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An Optimized Group Formation Scheme to Promote Collaborative Problem-based Learning

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Abstract

Group formation is one of the key processes in collaborative learning because having adequate members in the learning groups supports good collaborative interactions among members and is fundamental to ensuring satisfactory learning performance. Several previous studies have proposed genetic algorithm-based group formation scheme that considers multiple student characteristics to optimize collaborative learning groups. However, the fitness function used in the genetic algorithm (GA) for assessing the quality of group formation may determine collaborative learning groups with unbalanced learning characteristics. Additionally, few studies considered how learning roles and interactions among peers can be used to optimize collaborative learning groups and confirmed the effects of different group formation schemes on learning performance and peer interaction. Therefore, this work proposes a novel genetic algorithm-based group formation scheme with penalty function (GAGFS-PF) that considers the heterogeneous of students' knowledge levels and learning roles, and the homogeneity of social interactions measured by social network analysis among the members in the learning group, to generate collaborative learning groups with balanced learning characteristics for improving students' learning performance and facilitate students' interactions in a collaborative problem-based learning (CPBL) environment. This work uses a quasi-experimental research method to collect quantitative data to assess the effects of three group formation schemes - the proposed GAGFS-PF, the random group formation scheme, and the self-selection group formation scheme - on the learning performance and effects of interaction in a CPBL environment and also adopts interview to enhance the results of qualitative data analysis. Namely, this study adopts a mixed study to examine the research findings. Eighty-three students from three Grade 6 classes at an elementary school in New Taipei City, Taiwan were invited to participate in the experiment. Three classes were randomly assigned to the three experimental groups that used different group formation schemes including the proposed GAGFS-PF, random group formation scheme, and self-selection group formation scheme for CPBL activities on the topic of "global warming." The results reveal that the proposed GAGFS-PF is significantly superior to the random group formation scheme in the score of a completed report assessed by two teachers during the "action 2" learning stage, among the four CPBL stages. Analytical results also show that the proposed GAGFS-PF for group formation is significantly superior to the random and self-selection group formation schemes in the effects of peer interaction, as assessed using social network measures. The interview results also support that the proposed GAGFS-PF provides benefits in determining collaborative learning groups. This work contributes a novel and useful group formation scheme for enhancing collaborative learning performance and also helps in calling for future research in this field as well.

Keywords: Collaborative learning; Group formation; Learning communities; Interactive learning environments

1. Introduction

Collaborative learning is known to be an effective teaching method that can facilitate students' working together in small groups to achieve a common goal, and it has been widely used teaching in physical classrooms and in online learning (Ormrod, 2008; Liu & Tsai, 2008). The members of a collaborative learning group must depend on and help each other, and must assume responsibility for success or failure. Collaborative learning benefits students in terms achievement, motivation, and social skills (Slavin, 1995). Many studies (Knight & Bohlmeyer, 1990; Gillies, 2003) have verified that students who work in collaborative learning groups commonly outperform students who work independently or in competition with each other. Chan *et al*. (2010) argued that dividing learners into appropriate groups is the most important step in collaborative learning activities to ensure the success of collaborative learning. However, few studies have focused on group formation to improve collaborative learning performance (Moreno, Ovalle, & Vicari, 2012). Moreno, Ovalle and Vicari (2012) indicated that having adequate groups enables good interactions among the group members and is fundamental to achieving appropriate learning results. Lei, Kuestermeyer, Bailey, and Westmeyer (2010) also showed that collaborative learning groups should be structured to improve collaborative and facilitate student learning within the groups.

The most frequently used methods for group formation include random grouping (Chan *et al.*, 2010; Huxland & Land, 2000), selection by teacher (Hilton & Phillips, 2010), and selection by students (Hilton & Phillips, 2010). Each method has advantages and disadvantages. A disadvantage of all three group formation methods is that they cannot form optimized collaborative groups. Therefore, many studies (Moreno, Ovalle, & Vicari, 2012; Chen, Chen, Fan, & Chen, 2012; Chan *et al.*, 2010; Wang, Lin, & Sun, 2007) have proposed automatically optimized grouping schemes for collaborative learning that find global optimization solutions using several considered factors that influence collaborative learning performance. Hu¨bscher (2010) argued that automatic grouping for collaborative learning that considers the characteristics of students should maximize the group's learning effectiveness. Moreno, Ovalle and Vicari (2012) claimed that the ideal situation is to form groups that are as similar among themselves as possible (inter-homogeneous), while maximizing the students' individual differences inside such groups (intra-heterogeneous). Many studies (Johnson, Johnson, & Holubec, 1994; Scheurell, 2010) claimed that the most effective collaborative work groups include a mixture of students in terms of ability, gender, and ethnic background.

Gruenfeld, Mannix, Williams, & Neale (1996) also claimed that major factors that affect the learning processes in a group include gender, ability, and familiarity of members with each other, and identified heterogeneity of grouping as an important factor that favors collaborative learning.

Many studies (Moreno, Ovalle, & Vicari, 2012; Chen, Chen, Fan, & Chen, 2012; Chan *et al.*, 2010; Wang, Lin, & Sun, 2007) have successfully applied a genetic algorithm (GA) to optimize group formation based on student characteristics. For example, Moreno, Ovalle and Vicari (2012) proposed a group formation scheme that considers multiple student characteristics using a determined fitness function in a genetic algorithm. However, the defined fitness function for assessing the quality of group formation in their studies may determine collaborative learning groups with unbalanced learning characteristics. The present study claims that an excellent group formation scheme should consider whether all determined collaborative learning groups have balanced learning characteristics, while optimizing the overall learning characteristics of the group. In this work, forming collaborative learning groups with balanced learning characteristics means that each group is composed of members with similar personal characteristics and interaction relationship so that the collaborative learning performance of each group can be as identical as possible. To avoid forming collaborative learning groups with unbalanced students' learning characteristics, this work defines a penalty function that considers the variance of fitness function values among all formed learning groups to eliminate group formation solutions with unbalanced students' learning characteristics. To the best of our knowledge, few studies have considered learning roles and the interactions among peers to optimize collaborative learning groups and few studies have confirmed the effects of different group formation schemes on learning performance or their ability to facilitate collaborative interaction using actual experiments in online learning environments. Therefore, based on a revision of the group formation scheme that was proposed by Moreno, Ovalle and Vicari (2012), this work presents a novel GAGFS-PF that includes a penalty function in the fitness function of the genetic algorithm to prevent the formation of collaborative learning groups with unbalanced learning characteristics. The heterogeneous of students' knowledge levels and learning roles, and the homogeneity of social interactions among the members of each learning group are considered to optimize the group formation performance in a CPBL environment. Unlike other optimized group formation schemes that are based on GA, the proposed GAGFS-PF does not create exceptionally weak groups. Additionally, in addition to considering the knowledge levels of individual learners, this work considers the learning roles and interactions among peers, as identified by social networks analysis, as new factors in group formation. The study aims to examine whether using the proposed GAGFS-PF as the group formation scheme for CPBL activities is significantly superior to the random group formation scheme and self-selection group formation scheme in learning performance and peer interaction.

