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A NEURAL NETWORK-BASED METHOD IN COMPUTER-SUPPORTED COLLABORATIVE LEARNING SYSTEMS

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Abstract Nobody can cast doubt on the fact that the advent of computer-supported collaborative learning (CSCL) has made a great revolution in educational systems. The first phase in CSCL is creating different learning groups with compatible members. It is a key factor because having a prosperous collaboration depend on having compatible team-mates to do their tasks collaboratively. Although, a great number of studies in the literature reported several methods for assigning students to fitting groups all of them are bereft of offering a completely independent and intelligent system. This contribution suggests a neural-network grouping method in order to enhance speed, simplification, and correctness of group composition. Extensive experiments and evaluation illustrate the success of our method and students are more satisfied and seize high knowledge levels when they are grouped via the proposed method.

Keywords: **Computer-supported collaborative learning; CSCL; Neural network; MLP; Group composition.**

1. Introduction

The concept of collaboration originated from interaction and participation of a group of people in order to fulfill a common target (Cambridge Dictionaries Online, 2017). Collaborative learning method which was suggested by Bruffee (1984) for the first time has a wide range of advantages as follows:

- It creates regulation of activities, peer-to-peer contribution and participation, intrinsic motivation, positive interdependence, and individual accountability (Jarvela et al., 2015; Swanson, Gross, & Kramer, 1998, Lytras, & Sun, 2016).
- It magnifies active and constructive learning and enhances process of knowledge and data gathering, as well as evoking critical thinking (Schneider & Pea, 2013, Rodriguez, Riaza, & Gomez, 2017, Zhang, Chen, de Pablos, Lytras, & Sun, 2016).
- The collaborative learning method is superior to competitive or individual learning (Johnson & Johnson, 1989).
- Learners in a common group feel themselves responsible in teaching their peers (Bossert, 1988, Takaci, Maric, Stankov, & Djenic, 2017, Higgins, &Joyce-Gibbons, 2014).
- It causes an assured environment for students to express their feeling, represent their perspectives, and ask their questions without seeking support from the lecturer and also it eliminates the fear of failure or criticism in a public classroom which has a negative effect on the learning process. Consequently, it augments learners' self-esteem and satisfaction (Marsh, 2010, Rodriguez, Riaza, & Gomez, 2017).
- It is suggested not only in terms of academic productivity but also in improving the social and psychological aspects of learning (Bossert, 1988; Kreijns, Kirschner, Jochems, &Buuren, 2007; Marsh, 2010; Roberts, 2005; So & Brush, 2007; Mercier, Higgins, &Joyce-Gibbons, 2014).

In 1990, the theory of computer supported collaborative learning (CSCL) was offered by O'Malley and Scanlon for the first time. The initial phase in CSCL, named group composition, is allocating learners to appropriate groups. It is the most imperative element to evaluate usefulness and prosperity of collaborative learning since it has effects on the quality and quantity of participation and negotiation among the learners (Martin & Paredes, 2004; Webster & Sudweeks, 2006). Actually, creating a judicious and proper group formation method will cause a beneficial CSCL and prevent difficulties before they occur (Muehlenbrock, 2006).

A great number of methods has been applied for group composition. The first superficial one is random grouping which is a rudimentary and uncomplicated strategy. Extensive literature denotes that it is not a satisfactory method for both learners and teacher because it is bereft of any logical criteria (Dillenbourg, 2002; Huxland & Land, 2000). Another existing grouping viewpoint originates from the interest of learners named learner-based group composition (Eshel & Kohavi, 2003; Kulikand & Kulik, 1987; Moreno, 2012). This method generates the high empathy, sympathy, cooperation, and interaction among the learners (Bacon, Stewart, & Silver,1999; Mello, 1993), but it is deprived of containing any academic and scientific criteria and it only utilized the friendships criterion which makes students far from doing their tasks perfectly (Moreno, 2012). Another theory to produce different groups of learners, called instructor-based grouping, originates from instructor's preferences for group-mate selection and instructor determines the group formation parameters (Dillenbourg, 1999). The group formation parameters are such as: the criteria (e.g. knowledge level, GPA, sex, age, marital state, etc.), the level of heterogeneous and homogeneous of groups, size of group, and upper and lower bounds of the group size (Sadeghi & Kardan, 2015). Related literature on collaborative learning illustrate the benefit of the suggested instructor-based method by (Sadeghi & Kardan, 2015), particularly the mathematical model in this method is really efficacious. Fig. 1 graphically depicts the dynamic process of this method but Sadeghi & Kardan's work (2015) has an unavoidable shortcoming that teacher must be accomplished and experienced and dedicate a copious amount of her/his time to specify the values of all required grouping parameters particularly when the population of students increase dramatically. Thus, the instructor-based grouping method will be a difficult, stressful, and exhausting task for the instructor. This contribution offers a novel neural-network based method as a self-sufficient and intelligent system to assist the lecturer and improve simplification, speed, and precision of group creation phase. Indeed, the value of the required parameters will be predicted by the proposed neural network, then the dynamic process displayed in Fig.1 will be continued as well.

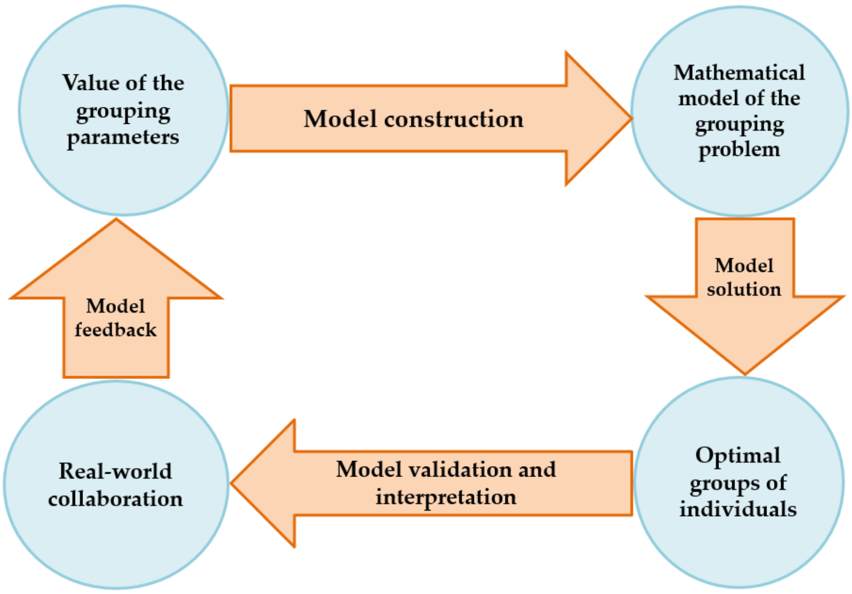

Fig.1. Dynamic process of problem modeling

2. Previous work

On account of the vastness of CSCL, a comparative article has been published to analyze the remarkable progress and evaluate the performance of various recent methods on group composition (Maqtary, Mohsen, & Bechkoum, 2017).

