL*) installed in the server side, and temporal databases (log files) installed on the users’ devices.

## 6 EVALUATION

### 6.1 Comparison-based Evaluation

Table 2 shows a comparison between the proposed group formation approach with the existing studies presented in Section 2. Through this comparison, one can remark that the proposed approach is the only solution that supports the formation of both types of learning group (homogeneous and heterogeneous). It is among the few solutions that consider the three kinds of grouping criteria (learners’ personal characteristics, learners’ learning behaviours, and context information). It is one of the few approaches that enable the user to customize the

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

Study	Grouping type		Group formation criteria			Group formation characteristics		
	Heterogeneous	Homogeneous	Personal characteristics	Learning behaviours	Context information	Customized	Dynamic	Continuous Control of learners
S1	✓	✗	✗	✓	✓	✓	✗	✓
S2	✓	✗	✓	✗	✗	✓	✓	✗
S3	✗	✓	✗	✓	✗	✗	✗	✗
S4	✗	✗	✗	✓	✓	✗	✗	✗
S5	✗	✗	✓	✗	✓	✗	✗	✗
S6	✓	✗	✓	✓	✓	✗	✗	✗
S7	✗	✓	✓	✗	✓	✗	✓	✗
S8	✗	✓	✓	✓	✗	✗	✗	✗
S9	✗	✗	✓	✗	✗	✗	✗	✗
S10	✗	✓	✗	✓	✗	✗	✗	✗
Proposed approach	✓	✓	✓	✓	✓	✓	✓	✓

grouping process, and that provide dynamic formation of learning groups during the learning process. Contrarily to the majority of existing approaches that focus only on the task of group formation, our approach allows instructors to permanently control the development of their learners at several levels (e.g., cognitive, social, psychological).

### 6.2 Simulation-based Evaluation

In this subsection, we propose the use of a simulation method to compare the average intra-cluster distance (AID) of three grouping methods: (a) the proposed homogenous grouping approach; (b) the proposed heterogeneous grouping approach; (c) a random grouping method. The AID shows how the learners of a given group are similar or different to each other. It provides, therefore, a clear idea about the level of homogeneity/heterogeneity of each grouping method. For instance, a low value of AID implies a great level of homogeneity within the learning groups, and a high value of AID implies a great level of heterogeneity. The dataset used in this simulation was randomly generated from a website for data generating (<http://www.generatedata.com/>). The following group formation criteria were considered:

- Age (calculated using learner’s date of birth. Random values from 01-01-1990 to 31-12-2000 were used);

- Gender (male or female);
- Level of communication with learners (random values from 0 to 6 were used);
- Level of interaction with learning objects (random values from 0 to 6 were used).

To assess and validate the implemented group formation algorithm, the simulation process has been run several times using different settings (e.g., different number of learners, different types of learning group, different number of group formation criteria).

Figure 3 shows a comparison between the AIDs of the proposed grouping algorithm (heterogeneous and homogenous approaches) with the AID of a random grouping method. The X-Axis represents the number of learners considered in each phase, and the Y-Axis represents the AID values. In this first evaluation process, we have used only one grouping criteria (the learners age) to evaluate the three group formation methods. The results show that, whatever the number of learners (groups) considered in each simulation session, the resulting AID values of the proposed heterogeneous grouping approach are always higher than that of the random method. Conversely, the AID values of the homogeneous grouping method are always low compared to the random method. That implies that the proposed grouping method forms the most effective groups in terms of intra-cluster distance.

Figure 4 shows the simulation results of the three grouping methods considering this time four



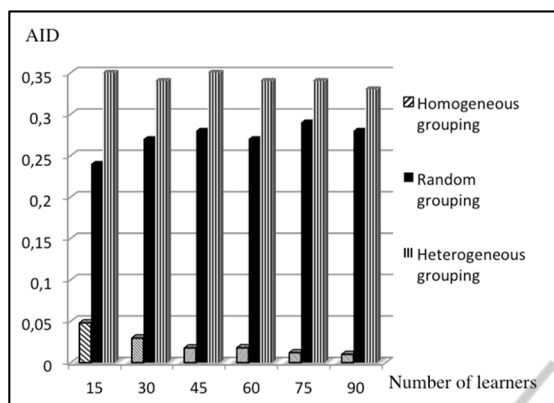


Figure 3: Average intra-cluster distance of three grouping methods considering one grouping criterion.

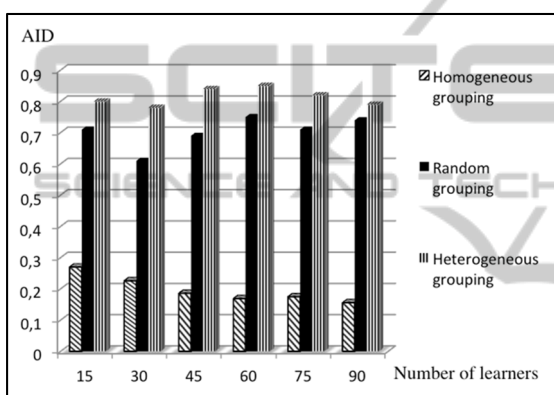


Figure 4: Average intra-cluster distance of three grouping methods considering multiple grouping criteria.

grouping criteria: age, gender, level of communication with partners, and level of interaction with learning objects. Although the number of criteria increased, the proposed heterogeneous grouping method forms always groups with the highest values of AID, while the lowest AID values are always given by the homogenous grouping method. That confirms the effectiveness of the proposed grouping algorithm in forming the most appropriate groups.

By comparing the AID values resulting from the both evaluations (using one and multiple criteria), it is remarked that increasing the number of grouping criteria results in increasing the AID level, and therefore, increasing the heterogeneity of learning groups.

## 7 CONCLUSIONS

In this paper, a new approach for learning group

formation in Mobile Computer Supported Collaborative Learning (MCSCL) environments is presented. First, We have conducted a systematic literature review (SLR) to analyse the state of research on this topic. We have found, thanks to this SLR, that there are no specific grouping criteria that could be considered ideal. Therefore, we believe that the choice and selection of such criteria should be provided by the instructors depending on the scenarios of learning, the types of activities, the learning objectives, the needs, the places, the times, the types of learners, etc. Hence, we have proposed a customized grouping mechanism that gives the instructors a full freedom to select the type, the number, and the weight of grouping criteria. They could define also the number, the size, and the nature of groups in terms of homogeneity/heterogeneity.

The proposed approach considers three types of grouping criteria: learner’s personal characteristics, learner’s behaviours, and context information. This approach does not represent only a grouping tool in MCSCL environments, but also a very useful mean for a continuous control of the social, psychological and cognitive developments of the learners.

The proposed grouping algorithm supports homogeneous and heterogeneous grouping methods. To assess how effective this grouping algorithm is, we have carried out a simulation assessment to compare the average intra-cluster distance (AID) of groups created using the implemented algorithm with the AID of groups created randomly. The results show high AID values of the groups formed by the heterogeneous grouping approach, and low values resulting from the homogenous grouping approach. That implies a high effectiveness of the proposed algorithm in creating appropriate groups.

Our future work will deal with developing a new machine learning approach for criteria recommendation, to help the instructors for quickly selecting the proper grouping criteria. Moreover, evaluating the presented group formation approach in real world context will help us to extract relevant information about the relationships between the used grouping criteria and the corresponding learning and behavioural outcomes. This extracted information will be used to develop, train, and test the criteria recommendation system.

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