2. Literature Review

2.1 Effects of group formation schemes on collaborative learning performance

Collaborative learning helps students develop social, cognitive, and reasoning skills, such as thinking, making ideas explicit, and communicating ideas (Barros & Verdejo, 1998). A key issue in collaborative learning is group formation, because poorly selecting groups of colleagues can turn a potentially positive learning experience into a negative one (Alfonseca, Carro, Martín, Ortigosa, & Paredes, 2006). Restated, a group's productivity is determined by how well the members work together. Some studies (Johnson & Johnson, 1975; Hu¨bscher, 2010; Johnson, Johnson, & Holubec, 1994; Scheurell, 2010) of group formation and its effect on collaborative learning performance have been published. Generally, if teachers are responsible for group formation, they can determine whether the groups will be homogeneous or heterogeneous. These studies state that homogeneous groups that are formed by students with similar abilities, experiences and interests tend to be better at achieving specific goals. However, analyses show that heterogeneous groups outperform homogeneous groups in a broader range of tasks. Most researchers favor group formation for collaborative learning that is based on heterogeneous theory, which emphasizes variations in the learning proficiency, learning achievements, learning style, gender, race, within a group and whose effectiveness has been established (Jong, Wu, & Chan, 2006; Wang, Lin, & Sun, 2007; Webb, 1982). Unlike homogeneous groups, heterogeneous groups are formed with the goal of creating balanced teams of individuals who have a range of abilities, skills, majors, genders, and ethnic backgrounds (Smith & Spindle 2007). Webb (1982) noted that learners with moderate ability were suited to being homogenously grouped, while heterogeneous groups can include learners of mixed high and low abilities. The goal of group formation in collaborative learning is to make the learners to learn from each other, get to know different learners, and share ideas to achieve the best possible learning outcomes.

The most widely used methods for group formation include random grouping (Chan *et al.*, 2010; Huxland & Land, 2000), selection by teacher (Hilton & Phillips, 2010), and selection by students (Hilton & Phillips, 2010). In most collaborative learning activities, learners are randomly grouped (Chan *et al.*, 2010). However, simple random selection may allow just a few group members to perform well while the others fall far short of their goals; it may also result in "segregated" groups, in which all members exhibit some desirable or undesirable characteristics (Huxland & Land, 2000). Therefore, the formation of collaborative groups should not only consider the general performance of each group but also consider the results of individuals with various characteristics. Student-selected groups are formed by students, themselves, without intervention by an instructor. Students frequently form groups based on similarity, proximity, and prior acquaintance (Festinger, Schachter, & Back, 1950; Gruenfeld *et al.*, 1996; Mannix, Goins, & Carroll, 1996). Hilton and Phillips (2010) found that student-selected groups are typically homogeneous and their members typically get along better, communicate better, and are more enthusiastic about working together than members of randomly assigned groups, but they are less task-oriented. Student-selected groups commonly minimize the potential for quality learning while optimizing the peer relationships and potential for student interaction (Gruenfeld *et al.*, 1996). The selection-by-teacher approach to group formation is subjective because the considered factors vary among teachers. Accordingly, this approach is not one of the three group formation approaches that are considered herein.

Since a common disadvantage of non-automatic group formation methods is that they cannot find global optimal solutions, many studies (Moreno, Ovalle, & Vicari, 2012; Chen, Chen, Fan, & Chen, 2012; Chan *et al.*, 2010; Wang, Lin, & Sun, 2007) have successfully applied a genetic algorithm (GA) to optimize heterogeneous group formation based on considered student characteristics. For example, Moreno, Ovalle and Vicari (2012) proposed a group formation scheme that considers multiple student characteristics using a determined fitness function in a genetic algorithm for collaborative learning. Also, Chen, Chen, Fan, Chen (2012) used a novel method that is based on a genetic algorithm (GA) and social network analysis to group individuals for cooperative learning in the classroom. They used a GA to optimize the grouping while ensuring heterogeneity of grades, social status, and gender. Chan *et al.* (2010) presented a dynamic grouping strategy for grouping learners based on a group complementarity score and a genetic algorithm.

2.2 Factors that should be considered in group formation

Lei, Kuestermeyer, Bailey and Westmeyer (2010) identified at least six major factors - gender, ethnicity, familiarity among members, ability, motivational level, and source - that should be considered in grouping students for collaborative learning. Chan *et al*. (2010) noted that the academic achievements of learners must be considered when assigning individuals to heterogeneous groups. Liu and Tsai (2008) demonstrated that a group with both high and moderate achievers may have better peer interactions and, possibly, learning outcomes in terms of the distributive knowledge exchange pattern in collaborative learning. In contrast, Liu and Tsai (2008) indicated that a group with high-achieving members may not ensure that the work of the group is adequate for collaborative learning. Moreover, students in groups whose members are more familiar with each other may be more effective or interactive in sharing information and integrating alternative perspectives than those whose members are not familiar with each other, but are less likely to have unique knowledge or differing points of view (Jackson, 1992; Gruenfeld *et al.*, 1996). Groups of strangers are likely to know different facts and have various intellectual perspectives, but they may lack the social ties, frequency of interactions, and interpersonal knowledge to benefit from their intellectual diversity (Gruenfeld *et al.*, 1996). Therefore, teams of individuals that are cross-selected are more successful than those based exclusively on member familiarity (Lei, Kuestermeyer, & Westmeyer, 2010**)**.

Cesareni, Cacciamani and Fujita (2016) claimed that playing a specific role within a group could lead students to exercise collective cognitive responsibility for collaborative knowledge building. Their study revealed that role takers tended to vary their contributions more than non-role takers by proposing more problems, synthesizing the discourse, reflecting on the process and organization of activity. Yeh (2010) identified eight important online roles within a collaborative group: supervisors, information providers, group instructors, atmosphere constructors, opinion providers, reminders, trouble-makers, and problem solvers. The study indicated that the most frequently used roles determined using the across-group perspective are supervisors, trouble-makers, positive atmosphere constructors, reminders, and problem solvers. Moreover, Ormrod (2008) indicated that most relevant studies have suggested two findings concerning group collaboration: smaller groups are more effective and faculty must be available to offer proper guidance to the group. Additionally, Qiu and McDougall's study (2015) examined the effects of the three group configurations including large whole class, small whole class, large with subgroups on note reading workloads and participants' perceptions in online graduate-level courses. Their study confirmed that all three configurations had their own advantages and disadvantages in fostering online discourse reading, but suggested that the advantages of subgroup discussions in supporting note reading outweigh those of the small and large configurations. Lou *et al*. (1996) performed a meta-analysis of grouped versus ungrouped classes and found that the optimal group size for learning is three to four students. Based on above literature survey, this work thus claims that an effective collaborative learning group composed of four members should contain the supervisor, information provider, problem solver, and atmosphere creator as much as possible. The role of supervisors who give suggestions about creating high-quality work, request opinions from group members, set discussion schedules and assign work to group members is the key to good group functioning; the role of information providers typically provides and shares information related to assigned work; the role of problem solvers is to answer questions posed by group members as well as to correct and explain problems caused by group members; the role of atmosphere creators is to construct a positive and harmonious atmosphere of support, caring, and cooperation (Yeh, 2010).

Many studies (Alfonseca *et al*., 2006; Martín & Paredes, 2004; Deibel, 2005) have grouped students for collaborative learning based on learning style. Alfonseca *et al*. (2006) claimed that the advantage of considering learning styles can be exploited in collaborative learning as a key feature in group formation. They concluded that active-reflective and sensing-intuitive learners seem to influence the quality of collaborative work. Deibel (2005) proposed that groups should be formed by combining students using two learning style dimensions - active/reflective and sequential/global. They claimed that the members of a group should have similar values on these two dimensions. Martín and Paredes (2004) argued that the default approach to group formation should be to combine active students with reflective ones, such that they represent similar percentages of the group, and to combine students with a moderate or strong tendency to either visual or verbal styles, so that the collaboration works can be adapted accordingly.

To the best of our knowledge, few studies have considered how learning roles and interactions among peers can be used to optimize collaborative learning groups. This work thus proposes a novel GAGFS-PF that favors the heterogeneous of students' knowledge levels and learning roles, and the homogeneity of social interactions among members of each collaborative learning group to improve the learning performance of students and facilitate interaction in a CPBL environment.