These previous methods are compared with each other by three indicators as follows:

- The first indicator is optimality that determines if the reported approach is able to guarantee optimality or not.
- The second indicator is the duration of solving the problem that specifies how long the solving process takes and if the method consumes a considerable amount of time or not.
- The third indicator is constraint satisfaction that denotes constraints which can be satisfied by employing the suggested strategy. Constraints are such facilitator requirements as: variability or invariability of group size, importance degrees of each grouping criteria, homogeneity or heterogeneity of teams, overlapping level of teams, and amount of consideration to the preferences of individuals (Sadeghi & Kardan,2015).

The aforementioned indicators are utilized to scrutinize the current group composition's methods in the following lines.

It is an undeniable fact that the simplest technique for group formation is exhaustive search which can guarantee the first factor named optimality. On the other hand, all the states should be compared to each other and possible states for assigning students to proper groups increase exponentially when the number of learners grows. Hence, finding the optimal solution is time-consuming and inefficient (Moreno, 2012, Sadeghi & Kardan, 2015). Furthermore, evaluating all possible states is impossible. Thus, advantageous algorithms were applied to eliminate this drawback including matrix-based clustering algorithm (Zhang, Cui, Wang, & Sui, 2007; Pollalis, & Mavrommatis, 2009; Gogoulou, Gouli, & Grigoriadou, 2007), K-Mean clustering (Jin, Qinghua, &Zhiyong, 2006), hierarchical clustering algorithm (Zakrzewska, 2009), fuzzy clustering algorithm (Montazr, &Rezaei, 2012; Tian, Wang, Zheng, & Zheng, 2008), and a heuristic squeaky wheel algorithm (Tanimoto, 2007). The aforementioned algorithms, though, solve the problem quickly but they were not optimal. Ounnas in (2010) modeled the question and supported optimality indicator but his suggested model was bereft of satisfying some constraint such as constructing overlapping teams with a wide range of sizes. Afterwards, a linear model was provided which could satisfy all the three aforementioned indicators (optimality, constraint satisfaction, and reasonable solving time) (Sadeghi & Kardan, 2015). Despite the completeness of the proposed approach some problem still remains due to the nature of the instructor-based method. Indeed, the instructor has to be skillful, practiced, and need to dedicate a lot of time and energy to acquire the quantities of grouping parameters. we aim to propose a novel intelligent group composition method without seeking help from the teacher.

3. A neural-network- based system for group formation

In this part, the creation of a collaborative E-learning system, the manner of obtaining attributes from student behaviors, and generation of an intelligent strategy to assign learners to proper groups are explained comprehensively.

3.1 Creation of a collaborative E-learning system

We design an E-learning website as a test environment. Learner registrations, grouping, discussion, cooperation, learning, commenting, and evaluation are analyzed in the designed website. At the first phase, students should log into the forum of the website with their private usernames and passwords to see the condition of their registered classes and complete their personal pedagogical profiles including name and surname, sex, personal photo, birth-year, birthplace, marital status, entrance year, entrance term, field of study, grade point average (GPA), relative passed courses, and biography to be introduced to other participants. All students are able to see the profiles of other contributors and determine the level of their interest to each other as a group mate candidate optionally. Indeed, the interest degree can be employed as an explicit input to feed our suggested intelligent group composition scheme. Its details will be discussed in the next part. In each collaboration process, students should find a judicious solution collaboratively for the homework designated by the teacher. Moreover, they are asked to share their different ideas with each other in order to gather more proficiency and experience. Consequently, they have the opportunity to find the best solution for the homework by discussion and collaboration. All the sent topics to the forum have learner-id (to display the sender of the topic), title, body, date time, and the number of replies to the topic. Furthermore, other contributors have access to the sent topics and can read them. Productivity and reliability of each sent message to the forum are evaluated by learner’s votes in every collaboration process. In addition, learners give scores to their team-mates to determine the level of their satisfaction with their performance at the end of team-working cycle. This votes and scores indicate the degree of learner satisfaction using a Likert scale of 1–5 in which 5 illustrates strong satisfaction, while 1 displays strong dissatisfaction. In order to prepare a more suitable and assured environment for learners, their votes and scores to other students are secret as well. The diagram of this E-learning environment is denoted in Fig.2.

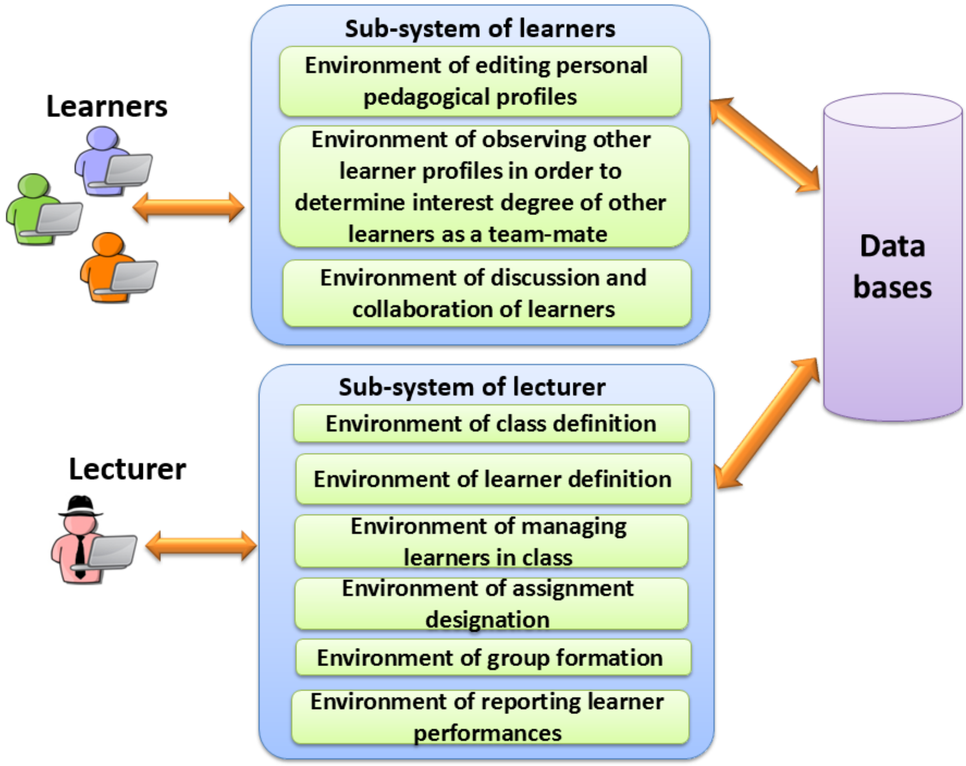

Fig.2. Diagram of the E-learning environment

3.2 Obtaining attributes from student behaviors

In our study, we employ a learning forum in an E-learning website as a test environment due to the fact that many previous works have already utilized forum to scrutinize activities, negotiations, operations, and interactions among learners in order to attain such different aims as:

- Identifying weak, average, and strong students and offering desirable recommendations in order to enhance the training process (Anaya & Boticario, 2009).
- Giving necessary guidance to the lecturer based on learner discussions and operations in the forum to improve the quality of learning process (Santos et al., 2003).
- Predicting student scores based on their operations in the forum (Lopez et al., 2012).
- Adapting E-learning system based on different information acquired from learner participations in the forum (Gaudioso & Boticario, 2002).
- Evaluating the process of student progress in the forum (Pozzi et al., 2007; Dannil et al., 2012, Zhang, Pablos, & Xu, 2014).