2.3 Social networks analysis and its potential use in collaborative learning

A social network is defined as a network of interactions or relationships, in which the nodes consist of actors and the edges are relationships or interactions among these actors (Aggarwal, 2011). These edges in the network that connect actors, representing relationships, may have directions, indicating the flow from one actor to the other, and a strength, denoting the importance of the relationship (Rabbany, Elatia, Takaffoli, & Zaïane, 2014). Learners who perform a collaborative learning activity can be regarded as social group in which they socially interact with each other, share ideas, and have a common goal of completing a project or assignment, such that effort can ideally be divided equally among all participants. A growing body of research has demonstrated that a social network is critical in a collaborative learning environment (Harasim, Hiltz, Teles, & Turoff, 1995; Cho, Gay, Davidson, & Ingraffea, 2007). Social networks may have a significant impact on learning performance in a computer-supported collaborative learning (CSCL) setting, because learning activities in such a collaborative environment are predominantly based on communication, social interactions, and coordination among distributed learners (Cho, Gay, Davidson, & Ingraffea, 2007). Moreover, Lin, Huang and Chuang (2015) found that an e-learning environment with social network awareness (SNA) support is highly effective in increasing peer interaction and improving student learning.

Many measures of centrality in social networks exist. Individuals are most commonly ranked using different centrality measures to identify the actors with the most prestige, influence, prominence, or to detect outlier actors (Rabbany, Elatia, Takaffoli, & Zaïane, 2014). The three most commonly used measures of centrality are degree centrality, betweenness centrality, and closeness centrality (Wasserman & Faust, 2000). Of these three most commonly used measures of centrality in social networks, closeness centrality ranks nodes based on their position in the network, and represents the speed with which they can spread information throughout the network, which can be estimated by averaging the shortest paths from the node of interest to all the other nodes (Rabbany, Elatia, Takaffoli, & Zaïane, 2014). A collaborative learning group with high closeness centrality is one whose members have direct and strong interactions with each other, favoring collaborative learning performance. Gruenfeld *et al.* (1996) indicated that groups whose members are more familiar with each other may be more effective or interactive in sharing information and integrating alternative perspectives than those whose members are not familiar with each other. This work thus argues that the formation of collaborative learning groups should consider the homogeneity of social interactions among members within each group, as measured by closeness centrality.

Rabbany, Elatia, Takaffoli, and Zaïane (2014) emphasized the importance of social network analysis in mining structural data to evaluate the collaborative learning of students in discussion forums. They developed Meerkat-ED, which is a practical toolbox that is specifically designed for analyzing interactions among students in asynchronous discussion forums as part of online courses. Crespo and Antunes (2015) used social network analysis to predict teamwork results and proposed a recommendation system that suggests new teams in the context of a given curricular unit. Cho, Gay, Davidson and Ingraffea (2007) studied relationships among communication styles, social networks, and learning performance in a CSCL community. They showed that both communication styles and a pre-existing friendship network significantly influenced the way in which learners develop collaborative learning social networks. Chen and Cheng (2014) presented a novel scheme for recommending learning partners for individual learners by mining learning interactive social networks in a CPBL environment. Their results demonstrated that the proposed scheme helps to encourage learners to interact with peers more actively and positively, and improves learning performance in a CPBL environment. Lin, Huang and Chuang (2015) studied how network centrality and self-regulation affect student learning in an SNA-related e-learning environment. Their analytical results revealed that a student group with high centrality and low self-regulation achieve greater learning than other groups. Moreover, Reffay and Chanier (2003) proposed that social network analysis concepts, adapted to the collaborative distance-learning context, can help measuring the cohesion of small groups. Their study computed cohesion in several ways in order to highlight isolated people, active sub-groups, and various roles of the members in the group communication structure. This work claims that the roles of members should be considered while forming a collaborative learning group because role within a group could lead students to exercise collective cognitive responsibility for collaborative knowledge building (Cesareni, Cacciamani, & Fujita, 2016). This work thus presents a novel scheme to identify the roles of learners according to their interaction relationship with peers measured by social networks analysis and communication message type.

3. The Proposed Optimized Group Formation Scheme based on Genetic Algorithm

This section briefly introduces the proposed optimized group formation scheme that enhances the CPBL system developed in our previous work (Chen & Chen, 2010; Chen & Cheng, 2014; Chen, 2013).

3.1 Functions of CPBL system

The presented CPBL procedure involves four major learning stages for solving a target problem: 1) identifying the problem and situation; 2) designing the problem-solving method; 3) solving the problem; 4) reflecting on the process and its results. The four problem-solving learning stages were summarized as corresponding to "cognition", "action 1", "action 2", and "reflection" (knowing, doing 1, doing 2, and thinking) mental processes. Based on the proposed four main learning stages that are associated with solving target problems, a CPBL system, based on the "cognition-action-reflection" mental process, was implemented herein to assist in learning problem-solving skills. The system helps learners to solve the target problem using the proposed problem-solving procedure with four learning stages, and provides a friendly user interface that can assist course instructors in designing learning scaffolds for solving the target problem. Based on the designed learning scaffolds, the CPBL system asks learners to solve a semi-structured problem through higher-order thinking. A report concerning the solving of the target problem is completed by the writing of a report in each stage.

Figure 1 shows an example of the user interface that the course instructor can use to plan the learning scaffolds in the first learning stage of a task related to the ‘‘global warming problem’’ in order to assist students’ learning of the three groups. Figure 2 shows an example of the user interface that the learner can use to write up a task report in the first learning stage of a task related to the ‘‘global warming problem’’ according to the learning scaffolds designed by the course instructor. The learning scaffolds provide students with the well-organized basic knowledge, designed learning guideline, gathered reference websites, gathered reference videos, or predesigned forms that students can easily follow or fill in. The learning scaffolds aim at guiding the learning directions of students and assisting them to learn in solving complex problems that would otherwise be beyond their current abilities. On the left-hand side of the user interface, the system provides a system function menu that supports the CPBL in the third state. The task content in the third learning stage is displayed at the top right of the user interface. The bottom right of the user interface displays a friendly HTML editor that learners can use to edit their task reports. Learners can upload finished reports to the learning record database of the proposed system. The other learning stages provide corresponding user interfaces to support PBL.

Insert Figure 1 about here

Insert Figure 2 about here

3.2 Identifying knowledge levels, learning roles, and interactions in a CPBL environment

The score achieved by each learner for the task report in the first learning stage is used herein to determine the knowledge levels of learners because the first learning stage is the stage that depends on the knowledge that will be required to solve the target problem. Based on capturing the interactions among learners in the first learning stage, the learning role of each individual learner in the CPBL activity is identified, along with the closeness of the interactions each learners with peers. To identify the learning roles of each learner in performing a CPBL activity, Chen and Cheng (2014) divided learners into four types - hub, source, sink, and island - based on in-degree and out-degree interaction times with peers in a CPBL environment. Their study identified a learner whose in-degree and out-degree interaction times while communicating with their peers using the instant message tool of the CPBL system are both higher than the medians of the whole learning community as a hub. Hub learners are popular and authoritative in collaborative learning social networks because they frequently help peers to solve problems and frequently actively interact with the other learning peers. Each message that is sent using the instant message tool to learning peers to seek support in solving the target CPBL problems is of one of four types - chat, sharing information, discussion, and communication and coordination. That is, each learner was asked to assign the instant message that he/she would like to send to some learning peer to seek the assistance of solving a problem to a corresponding message type according to the contents of the instant message. The types of the instant messages assigned by each learner can help the CPBL system identify correctly learners' roles. Learners are identified herein as supervisors if they are hub learners and their in-degree and out-degree interactions are of the communication and coordination type; they are information providers if they are hub learners and their in-degree and out-degree interactions are of the information-sharing type; they are problem solvers if they are hub learners and their in-degree and out-degree interactions are of the discussion type, and there are atmosphere creators if they are hub learners and their in-degree and out-degree interactions are of the chat type. This work claims that an effective collaborative learning group should contain learns of all four types - supervisor, information provider, problem solver, and atmosphere creator. However, the roles that a learner played identified by the CPBL system may be over one type or even no significant type. Therefore, the CPBL system identified a learner as the role with the highest normalized value of in-degree and out-degree interactions when the roles that a learner played identified by the CPBL system are over one type. That is, the types of the roles of the learners in the experimental group identified by the CPBL system include supervisor, information provider, problem solver, atmosphere creator, and no significant role. Finally, closeness centrality (Freeman, 1978), defined as the inverse of farness, which is the sum of the lengths of the shortest paths from a node to all other nodes, is used to assess the closeness of the interaction between learners in the same group.

3.3 Proposed GAGFS-PF considering knowledge levels, learning roles, and interaction within a group

This section explains the implementation of the proposed GAGFS-PF that considers knowledge levels, learning roles, and interactions. The group formation scheme that is based on GA and considers multiple student characteristics, proposed by Moreno, Ovalle and Vicari (2012), is used herein to find optimal groups. The problem of specifying groups with unbalance fitness function values is overcome by using a penalty function that is based on the variance of fitness function values. First, a characteristic matrix of all learners is defined (1) to describe the mapping of characteristic values for individual learners with the characteristics that are considered in optimizing group formation.

$$C_{N\times M} = \begin{bmatrix} C_{1,1} & \cdots & C_{1,i} & \cdots & C_{1,M} \\ \vdots & & & & \vdots \\ C_{j,1} & & C_{j,i} & & C_{j,M} \\ \vdots & & & & \vdots \\ C_{N,1} & \cdots & C_{N,i} & \cdots & C_{N,M} \end{bmatrix} \tag{1}$$

where $C_{N\times M}$ is a characteristic matrix of all learners; *N* denotes the number of learners; *M* is the number of characteristics that are considered in group formation, and $C_{j,i}$ represents the value of the *ith* characteristic of the *jth* learner.

Once the elements have been organized into this characteristic matrix, all data must be normalized to the same scale in the calculation of the fitness function. Therefore, the considered characteristic values of individual learners are normalized using formula (2).

$$C^{*}{}_{j,i} = \frac{C_{j,i} - C_{min}}{C_{max} - C_{min}} \tag{2}$$

where $C^{*}{}_{j,i}$ is the normalized value of the *ith* characteristic of the *jth* learner; $C_{j,i}$ represents the value of the *ith* characteristic of the *jth* learner, and C_{min} and C_{max} are respectively the minimum and maximum values of the *ith* characteristic among all learners.

Accordingly, a normalized mean characteristic matrix of all learners is given by formula (3).

$$NC_{N\times M} = \begin{bmatrix} \overline{C_{1,1}} & \cdots & \overline{C_{1,i}} & \cdots & \overline{C_{1,M}} \\ \vdots & & & & \vdots \\ \overline{C_{j,1}} & & \overline{C_{j,i}} & & \overline{C_{j,M}} \\ \vdots & & & & \vdots \\ \overline{C_{N,1}} & \cdots & \overline{C_{N,i}} & \cdots & \overline{C_{N,M}} \end{bmatrix} \tag{3}$$

where $NC_{N\times M}$ is a normalized mean characteristic matrix of all learners; *N* represents the number of learners; *M* is the number of the characteristics that are considered in group formation, and $\overline{C_{j,i}}$ represents the normalized mean of the *ith* characteristic of the *jth* learner.

$$IM_g^j = \{\overline{C_{j,1,g}}, \dots, \overline{C_{j,i,g}} \dots, \overline{C_{j,M,g}}\} \tag{4}$$

where IM_g^j are the individual means of the *M* characteristics of the *jth* learner in the *gth* group; *M* is the number of characteristics; $\overline{C_{j,i,g}}$ represents the mean value of the *ith* characteristic of the *jth* learner in the *gth* group.

$$SD_g = \sum_{j=1}^{K}\left\{w_1\left(\overline{C_{1,g}} - \overline{C_{j,1,g}}\right)^2 + \cdots + w_i\left(\overline{C_{i,g}} - \overline{C_{j,i,g}}\right)^2 + \cdots + w_{\mathrm{M}}\left(\overline{C_{M,g}} - \overline{C_{j,M,g}}\right)^2\right\} \quad (5)$$

where SD_g represents the sum of the squared differences (SD) of the *M* characteristics of the *gth* group; *K* is the number of learners in the *gth* group; $\overline{C_{i,g}}$ is the mean value of the *ith* characteristic across the members of the *gth* group; $\overline{C_{j,i,g}}$ represents the mean value of the *ith* characteristic of the *jth* learner in the *gth* group, and w_i is the weight of the *ith* considered characteristic.

$$SSD^l = \sum_{g=1}^{G} SD_g \quad (6)$$

where SSD^l stands for the sum of the squared differences (SD) of the *M* characteristics of the *lth* population that are generated by the GA for group formation, and *G* is the number of groups formed.

$$P_l = \sqrt[2]{\frac{\sum_{p=1}^{G}\left(SD_p - \frac{SSD^l}{G}\right)^2}{G-1}} \quad (7)$$

where P_l is the penalty function for the *lth* population that is generated by GA for optimal group formation; SD_p represents the sum of the squared differences (SD) with regard to the *M* characteristics of the *pth* group, SSD^l stands for the sum of the squared differences (SD) with regard to the *M* characteristics for the *lth* population that is generated by the GA for group formation, and *G* is the number of groups formed.

$$F_l = \frac{SSD^l}{P_l} \quad (8)$$

where F_l is the fitness function of the *lth* population that is generated by GA for optimal group formation; *P* is the penalty function, and SSD^l stands for the sum of the squared differences (SD) with regard to the *M* characteristics for the *lth* population that is generated by GA for group formation.

The swap method is used as a crossover scheme in the proposed GA to optimize group formation. In the swap method, two genes are randomly selected and their values are exchanged with each other. The swap method has the advantage of preventing the formation of illegal groups. The proposed CPBL system supports the automatic grouping of learners using a teacher interface. Figure 3 shows the teacher interface for automatic grouping for collaborative learning. Figure 4 shows the user interface of the collaborative learning groups that are determined by the proposed genetic algorithm using the considered factors. In this work, the three equally weighted characteristics that are considered in the formation of optimal collaborative learning groups are the students' knowledge levels, their learning roles, and the social interactions of the members in each learning group. The crossover and mutation probabilities used in the employed GA were respectively set as 1 and 0.2 in this study. The proposed GAGFS-PF can optimize the collaborative groups with the heterogeneous of students' knowledge levels and learning roles, and the homogeneity of social interactions according to the defined fitness function shown as formula (8), but it cannot guarantee to exactly form all collaborative groups with four different roles because it is almost impossible that a class can have four different roles averagely or the number of the students in a class is exactly a multiple of four. Therefore, part of collaborative learning groups will be assigned with five members by the proposed GAGFS-PF when the number of the students in a class is not exactly a multiple of four as well as the proposed GAGFS-PF will balance the learning roles in each learning group as optimized as possible so that each learning group owns four different roles.