Each of the aforementioned works concentrated on some attributes obtained from student operations and behaviors in the forum during E-learning process. This contribution exploits attributes of student behaviors which were utilized at least in two above mentioned studies. The explanation of these attributes and their measurement styles are elaborated in Table.1 comprehensively. As is obvious from the Table.1 these 7 attributes are as follow:

1- Attractiveness; if the specified sent topic to the forum is more attractive, more members will be encouraged to participate in discussionb(So & Brush, 2007; Santos et al., 2003; Daniil et al., 20012).
2- Creativeness; topics sent by a creative member will be included more replies. In addition, more discussions about that creative subject will be sent in the forum (Santos et al., 2003; Anaya & Boticario, 2009).
3- Intensity of learner's interest; if a learner is an interested and motivated person, he/she will be the beginner of new subjects in the group (Anaya & Boticario, 2009; Gaudioso & Boticario, 2002; Pozzi et al.,2007; Santos et al., 2003).
4- Following up the subjects; if a learner visit the forum regularly, it means he/she is following up the discussions (Gaudioso & Boticario, 2002; Pozzi et al.,2007).
5- Quantities of replies; if a learner is responsible, he/she will answer responsibly to other member questions(Anaya & Boticario, 2009; Lopez et al., 2912; Gaudioso & Boticario, 2002; Pozzi et al.,2007; Santos et al., 2003; Daniil et al., 20012).
6- Qualities of replies; each learner should vote for all of the sent messages after reading them to show the degree of agreement on sent topics(Lopez et al., 2912; Santos et al., 2003; Daniil et al., 20012).
7- Amount of learners satisfaction; at the end of team-working, each of learners should vote for other members to declare if they interact efficiently or poorly (Santos et al., 2003; Lopez et al., 2912).

The general methodology of attribute extraction from learner behaviors in the forum is displayed in Fig.3. As can be observed, five number of these attributes are obtained implicitly from student behaviors and the two remained attributes are captured explicitly by voting for student performance in the collaborative learning process. The key factor is that the aforementioned attributes will be used in the next phase in order to design a neural-network-based system for group composition.

NO. of attributes	Type	Mathematical formula	Parameters in the formula
1- Attractiveness	**Implicit**	$\sum_{k=1}^{P} A_{ki} \Big/ N_{Pi}\,(N_G - 1)$	**A_{ki} : No. of team-mates who replies to the sent topic by learner L_i** **N_{Pi} :No. of topics which were sent by learner L_i** **N_G: No. of learners in the group**

2- Creativeness	**Implicit**	$$\frac{N_{GRi} \cdot S_{GRi}}{N_R \cdot S_R}$$	**N_{GRi}: No. of replies to the all sent topics by learner L_i** **S_{GRi}: total size of replies to the all sent topics by learner L_i** **N_R: No. of all sent replies to the group** **S_R: total size of all sent replies to the group**
3- Intensity of learner's interest	**Implicit**	$$\frac{N_{Pi}}{N_P}$$	**N_{Pi}: No. of sent topics by learner L_i** **N_P: No. of all sent topics to the group**
4- Following up	**Implicit**	$$E_i$$	**E_i: No. of logins made by learner L_i during a week subject to doing a helpful act such as: replying and voting.**
5- Replies quantities	**Implicit**	$$\frac{N_{Ri} \cdot S_{Ri}}{N_R \cdot S_R}$$	**N_{Ri}: No. of replies sent by learner L_i** **S_{Ri}: total size of sent replies by learner L_i** **N_R: No. of all sent replies to the group** **S_R: total size of all sent replies to the group**
6- Replies qualities	**Explicit**	$$\sum_{j=1}^{N_G-1}\left(\sum_{P=1}^{N_{Pi}} V_{Pj} + \sum_{R=1}^{N_{Ri}} V_{Rj}\right)$$	**V_{Pj}: score given by learner j to the topic P which was sent by learner L_i** **N_{Pi}: No. of sent topics by learner L_i** **V_{Rj}:score given by learner j to the replies R which was sent by learner L_i** **N_{Ri}: No. of replies sent by learner L_i** **N_G: No. of learners in the group**
7- Amount of learners satisfaction	**Explicit**	$$\frac{Q_{ij} + Q_{ji}}{2}$$	**Q_{ij} :final score given to L_i by L_j** **Q_{ji} : final score given to L_j by L_i**

Table.1. Definitions of attributes obtained from learner operations

Fig.3. Methodology of attribute extraction in the forum

3.3 Implementation of a neural-network for group formation

Our method contains 5 phases as follows:

1- At first, facts about discussions and contributions from previous collaborations among learners are gathered. Actually, these facts are the seven aforementioned attributes in Table.1 which have been collected from learner behavior in former participations.

2- In the second phase, in order to generate a simulated model of the relationship among students, the formerly obtained attributes has been evaluated. The simulated model aims to discover the connection between inputs and outputs by imitating the real system. Thus, it has the ability to predict the system behavior and reaction by injecting the qualified input (Sterman, 1991; Haykin, 1999). The most prominent method to simulate a real system is neural network which has been used in wide range of fields such as education (Lo et al.,2012; Kardan & Sadeghi, 2013). A special kind of neural network named multilayer perceptron (MLPs) containing three main layers (input layer, hidden layer, and output layer). Here, the 7 obtained attributes from previous collaboration among learners are assumed as the input of the MLPs and are linked to the neurons of the hidden layers by their weights. The output layer with one node predicts the compatibility degrees between students. The proposed MLPs is denoted in Fig.4.