Insert Figure 3 about here

Insert Figure 4 about here

4. Research Methodology

4.1 The theoretical framework of the proposed GAGFS-PF from the perspective of knowledge building

The knowledge building theory was created and developed by Bereiter and Scardamalia (1993) for describing what a community of learners needs to accomplish in order to create knowledge. The study tried to propose the theoretical framework of connecting knowledge building and the proposed GAGFS-PF that simultaneously considers heterogeneous knowledge levels, homogenous interactions among learning peers, and heterogeneous learning roles to form collaborative learning groups in a CPBL environment. First, Kimmerle, Moskaliuk and Cress (2011) examined the collaborative learning processes of knowledge building by working on wikis. Their study confirmed assimilative knowledge building and the development of factual knowledge depends largely on learners' prior knowledge. This research finding supports that forming collaborative learning groups should consider learners' prior knowledge. Additionally, Yücel and Usluel investigated the processes of knowledge building, the interaction and participation of students in an online collaborative learning environment, and the relations among them. Their study revealed that the quantity, content and quality of interaction and participation affect collaborative learning performance. This research finding supports that forming collaborative learning groups should consider interaction relationship between peers. Finally, Cesareni, Cacciamani and Fujita (2016) claimed that playing a specific role within a group could lead students to exercise collective cognitive responsibility for collaborative knowledge building. Their study confirmed that role takers tended to vary their contributions more than non-role takers by proposing more problems, synthesizing the discourse, reflecting on the process and organization of activity. This research finding supports that forming collaborative learning groups should consider learning roles. Thus, this study presents the GAGFS-PF based on genetic algorithm to form collaborative learning groups with as balanced learning characteristics in terms of heterogeneous knowledge levels, homogenous interactions among learning peers, and heterogeneous learning roles as possible so that the collaborative learning performance of each group can be as identical as possible. The proposed GAGFS-PF aims to maximize the learning performance of collaborative learning groups and this study examines the performance of the proposed GAGFS-PF in a CPBL environment.

4.2Experimental design

The experimental design compares learners who are attempting to solve a target problem that is supported by the CPBL system, in groups formed using different schemes, in terms of collaborative learning performance. Accordingly, 83 sixth-grade primary school students were recruited from three classes at Rongfu Primary School in New Taipei City, Taiwan. The students were taught computer course by the same instructor before taking part in an eight week-long experiment. A nonequivalent pre-test-post-test group based on a quasi-experimental design performed the PBL activity. Hence, the three classes were randomly assigned to either the experimental group, control group 1 or control group 2. The experimental group comprised 27 primary school students who performed problem-solving learning using the CPBL system with the GAGFS-PF. Control group 1, formed using the random group formation scheme, comprised 28 primary school students who performed problem-solving learning using the CPBL system; control group 2, formed by the self-selection group formation scheme, comprised 28 primary school students who performed problem-solving learning using the CPBL system. Each learner had to follow the “cognition”, “action 1”, “action 2”, and “reflection” mental processes to solve a target problem that was associated with “global warming problem” using the CPBL system for problem-based learning. The course instructor designed suitable learning scaffolds for each learning stage to support learner problem-solving learning.

The course instructor assessed the task report that was completed and submitted by each learner during each learning stage and made a professional judgment regarding whether each learner should pass that stage and progress to the next one. The submitted task reports would be returned by the course instructor if they did not satisfy the passing criteria that were determined by the instructor in advance. Students were strongly encouraged to seek assistance from members of their group to solve problems by the instant message when their submitted task reports were returned and they had to resubmit their task reports to the PBL system for subsequent evaluation. Although the learners of the three groups were determined their learning partners for collaborative learning by three different group formation schemes, the instant message tool provided in the CPBL system did not limit that the learners can only interact with the members of the same group. That is, the learners of the three groups can also communicate with the members of other groups to seek the assistance of solving a problem according to their willingness through the instant message tool. Before the experiment was performed, all participants underwent a one-hour training session in operating the CPBL system in a computer classroom. During the experiment, except when they were formally attending the courses at school, the participants used their own personal computers to conduct asynchronous learning to solve the target problem during out-of-school time via the Internet. Additionally, to increase learning motivation, the course instructor provided explanations of the assigned CPBL tasks in each learning stage on four occasions during face-to-face classroom teaching time for three groups.

During the first learning stage, learners in three groups performed the same learning activity with the support of the CPBL system, but the group formation scheme was not implemented for collaborative learning, so all learners freely interacted or communicated with their peers using the immediate message communication or asynchronous discussion board. In the second to fourth learning stages, three groups, formed using different group formation schemes, performed collaborative problem-solving learning processes. The experimental group was formed using the GAGFS-PF, considering knowledge levels, learning roles, and interactions; the other two control groups were formed using the random group formation scheme and the self-selection group formation scheme.

4.3 Experimental procedure

First, each group received a one-hour training course in operating the CPBL system and completing the assignments. The CPBL activities were then performed. Finally, several randomly selected participants from three groups were interviewed to elicit their thoughts and feelings about this learning activity. The details of each step of the experimental procedure are described as follows.

(1) Explaining the supported CPBL system and problem-based learning tasks to three groups

In the first step, the instructor introduced the CPBL activities in a computer classroom. The teacher then randomly assigned students from three classes into the three groups using the different group formation schemes. Next, the researchers explained to the learners the upcoming procedure for performing CPBL activities and operating the system. The three groups of learners, formed using different group formation schemes, performed the same procedures to complete the CPBL activities.

(2) Performing the problem-based learning activities during formal course time in the computer classroom and available time at home

Following instruction in the subject and operation of the system, the experiment enters the second stage. Learners were invited to participate in CPBL activities to solve a problem that is associated with the topic of "global warming". The three learning groups were required to perform assigned tasks using the CPBL system to experience the four learning stages of "cognition", "action 1", "action 2", and "reflection". Each learning stage lasted for two weeks. All students had to complete a report in each learning stage using the scaffolds that were designed by the instructor.

(3) Learning performance assessment, collaborative social networks analysis, and interview

After the learners had completed all CPBL assignments, their assessed learning performance and collaborative social network interactions in the CPBL activities were assessed based on a completed final report and social network measures. Finally, selected participants from three groups were interviewed to elicit in detail their thoughts about CPBL learning activities in pursuit of solving the "global warming problem".

4.4 Research participants

A total of 83 Grade 6 primary school students of ages 11–12 years old from three classes at Rongfu Primary School in New Taipei City, Taiwan, were randomly invited to participate in a CPBL activity. Therefore, the Rongfu Elementary School computer classroom was the learning field. The main reason that chose Grade 6 primary school students as the research subjects is that cultivating problem-solving abilities for young children has been regarded as an important educational goal in Taiwan's education system. However, problem-solving abilities are high-level cognitive skills to primary school students. This study thus chose Grade 6 primary school students as the research subjects because they have the highest educational level in Taiwan's primary schools. Compared to the primary schools' students with lower educational level than Grade 6, Grade 6 students have relatively enough cognitive abilities to achieve a problem-solving mission. All participants were also encouraged to perform the CPBL learning activity using available time at home. One instructor taught the computer course for all participants of three groups. All participants not only learned the use of word processing and slide production software, but also were familiar with using a browser to find web resources to support CPBL activities. All participants knew how to post messages to a discussion board, to respond to issues raised on the discussion board, and to edit PBL task reports using the CPBL system. All participants provided written informed consent after the experimental details were explained. One class with 27 students, comprising 14 males and 13 females, was randomly chosen as the experimental group; one class with 28 students, comprising 15 males and 13 females, was randomly chosen as control group 1, and the remaining class of 28 students, comprising 16 males and 12 females, was randomly chosen as control group 2. The three groups were formed using the CPBL system with the GAGFS-PF, the random group formation scheme, and the self-selection group formation scheme, respectively; all performed the same eight-week CPBL activity. The 27 students in the experimental group were determined as six collaborative learning groups that were respectively composed of 5, 5, 5, 4, 4, and 4 members by the proposed GAGFS-PF; the 28 students in the control group 1 were determined as seven collaborative learning groups that were respectively composed of 4, 4, 4, 4, 4, 4, and 4 members by the random group formation scheme; the 28 students in the control group 2 were determined as seven collaborative learning groups that were respectively composed of 4, 4, 4, 4, 4, 4, and 4 members by the self-selection group formation scheme.