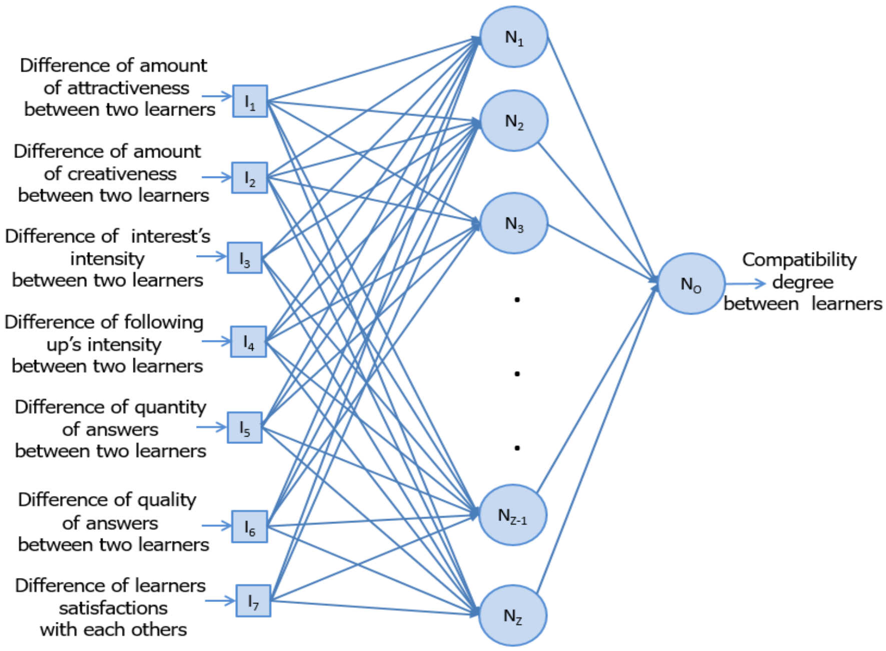

Fig.4.The proposed MLPs for group composition

3- In the third step, the compatibility degrees between two students who have never been in the same group, will be predicted by substituting the parameters in the suggested MLPs neural network. Actually, the output of this neural network illustrates the compatibility degree and the level of student satisfaction with each other before passing a group working.

4- In this phase, the quantity of predicted compatibility degree between learners will be send to the mathematical model of Sadeghi & Kardan (2015) to create appropriate groups with the maximum total compatibility degrees.

5- The procedure will continue to exist and new facts (the 7 attributes) captured from phase 4 will be added to phase 1 as former facts to generate a new neural-network system.

4. Experiments

In this section, the suggested method for group composition is compared and scrutinized comprehensively. For this purpose, we introduce the statistical society in this study; Afterwards, evaluation manners and styles of extracting data and modeling will be discussed.

4.1 The statistical society of this study

In this study, 4 various classes in computer science major in bachelor degree are employed in order to evaluate, measure and compare different methods for group composition. Each class was established 3 hours a session for 6 consecutive weeks. Two classes of these 4 classes were data mining course and the two remain classes were database course. The detailed information on these classes is illustrated in Table.2. As is depicted in Table.2, we endeavor to propose a wide array of classes with the maximum variability. For instance, the number of students in each classes, number of females and males, marital status of students, average of student ages and its standard deviation, grade point average (GPA) of students and its standard deviation in each classes is completely different from other classes in order to have a more reliable statistical society and imitate a real circumstance for group formation.

Class	Course	NO. of Students	NO. of female students	NO. of Male students	NO. of Married students	NO. of Single students	Age average of students	Standard deviation of student ages	GPA of students	Standard deviation of student GPA
Class 1	Data bases	26	10	16	11	15	25/92	1/73	14/94	4/91
Class 2	Data mining	33	13	20	13	20	27/39	1/98	15/58	5/03
Class 3	Data bases	22	5	17	8	14	27/95	1/50	14/55	5/68
Class 4	Data mining	18	9	9	10	8	33/61	1/17	14/97	9/78

Table.2. Detail information of experimented students in different 4 classes

4.2 The evaluation styles

In the first session of the 4 experimented classes, the lecturer clarified the aims of given courses. Afterwards, the concept, boon, and purpose of collaborative learning in comparison with individual or competitive learning were elucidated for students. Moreover, the designed e-learning environment and ways of its utilization were presented for learners and the lecturer asked them to register in the specified e-learning website. When the instructor gets students informed insight into the process completely, in the remained sessions of the classes, the determined courses were taught and learners in different teams consist of 3-4 members are asked to collaboratively find an acceptable solution for the assignment designated by the lecturer at the end of each session. The crucial purpose of giving this assignment was evaluation of learner-based, instructor-based and intelligent-based group composition. The detail of these experiments in e-learning environment is illustrated in Table.3.

Group formation type \ Class	Class 1	Class 2	Class 3	Class 4
Learner-based group formation	Experiment 1	Experiment 2	Experiment 3	Experiment 4
Instructor-based group formation	Experiment 5	Experiment 6	Experiment 7	Experiment 8
Intelligent-based group formation	Experiment 9	Experiment 10	Experiment 11	Experiment 12

Table.3. Applied experiments in order to evaluate our suggested group composition method

4.2.1 Learner-based group formation

As mentioned in part 3, all students should fill their personal pedagogical profiles in the suggested virtual collaborative learning system and all learners are able to observe the profiles of other classmates and submit their interest to each other as a group mate candidate optionally. As a result, the intensity of learner interest to each other are acquired and students choose their team-mate optionally in order to solve the designated assignment by discussions.

4.2.2 Instructor-based group formation

In instructor-based group formation method, we pay more attention to the pedagogical criteria in comparison with friendship criteria in learner-based method. Here, we resort to the 7 attributes which were mentioned in Table.1 previously. In fact, the seven aforementioned attributes for both pair members should be gathered by the instructor in order to create different groups. Needless to say that it is a difficult task for the teachers.

4.2.3 Neural network-based group formation

The 5 steps for the proposed neural network-based group formation were explained in part 3 comprehensively. By applying these 5 steps, different groups have been made in our experiments in 4 classes.

Indeed, the 7 attributes were taken as input nodes of the MLPs and were linked to the neurons of the hidden layers by their different weights. The output layer, containing only one node, predicts the compatibility degrees between students. The question which may be asked here is do these 7 attributes have equal effects on predicting the compatibility degree or not? In order to answer this question, a statistical model, named Multiple Linear Regression, is used. The Multiple Linear Regression models the relationship between independent variables (the 7 attributes) and a dependent variable (the compatibility degree) by fitting a linear equation to observed data. The factor (parameters) of the dependent variables in the acquired linear equation denote importance degree of the 7 attributes.The seized result is illustrated in chart.1.

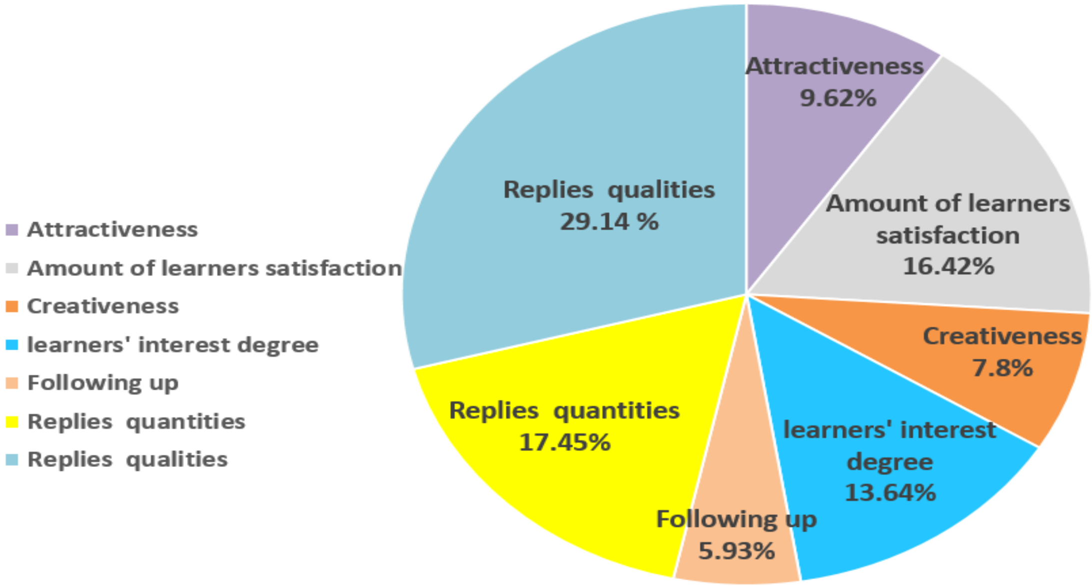

Chart.1. The importance degree of the attributes for predicting compatibility degree between two learners

5. Results

In this research, the results are scrutinized by three viewpoints as follows: using an expert evaluation, surveying satisfaction degrees of learners by their explicit votes, and surveying student behaviors and actions in e-learning environment implicitly.

5.1 Surveying group formation methods based on expert opinion

In these experiments, an expert idea is engaged to measure the quality of sent messages in an e-learning environment. The expert designates different scores to the sent topics and member interactions after evaluation in order to analyze the flourishing of different group composition. As is revealed in chart.2 grade point averages, dedicated to this 4 different classes, confirm the excellence of intelligent-based method.

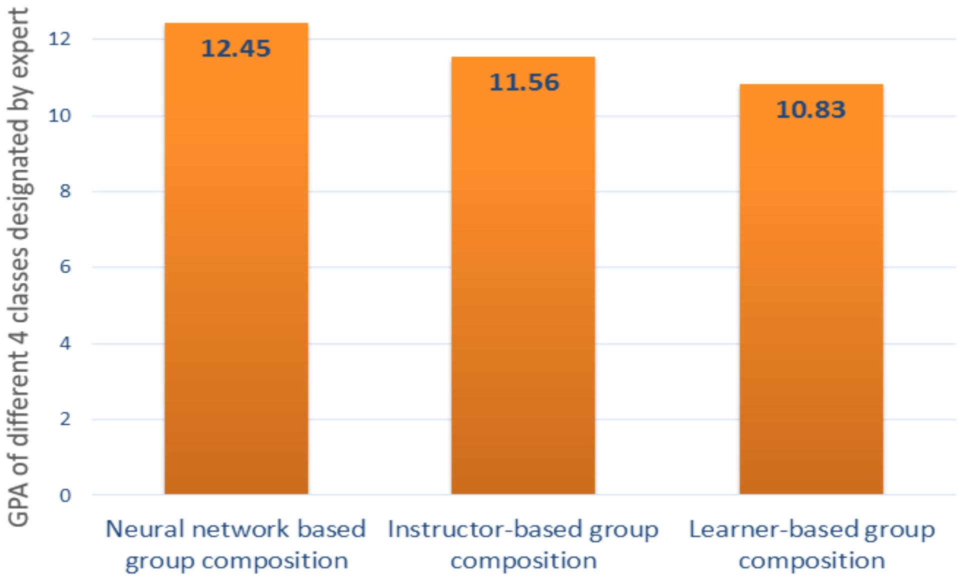

Chart.2. Surveying group formation methods based on expert opinion

5.2 Surveying different group formation methods by learner satisfaction explicitly

As it is obvious, the perfectness of group composition method has straight effects on learner satisfaction by having prosperous groups. Each student declares the amount of her/his satisfaction with her/his group-mate explicitly by two kinds of voting. The first voting is for calculating the value of consent and gladness from the sent messages in the forum by learners and the second voting computes general student satisfaction with their fellow-member interactions. After reading the sent messages, learners give scores in order to certify the worth of them. In addition, learners notify whether other member operations pleased them or not at the end of each collaboration process. This parameter is equal to the average of scores dedicated to each student by other trainees. Chart.3 demonstrates the average of general satisfaction from the operation of students during team working and the average of sent messages' qualities in 4 different classes.