4.5 Methods for assessing the learning performance and peer interaction of the proposed GAGFS-PF by using a mixed study

This work uses a quasi-experimental research method to collect quantitative data to assess the effects of three group formation schemes on the learning performance and effects of interaction in a CPBL environment and also adopts interview to enhance the results of qualitative data analysis. Namely, this study adopts a mixed study to examine the research findings because no one research method is completely perfect, with each research method having its own strengths and weaknesses. Adopting mixed methods research can help to overcome some of the methodological weaknesses of single-method research as well as the multiple data analysis methods based on quantitative and qualitative data can support triangulation (Creswell, 2003). First, to assess the differences in the learning performance of the groups that were formed using the various group formation schemes, the scores of the learners' task reports in the four PBL learning stages were assessed by their instructor and another teacher. Pearson correlation analysis was performed to assess the inter-rater reliability of the two teachers. The learning performance in each CPBL learning stage was assessed based on the report whose total score comprised 40% for accuracy, 30% for completeness, and 30% for originality. The Pearson correlation coefficient between two raters' scores yielded an overall correlation of 0.96 at the .05 significance level, indicating that the inter-rater reliability in assessing the learning performance of the learners was relatively high. The average of the scores that were given by the two teachers was used as the measure of learning performance in each PBL learning stage. Additionally, to collect qualitative data that may not be revealed by the learning performance and interaction effects, semi-structured interviews were performed at the end of the experiment. Exploiting the inherent flexibility of a semi-structured interview, the interviewer reused or repurposed questions to obtain in-depth information on the perspectives and personal experiences of each interviewee. Two learners with significantly improved learning performance and two learners with significantly poor learning performance in each group were interviewed. Therefore, a total of 12 learners across the three groups participated in semi-structured interviews.

5 Experimental Analysis and Findings

This study used IBM SPSS Statistics Base 22.0 to assess the differences in the learning performance among three groups and employed UCINET 6.0 to measure and show the social network relationships among three groups. Section 5.1 compares the learning performance of three groups across the four CPBL learning stages. Section 5.2 assesses the variations in the interaction structures of the three learning groups using social network measures. Finally, Section 5.3 presents the outcomes of the in-depth interviews.

5.1 Comparison of learning performance of three groups

Table 1 shows the passing rates of the three groups in the three PBL stages. Whereas 63% of the learners in the group that was formed using the GAGFS-PF passed all learning stages, only 36% of learners in the group that was randomly formed did so and only 43% of those in the self-selection group did so. This result reveals that the group that was formed using the GAGFS-PF had the highest pass rate across all learning stages.

Table 2 shows descriptive statistics concerning the learning performance of the three groups in CPBL in the four stages. Since the “cognition” (knowing) learning stage is used to assess the initial level of learner knowledge related to the target problem, the mean score in the “cognition” stage was taken as a measure of a learner’s knowledge level concerning the topic related to “global warming” that was assigned by instructor, whereas the mean scores of each learner’s report in the “action 1”, “action 2”, and “reflection” (doing and thinking) stages are treated as indicating learning performance. One-way analysis of variance (ANOVA) was performed on the mean scores of the three learning groups in the “cognition” learning stage to determine whether the prior knowledge of learners related to the “global warming” topic differed significantly. The means score of the three groups in the “cognition” learning did not differ significantly ($F=0.096$, $p=.908>.05$), indicating that the three groups had equivalent levels of prior knowledge related to the “global warming” topic. Next, one-way analysis of covariance (ANCOVA) was applied to the learning performance of the three groups in “action 1”, “action 2”, and “reflection” learning stages. In one-way ANCOVA, the mean score in the “cognition” learning stage was regarded as a covariance; the group was an independent variable, and the mean scores in the "action 1", "action 2", and "reflection" stages were dependent variables. In one-way ANCOVA to assess the learning performance in the "action 1", "action 2", and "reflection" stages, the first step was to analyze the homogeneity of the regression coefficients. The F test results ($F=2.795$, $p=.067>.05$; $F=1.811$, $p=.170>.05$; $F=0.116$, $p=.891>.05$) did not reach significance in any of the three learning stages, revealing that the regression slopes of the three groups are equivalent, confirming the assumed homogeneity of coefficients. The ANCOVA result for the "action 1" stage did not reach significance ($F=2.176$, $p=.120>.05$) after an adjustment was made for the dependent effect with respect to the covariance. This result reveals that the mean scores for the "action 1" learning stage among the three groups did not vary significantly. The ANCOVA result for the "action 2" stage did reach significance ($F=3.356$, $p=.040<.05$) after an adjustment was made for the dependent effect with respect to the covariance. This result shows that the mean scores in the "action 2" learning stage varied significantly among the three groups. Therefore, a *post-hoc* multiple comparison was performed, and its results revealed that the learning performance of the group that was formed using the GAGFS-PF was significantly better than that of the learning group that was formed using the random group formation scheme. However, no significant differences existed between the learning group that was formed using the GAGFS-PF and that formed by self-selection or between the learning group that was formed using the random group formation scheme and that formed by self-selection. The ANCOVA result for the "reflection" stage did not reach significance ($F=2.107$, $p=.128>.05$) after an adjusting was made for the dependent effect with respect to the covariance. This result reveals that the learning performance of the "reflection" learning stage did not vary significantly among the three groups.

Finally, in performing a one-way ANCOVA to assessing the overall learning performance in the "action 1", "action 2" and "reflection" stages, the first step was to analyze the homogeneity of the regression coefficients. The F test result ($F=1.181$, $p=.312>.05$) did not reach significance, indicating that the regression slopes of the three groups were equivalent, confirming the assumed homogeneity of coefficients. The ANCOVA result reached significance ($F=3.851$, $p=.025<.05$) after an adjustment was made for the dependent effect with respect to the covariance, indicating that the entire learning performance in "action 1", "action 2", and "reflection" stages varied significantly among the three groups. Therefore, a *post-hoc* multiple comparison was performed. The overall learning performance of the group that was formed using the GAGFS-PF significantly exceeded that of the learning group that was formed using the random group formation scheme. However, no significant difference existed in this respect between the group that was formed using the GAGFS-PF and that formed using the self-selection group formation scheme or between the group formed using the random group formation scheme and that formed using the self-selection group formation scheme.