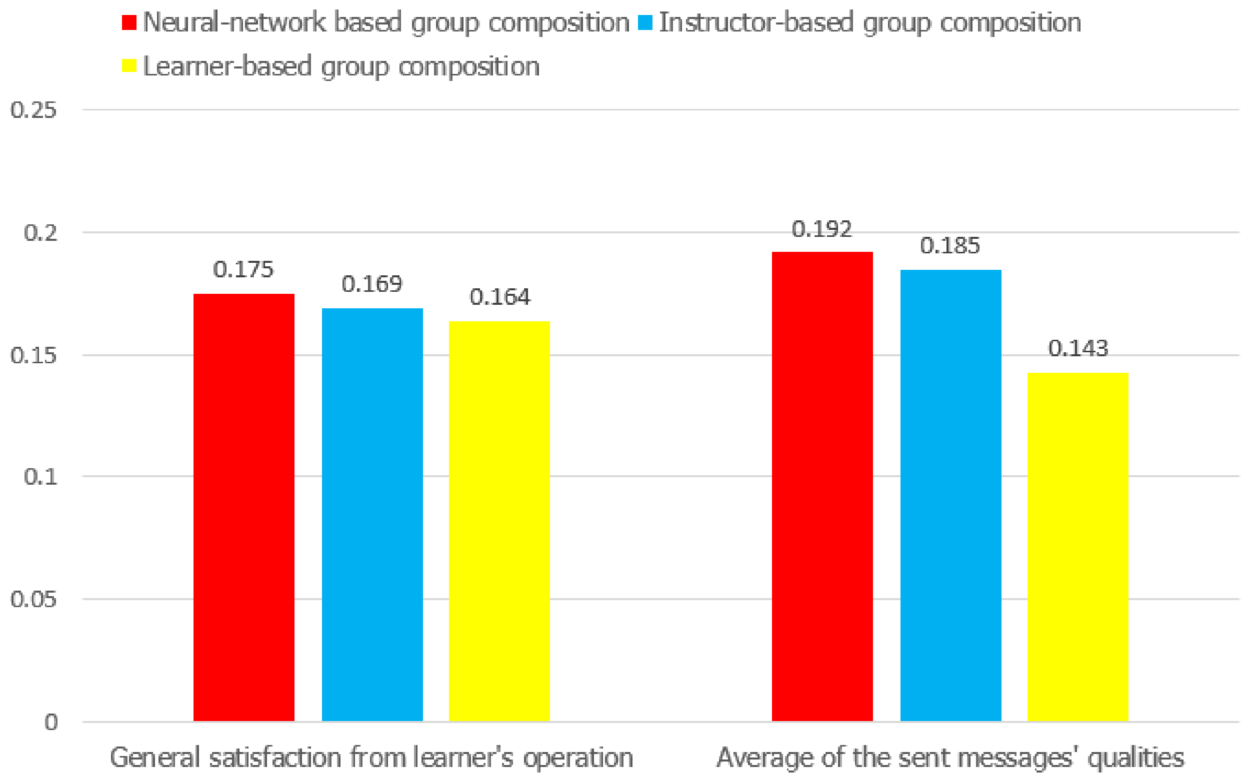

Chart.3. Surveying different group formation by learner satisfaction explicitly

5.3 Surveying different group formation methods by student behaviors implicitly

In this contribution, novel implicit methods are employed to evaluate group composition. Nobody can cast doubt on the fact that learners have a better relationship in group with high compatibility degrees. Accordingly, by changing the combination of members in different groups in order to augment the compatibility degrees between students we can lead students toward prosperity and progress in collaborative learning systems. There are five evaluation criteria including the average of the number and size of the sent subjects into the forum, the average of the number and size of the sent replies by learners, and the average number of visitors of the forum. The implicit results, derived from these five above-mentioned criteria, are illustrated in Chart.4. As can be observed, using neural-network-based group combination, motivate students to behave better and direct them toward promotion because of existence of optimum compatibility, discipline, and arrangement among learners and lack of human mistake (in instructor-based group formation) and only friendship-oriented group composition (in learner-based group formation).

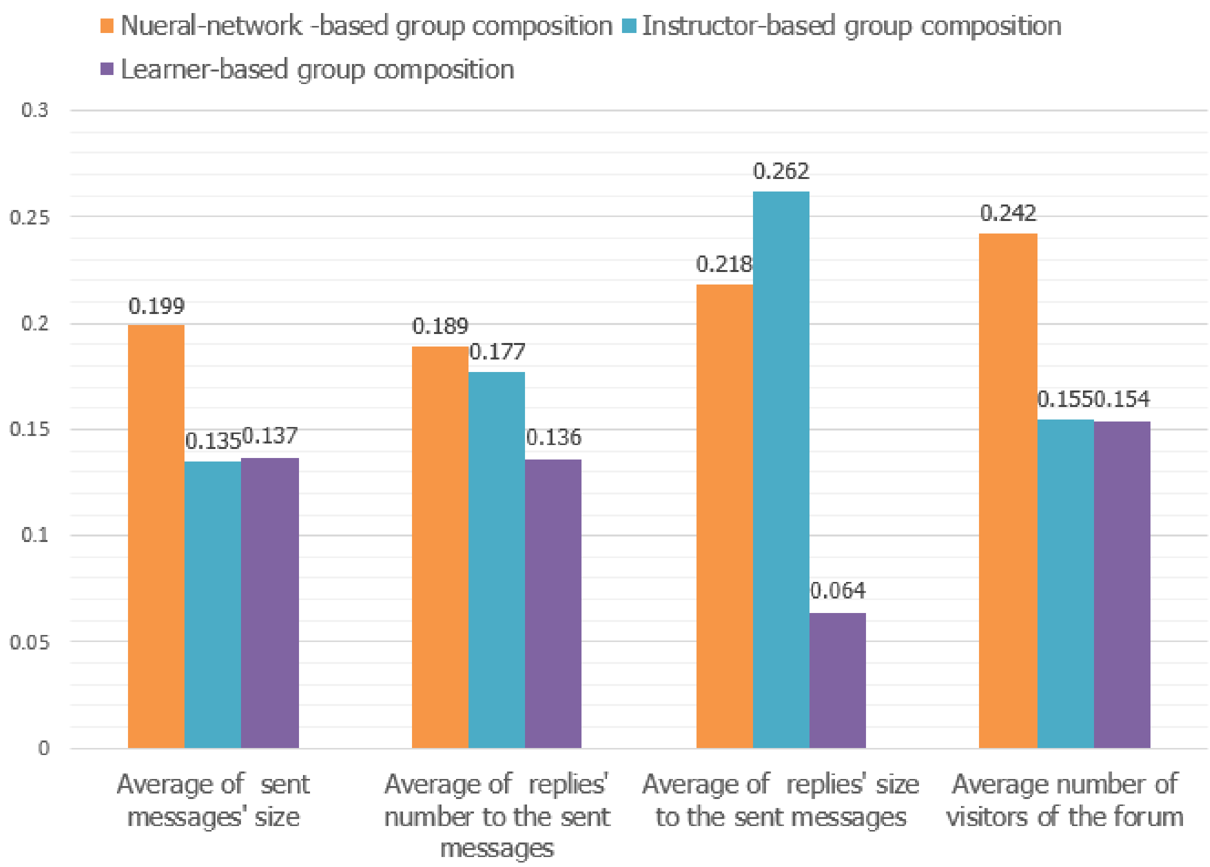

Chart.4. Surveying different group formation methods by student behaviors implicitly

6. Conclusion

In this contribution, a novel intelligent method to efficiently create learning groups and guarantee widespread support of the lecturer was proposed. Indeed, a neural network-based system was suggested to imitate the student behavior and select the best compatible members in a group. Another novelty in this contribution was exploiting implicit evaluation strategy which has not been used in collaborative learning yet. Extensive experiments on different classes denote that our method outperformed the state of the art methods (learner-based group composition and lecturer-based group composition). The designed intelligent method had several benefits. First, it could successfully eliminate lecturer faults in instructor-based group composition because of tiredness, carelessness, and computational limitation of the lecturer. Second, it could obtain the maximum compatibility degrees among team-mates in a group working optimally. Third, it increases acceleration, simplification, and correctness of group formation procedure. Fourth, it enhanced learner satisfaction, performance, and acquired knowledge levels. Fifth, although this study was conducted on collaborative learning system, the approach was context-independent and could be applied to other scopes which are based on collaboration.

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References

Anaya, A. R., & Boticario, J. G. (2009). A data mining approach to reveal representative collaboration indicators in open collaboration frameworks. In Educational Data Mining.

Bacon, D. R., Stewart, K. A., & Silver, W. S. (1999). Lessons from the best and worst student team experiences: How a teacher can make a difference. Journal of Management Education, 23(5), 467–488.

Bekele, R. (2005, October). Computer-assisted learner group formation based on personality traits (PhD dissertation). Hamburg University.

Bossert, S. T. (1988). Cooperative activities in the classroom. Review of Research in Education, 15, 225–253.

Bruffee, K. A. (1984). Collaborative learning and the conversation of mankind. College English,46(7), 635–652.

Cambridge Dictionaries Online (2017). <http://dictionary.cambridge.org>.

Capuano, N., D'Aniello, G., Gaeta, A., & Miranda, S. (2015). A personality based adaptive approach for information systems. Computers in Human Behavior, 44,156–165. Future work

Chan, T., Cheng, Y., Wu, Y., Jong, B., & Lin, T. (2007). Applying learning achievement and thinking styles to cooperative learning grouping. Proceedings of 37th ASEE/IEEE Frontiers in Education Conference (pp. T1C9-T1C13).

Chin, C., & Chia, L. G. (2004). Problem-based learning: Using students' questions to drive knowledge construction. Science Education, 88(5), 707–727.

Chiu, C.H. & Hsiao, H.F. (2010), Group differences in computer supported collaborative learning: Evidence from patterns of Taiwanese students' online communication. Computers & Education, 54 (2), 427–435.

Daniil, C., Dascalu, M., & Trausan-Matu, S. (2012). Automatic forum analysis: a thorough method of assessing the importance of posts, discussion threads and of users' involvement. In Proceedings of the 2nd International Conference on Web Intelligence, Mining and Semantics (p. 37). ACM.

Dascalu, M., Bodea, C., Lytras, M., Pablos, P., Burlacu, A. (2014). Improving e-learning communities through optimal composition of multidisciplinary learning groups. Elsevier. Computers in Human Behavior.

Dillenbourg, P. (1999). What do you mean by collaborative learning?. In Collaborative learning: Cognitive Approaches, Elsevier, Oxford, 1–19.

Dillenbourg, P. (2002). Over-scripting CSCL: The risks of blending collaborative learning with instructional design. In Kirschner, P.A. (Ed.), three worlds of CSCL: Can we support CSCL?, Heerlen, Open University Nederland, 61–91.

Eric Scharff.(2002) Applying Open Source Principles to Collaborative Learning Environments. Proceedings of the Conference on Computer Support for Collaborative learning. 499-500

Eshel, Y., & Kohavi, R. (2003). Perceived classroom control, self-regulated learning strategies, and academic achievement. Educational Psychology, 23(3), 249-260.

Gaudioso, E., & Boticario, J. G. (2002). User data management and usage model acquisition in an adaptive educational collaborative environment. In Proceedings of the 5th International Conference on Adaptive Hypermedia and Adaptive Web-Based Systems (pp. 143-152). Springer Berlin Heidelberg.

Gogoulou, A., Gouli, E., Boas, G., Liakou, E., & Grigoriadou, M. (2007). Forming homogeneous, heterogeneous and mixed groups of learners. In P. Brusilovsky, M. Grigoriadou, K. Papanikolaou (Eds.), Proceeding of workshop on personalization in learning environments at individual and group level in conjunction with the 11th international conference on user modeling (pp. 33–40), Corfu, Greece.

Gokhale, A. (1995). Collaborative learning enhances critical thinking. Journal of Technology Education, 7 (1), 22-30.

Haykin, S. (1999). Neural networks: A comprehensive foundation (2nd ed.). New York: Prentice-Hall.

Hilton, S., Phillips, F. (2010). Instructor-assigned and student-selected groups:A view from inside. Issues in Accounting Education, 25 (1), 15–33.

Hmelo-Silver, C. E., Chinn, C. A., O'Donnell, A. M., & Chan, C. (2013). The international handbook of collaborative learning. New York: Routledge.

Huxland, M., & Land, R. (2000). Assigning students in group work projects: can we do better than random? Innovations in Education and Training International, 37(1), 17–22.

Jarvela,S., Kirschner,P., Panadero, E., Malmberg, J., & Phielix, C. (2015). Enhancing socially shared regulation in collaborative learning groups: designing for CSCL regulation tools. Education Tech Research Dev. Springer. 63:125–142

Jin, D., Qinghua, Z., Jiao, D., & Zhiyong, G. (2006). A method for learner grouping based on personality clustering. Proceedings of the 10th international conference on computer supported cooperative work in design (pp. 1–6), Nanjing, China: IEEE.

Johnson, R. T., & Johnson, D. W. (1989). Cooperation and competition: Theory and Journal, 10(2), 1–13.

Kandlhofer, M., Steinbauer, G. (2016).Artificial Intelligence and Computer Science in Education: From Kindergarten to University. IEEE. Frontiers in Education Conference (FIE).

Kardan, A. A., & Sadeghi, H. (2013). A Decision Support System for Course Offering in Online Higher Education Institutes. International Journal of Computational Intelligence Systems, 6(5), 928-942.

Kardan, A., Sadeghi, H., Shiry, S., Fani, M. (2013). Prediction of student course selection in online higher education institutes using neural network. Computers & Education 65. Elsevier.

Kardan, Sadegi, An efficacious dynamic mathematical modelling approach for creation of best collaborative groups, Mathematical and Computer Modelling of Dynamical Systems, 2015

Kotsiantis, S. B. (2012). Use of machine learning techniques for educational proposes: a decision support system for forecasting students' grades. Artificial Intelligence Review, 37(4), 331-344.

Kreijns, K., Kirschner, P. A., Jochems, W., & van Buuren, H. (2007). Measuring perceived sociability of computer-supported collaborative learning environments. Computers and Education, 49(2), 176–192.

Kulikand, J. A., & Kulik, C. L. C. (1987). Effects of ability grouping on student achievement. Equity and Excellence in Education, 23(1-2), 22-30.

Lo, J.J., Chan, Y.C., & Yeh, S.W. (2012). Designing an adaptive web-based learning system based on students' cognitive styles identified online, Computers & Education, 58(1), 209-222.

Lopez, M. I., Luna, J. M., Romero, C., & Ventura, S. (2012). Classification via Clustering for Predicting Final Marks Based on Student Participation in Forums. In Proceedings of the 5th International Conference on Educational Data Mining.

Magnisalis, I., Demetriadis, S., & Karakostas, A. (2011). Adaptive and intelligent systems for collaborative learning support: a review of the field. IEEE. Transactions on learning technologies. VOL. 4. NO. 1.
Maqtary, N., Mohsen, A., & Bechkoum, A. (2017). Group Formation Techniques in Computer-Supported Collaborative Learning: A Systematic Literature Review. Technology, Knowledge and Learning. pp 1–22, Springer Netherlands.

Marsh, C. (2010). Becoming a teacher: Knowledge, skills and issues (5th ed.). Sydney:Pearson.

Martin, E., & Paredes, P. (2004). Using learning styles for dynamic group formation in adaptive collaborative hypermedia systems. In Proceedings of workshops in connection with 4th international conference on web engineering (pp. 188–197). Munich: Rinton Press.