Insert Table 1 about here

Insert Table 2 about here

5.2 Comparison of social learning networks' properties of three groups

This section compares the properties of the social learning networks that were formed by the interactions among learners in the three groups that were formed using different group formation schemes, in problem-solving activities that were supported by the CPBL system. To measure the interactions within the three groups using social network measures, isolated learners who did not interact with peers were eliminated. Social network measures, including network density, network diameter, clustering coefficient, degree centrality, closeness centrality, and betweenness centrality, were used to elucidate the differences in the learning interactions among the learners of the three groups. The learning group that was formed using the GAGFS-PF had no isolated learner, but those formed using the random and self-selection group formation schemes had two and one isolated learners, respectively. Table 3 compares the properties of the social learning networks among the three groups. The results reveal that the group that was formed using the GAGFS-PF had the highest network density, clustering coefficient, degree centrality, closeness centrality, and betweenness centrality, and the lowest network diameter of any of the groups. The network density of a social network is defined as the ratio of the number of edges to the number of possible edges. A high network density indicates that learners interact strongly with each other. The network diameter of a social network represents the length of the longest interactive path between any two learners in the CPBL environment. A short network diameter indicates that learners rapidly exchange information (Chen & Cheng, 2014). The clustering coefficient indicates the degree of connectedness of the neighborhood of the node. If the neighborhood is fully connected, then the clustering coefficient is one, whereas a value of close to zero indicates that the neighborhood contains almost no connections. Degree centrality is the number of connections that a node has (Baglioni, Geraci, Pellegrini, & Lastres, 2014). The closeness centrality of a node is the sum of its shortest distances from all other nodes, and is used to identify nodes that are easily reachable from other nodes (Baglioni, Geraci, Pellegrini, & Lastres, 2014). Betweenness centrality is the number of times that a node acts as a bridge on the shortest path between two other nodes, and can be used to identify nodes that are more likely to act as information hubs (Baglioni, Geraci, Pellegrini, & Lastres, 2014).

One-way ANOVA was applied to the means of degree centrality, closeness centrality, and betweenness centrality for the three groups to determine whether these social network measures varied significantly among the groups. Table 4 shows the result. The result shows that the mean degree centrality and closeness centrality varied significantly among the groups (F=11.49, p=.000<.001; F=492.86, p=.000<.001), but the mean betweenness centrality did not (F=.80, p=.454>.05). Therefore, a *post-hoc* multiple comparison was performed, and it revealed that the mean betweenness centrality of the learning group that was formed using the GAGFS-PF significantly exceeded those of the learning groups formed using the random and self-selection group formation schemes, indicating that the formation of a learning group using the GAGFS-PF promoted social network interaction.

Insert Table 3 about here

Insert Table 4 about here

Figure 5 shows the global structure of social networks of the GAGFS-PF group. An edge in the social network represents that an interaction between two learners through the instant message service. A single arrow on an edge indicates the direction of interactions from one learner to the other. A two-way arrow on an edge indicates that the two learners interact bidirectionally. According to Fig. 5, the social networks of the GAGFS-PF group are relatively tight and no learner was isolated, without any interaction with peers. Furthermore, most learners not only interacted with the members of the same group, but also interacted with the members of other groups. Clearly, using the GAGFS-PF to generate collaborative groups improved the learners' willingness to communicate or collaborate with others. This work inferred that the main reason is that the proposed GAGFS-PF simultaneously considering the heterogeneous of students' knowledge levels and learning roles, and the homogeneity of social interactions measured by social network analysis among the members in the learning group can generate collaborative learning groups with good discussion atmosphere and appropriate members with the complementary abilities and roles, thus facilitating students' interactive and collaborative willingness in a CPBL environment. In contrast, Fig. 6 shows the global structure of social networks of the randomly selected group. The social networks of the random group are relatively loose and two isolated learners did not interact with others. The group comprised two cliques whose members interacted only with learners in the same group. Figure 7 shows the global structure of social networks of the self-selection group. The strength of the connections in the social networks of the self-selection group was between that of the GAGFS-PF group and that of the random group. Also, the self-selection group included one isolated learner who did not interact with peers; it otherwise comprised a clique whose members interacted only with the members of the same group. The self-selection group included four collaborative sub-groups who interacted almost exclusively with members of the same collaborative sub-group. In fact, the four collaborative groups were similar to cliques. Generally, the learners in a clique do not have a completely open friend group, reducing the effectiveness of collaborative learning. The use of the self-selection group scheme probably favored this phenomenon.

Insert Figure 5 about here

Insert Figure 6 about here

Insert Figure 7 about here

Figure 8 shows the local structure of social networks of the collaborative groups determined by different group formation schemes. According to Fig. 8, an edge with thick line in the social network represents that the frequency of interactions between two learners through the instant message tool is higher than an edge with thin line. Among the six collaborative groups determined by the GAGFS-PF, the groups with fully connected social networks are as high as five as well as the frequency of interactions of the group members with their peers in the five groups is relatively high. In contrast, among the seven collaborative groups determined by the random group formation scheme, the groups of 2, 6, and 7 show relatively loose interaction structure. This study inferred that the main reason is that the three groups were assigned unfavorable members, thus affecting their willingness of interacting with other group members. Similarly, among the seven collaborative groups determined by the self-selection group formation scheme, the groups of 1 and 4 show relatively loose interaction structure. This study inferred that the main reason is that the members of the two groups were passively grouped as collaborative groups, not deriving from their willingness. Therefore, the interaction willingness of the group members of the two groups is low. Analytical results of local structure of social networks show that the proposed GAGFS-PF for group formation is superior to the random and self-selection group formation schemes in terms of the effects of peer interactions.

Insert Figure 8 about here

5.3 Summary of interview results

To enhance the results of quantitative data analysis based on statistical analysis, twelve learners with especially excellent or poor learning performance were invited from the three groups to participate in a semi-structured interview in an attempt to understand why different group formation schemes yielded remarkably difference learning performances and interactions. Most of the interviewees agreed that collaborative learning provided benefits in terms of improving learning performance, and that they enjoyed collaborative learning activities to some degree. In particular, the interviewees with relatively poor knowledge level in the assigned CPBL topic indicated that collaborative learning helped them very much in solving problems that they could not solve alone. Most of the interviewees from the GAGFS-PF group and the randomly selected group stated that they needed to some time to get to know their members of their group before the initial stage of CPBL activities because they were assigned to a group with unfamiliar members. Additionally, several interviewees from the GAGFS-PF group and the randomly selected group noted their groups included differently gendered members or disfavour members. However, most of interviewees from the GAGFS-PF group agreed that they cultivated more and better collaborative relationships with the other members of their group during the four CPBL stages, than did the interviews of the randomly selected group. This study summarized that the main reasons may come from two aspects. First, this study found that the interviewees from the randomly selected group generated significantly more negative feelings towards their groups with unfamiliar members than the interviewees from the GAGFS-PF group. The possible reason is that the GAGFS-PF considers the interaction relationships of group members to some degree. Second, most of interviewees from the randomly selected group strongly felt that their group members have only low willingness to interact with other peers due to unfavorable group members, thus affecting collaborative relationships and learning performance. In contrast, most of interviewees from the GAGFS-PF approved that the group members determined by GAGFS-PF can facilitate broad discussion with different points of view while solving complex problems like “global warming problem” due to consisting of heterogeneous collaborative group members with different roles and knowledge levels. Moreover, most of the interviewees from the self-selection group indicated that they experienced no barrier to communicating with the members of their group while performing CPBL activities. However, they also indicated that they tended only to interact with peers from their group, seeking the help of members of other groups only on a few occasions. Interestingly, most of the interviewees from all three groups indicated that they preferred to select their peers with whom they performed CPBL activities even though they agreed that the GAGFS-PF indeed provided benefits in terms of generating better collaborative groups than did the randomly selected group and self-selection group to some degree. This study logically inferred that the main reason may come from a natural cognitive response in humans.