Mello, J. A. (1993). Improving individual member accountability in small work group settings. Journal of Management Education, 17(2), 253–259.

Mercier, E. M., Higgins, S. E., & Joyce-Gibbons, A. (2014). The effects of room design on computer-supported collaborative learning in a multi-touch classroom. Interactive Learning Environments. Published online.

Montazer, G. A., & Rezaei, M. S. (2012). A new approach in e-learners grouping using Hybrid Clustering Method. Proceedings of the international conference on Education and e-Learning Innovations (pp. 1-5). Sousse, Tunisia: IEEE.

Moreno, J., Ovalle, D. A., & Vicari, R. M. (2012). A genetic algorithm approach for group formation in collaborative learning considering multiple student characteristics. Computers & Education, 58(1), 560–569.

Muehlenbrock, M. (2006). Learning group formation based on learner profile and context. International Journal on E-learning, 5(1), 19–24.

Nijstad, B.A. & De Dreu, C.K.W. (2002). Creativity and group innovation. Applied Psychology, 51(3), 400–406.

O'Malley, C., & Scanlon, E. (1990). Computer-supported collaborative learning: Problem solving and distance education. Computers & Education, 15(1–3), 127–136.

Ounnas, A. (2010). Enhancing the automation of forming groups for education with semantics. PhD dissertation, University of Southampton, UK.

Pfister, H.R., & Oehl, M. (2009). The impact of goal focus, task type and group size on synchronous net-based collaborative learning discourses. Journal of Computer Assisted Learning, 25 (2), 161–176.

Pires, J., Cota, M. (2016). Intelligent adaptive learning objects applied to special education needs. Information Systems and Technologies (CISTI).

Pollalis, Y. A., & Mavrommatis, G. (2009). Using similarity measures for collaborating group formation: A model for distance learning environments. European Journal of Operational Research, 193(2), 626–636.

Pozzi, F., Manca, S., Persico, D., & Sarti, L. (2007). A general framework for tracking and analysing learning processes in computer- supported collaborative learning environments. Innovations in Education and Teaching International, 44(2), 169-179.
research. Edina, MN: Interaction Book.

Roberts, T. S. (2005). Computer supported collaborative learning in higher education: An introduction. In T. S. Roberts (Ed.), Computer-supported collaborative learning in higher education (pp. 1–18). Hershey, PA: Idea Group Publishing.

Rodríguez, A. I., Riaza, B. G., Gomez, M. C. S. (2017). Collaborative learning and mobile devices: An educational experience in Primary Education. Computers in Human Behavior. Volume 72. Pages 664-677.

Sadeghi, H., & Kardan, A. (2015) A novel justice-based linear model for optimal learner group formation in computer-supported collaborative learning environments, Computers in Human Behavior 48

Sadeghi, H., & Kardan, A. A. (2014). Toward effective group formation in computer supported collaborative learning. Interactive Learning Environments. Advance online publication doi:http://dx.doi.org/10.1080/10494820.2013.851090.

Santos, O. C., Rodríguez, A., Gaudioso, E., & Boticario, J. G. (2003). Helping the tutor to manage a collaborative task in a web-based learning environment. In AIED2003 Supplementary Proceedings (Vol. 4, pp. 153-162).

Schneider, B., & Pea, R. (2013). Real-time mutual gaze perception enhances collaborative learning and collaboration quality, International Journal of Computer-Supported Collaborative Learning, 8(4), 375-397.

Slavin, R.E. (1990). Cooperative learning: Theory, research, and practice. Englewood Cliffs, NJ: Prentice Hall.

So, H. J., & Brush, T. A. (2007). Student perceptions of collaborative learning, social presence and satisfaction in a blended learning environment: Relationships and critical factors. Computers & Education, 49(2), 176–192.

Spear, R. (1992). Appropriate grouping practices for middle level student In J Irvin (Ed.). Transforming Middle Level Education: Perspectives and Possibilities. Needham Heights, MA: Allyn and Bacon.

Sterman, J. D. (1991). A skeptic's guide to computer models. In G. O. Barney, W. B. Kreutzer, & M. J. Garrett (Eds.), Managing a nation: The microcomputer software catalog (pp. 209–229). Boulder: Westview Press.

Sungur, S., Tekkaya, C., & Geban, Ö. (2006). Improving achievement through problem-based learning. Journal of Biological Education, 40(4), 155–160.

Swanson, Z. L., Gross, N. J., & Kramer, T. (1998). Alternative modes of study group formation and student examination performance.

Takaci, D., Maric, M., Stankov, G., & Djenic, A., (2017). Efficiency of using VNS algorithm for forming heterogeneous groups for CSCL learning, Computers & Education 109, 98-108

Tanimoto, S. L. (2007). The squeaky wheel algorithm: Automatic grouping of students for collaborative projects. In P. Brusilovsky, M. Grigoriadou, K. Papanikolaou (Eds.), Proceeding of workshop on personalization in learning environments at individual and group level in conjunction with the 11th international conference on user modeling (pp. 79–80), Corfu, Greece.

Tian, F., Wang, S., Zheng, C., & Zheng, Q. (2008). Research on e-learner personality grouping based on fuzzy clustering analysis. Proceedings of the 12th international conference on computer supported cooperative work in design (pp. 1035-1040), Xi'an, China: IEEE.

Vimalla, K. (2011). A study of artificial intelligence in behavioral education. Second international conference on sustainable energy and intelligent system.

Webster, R., & Sudweeks, F. (2006). Enabling effective collaborative learning in networked virtual environments. In A. Méndez-Vilas, A. Solano Martín, J. A. Mesa González, & J. Mesa González (Eds.), Current developments in technology assisted education (pp. 1437–1440). Badajoz: Formatex.

Zakrzewska, D. (2009). Cluster analysis in personalized e-learning systems. In N. T. Nguyen & E. Szczerbicki (Eds.), Intelligent systems for knowledge management, studies in computational intelligence (Vol. 252, pp. 229–250). Heidelberg, Germany: Springer.

Zhang, K., Cui, L., Wang, H., & Sui, Q. (2007). An improvement of matrix-based clustering method for grouping learners in e-learning. Proceedings of the 11th international conference on computer supported cooperative work in design (pp. 1010–1015), Melbourne, Australia: IEEE.

Zhang, X., De Pablos, P.O., Xu, Q. (2014). Culture effects on the knowledge sharing in multi-national virtual classes: A mixed method. Computers in Human Behavior 31, 491–498.

Zhang, X., Chen, H., de Pablos, P.O., Lytras, M.D., & Sun, Y. (2016). Coordinated Implicitly? An Empirical Study on the Role of Social Media in Collaborative Learning. International Review of Research in Open and Distributed Learning.Volume 17, Number 6