6 Discussion

This work found that the learning performance of three groups that were formed using different group formation schemes differed significantly in the “action 2” stage during four CPBL learning stages, and that the GAGFS-PF group significantly outperformed the random group. However, no significant differences were found between the GAGFS-PF group and the self-selection group or between the random group and the self-selection group. Solving the problems in the “action 2” stage of the four CPBL learning stages required a higher level of problem-solving ability than was required in the “cognition”, “action 1”, and “reflection” learning stages. Considering the heterogeneous of students’ knowledge levels and learning roles favored the solving of high-level cognitive problems. This finding is consistent with the claims by most researchers in the field that effective collaborative learning requires heterogeneous groups (Jong, Wu, & Chan, 2006; Wang, Lin, & Sun, 2007; Webb, 1982), as well as that higher-quality solutions to problems are produced by heterogeneous groupings of people in terms of personality than are found homogeneous (Hoffman & Maier, 1961). Most of the interviewees from the GAGFS-PF group and the random group herein indicated that they required some time to get to know the members of their group before the initial stage of CPBL activities because they were assigned to a group with unfamiliar members. Clearly, a period of getting to know each other preceded the productive work on the task by the GAGFS-PF group, so no significant difference in learning performance was identified among the three groups in the “action 1” learning stage. Furthermore, the learning performance of the three groups did not significantly differ in the “reflection” learning stage because in this learning stage, only reflective activities are performed, based on peer review.

Analytical results of global and local structures of social networks reveal that the GAGFS-PF group was significantly better than the randomly selected and self-selected groups in terms of peer interactions. The main inferred cause is that the GAGFS-PF group could cultivate collaborative interactions with other members of their group more easily than could members of the random group, because the GAGFS-PF considered not only the heterogeneous of students’ knowledge levels and learning roles in the formation of a collaborative group, but also the homogeneity of the social interactions of the members in the group. Obviously, considering the homogeneity of social interactions of the members of a learning group shortens the period required for group members to adjust to each other. Briefly, the effect promotion of interaction among peers is the dominant reason why the learning performance of the GAGFS-PF group exceeded that of the random group. This result is consistent with that of Liu and Tsai (2008), who found that peer discussion or peer interaction facilitates learning.

Although several interviewees of the GAGFS-PF group and the random group noted that they were assigned to groups with differently gendered members or with disfavour members, the GAGFS-PF group exhibited good learning performance in the “action 2” learning stage. This result is consistent with that of Lei, Kuestermeyer and Westmeyer (2010), who found that gender diversity tends to influence student learning behavior, communication, and individual experience within groups, rather than group performance. Moreover, the proposed GAGFS-PF cannot guarantee to exactly form all collaborative groups with four different roles because it is almost impossible that a class can have four different roles averagely or the number of the students in a class is exactly a multiple of four. However, it was encouraging that most of interviewees from the GAGFS-PF approved that the group members determined by GAGFS-PF can facilitate broad discussion with different points of view while solving complex problems due to consisting of heterogeneous collaborative group members with different role. Additionally, this study found that the learning performance of a collaborative group that exactly contained four different roles is higher than a collaborative group that did not completely contain four different roles in the “action 2” stage during four CPBL learning stages, but the differences among them did not reach a statistically significant level. Therefore, how to promote the effects of the considered four roles in terms of promoting collaborative learning performance should be further investigated.

Despite its important contributions, this work has some limitations. First, gender was not considered in forming collaborative learning groups using the proposed GAGFS-PF. Generally, gender diversity in work groups importantly affects collaborative learning processes (Myaskovsky, Unikel & Dew, 2005; Johnson, Johnson, & Holubec, 1994; Scheurell, 2010). Second, owing to the limited instruction time, only an eight week-long experiment was performed. The effects of the proposed GAGFS-PF for generating collaborative groups on learning performance and interactions may differ from those herein in an experiment that lasts much longer, such as for a complete one-semester.

7 Conclusion and Future Works

To improve the learning performance of students and facilitate interaction among peers in a CPBL environment, this work proposes a novel GAGFS-PF that simultaneously considers the heterogeneous of students’ knowledge levels and learning roles and the homogeneity of social interactions of the members in a learning group, in forming collaborative learning groups with balanced learning characteristics. Analytical results show that the proposed GAGFS-PF is superior to the random group formation scheme in terms of the learning performance in CPBL activities that are performed by members of the formed group. Additionally, the effectiveness of peer interaction in the group that was formed using the proposed GAGFS-PF significantly exceeded that in the random and self-selection groups, based on the all considered social network measures. Also, the interview results show that most of interviewees from the GAGFS-PF approved that the group members determined by GAGFS-PF can facilitate broad discussion with different points of view and interaction relationships among group members while solving complex problems. In short, the main contributions of this work are considering learning roles and interactions among peers to optimize collaborative learning groups based on the proposed novel GAGFS-PF and confirming the effects of different group formation schemes on learning performance and peer interaction. This work brings the study of group formation for promoting collaborative learning performance into a new ground.

Several issues warrant further study. First, Myaskovsky, Unikel and Dew (2005) claimed that gender diversity in work groups is especially important. Future research should address the consideration of gender in the proposed GAGFS-PF. Second, the effects of other characteristics, such as personal interest and emotional factors such as the empathy among students and their motivation regarding the learning activities (Moreno, Ovalle, & Vicari, 2012), on group performance should be examined further. Finally, in this work the three considered characteristics - students' knowledge levels, learning roles, and the social interactions of the members of a learning group – were equally weighted in the formation of collaborative learning groups. Future research should explore how varying those weights affects collaborative learning performance and peer interaction.

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Captions of figures:

Figure 1. The user interface that the course instructor can plan the learning scaffolds of the first learning stage

Figure 2. The user interface that the learner can write the task report of the first learning stage according to the learning scaffolds designed by the course instructor

Figure 3. The teacher interface that can automatically generate optimized learning groups by the proposed GAGFS-PF through adjusting the corresponding weights of each considered group formation factor

Figure 4. The user interface of the collaborative learning groups determined by the proposed GAGFS-PF under the considered group formation factors

Figure 5. The global structure of social networks of the GAGFS-PF group

Figure 6. The global structure of social networks of the random group, where circle indicates a clique

Figure 7. The global structure of social networks of the self-selection group, where circle indicates a clique

Figure 8. The local structure of social networks of the collaborative groups determined by different group formation schemes

Table 1. The passing rates of the three different CPBL stages for three learning groups using different group formation schemes

Group formation scheme	Number of students	The cognition learning stage	The action 1 learning stage	The action 2 learning stage	The reflection learning stage
		Passing rate	Passing rate	Passing rate	Passing rate
GAGFS-PF	27	27(100%)	27(100%)	21(78%)	17(63%)
Random group	28	28(100%)	24(86%)	13(46%)	10(36%)
Self-selection group	28	28(100%)	26(93%)	19(68%)	12(43%)

Table 2. Comparison of learning performance of four learning stages for the three learning groups using different group formation schemes for CPBL

PBL learning stage	Group formation scheme	Number of students	Mean	Std.	F	Sig.	Multiple comparison
The cognition learning stage	GAGFS-PF	27	88.20	3.59	**0.096**	**.908**	---
	Random group	28	87.91	3.78			
	Self-selection group	28	87.76	3.85			
The action 1 learning stage	GAGFS-PF	27	89.02	3.49	**2.176**	**.120**	---
	Random group	28	76.21	31.91			
	Self-selection group	28	81.88	23.49			
The action 2 learning stage	GAGFS-PF	27	72.19	39.34	**3.356***	**.040**	GAGFS-PF > Random group
	Random group	28	43.50	47.60			
	Self-selection group	28	62.04	43.54			
The reflection learning stage	GAGFS-PF	27	57.56	45.00	**2.107**	**.128**	---
	Random group	28	33.09	45.21			
	Self-selection group	28	39.84	46.86			
The action 1, action 2 , and reflection learning stages	GAGFS-PF	27	72.92	26.62	**3.851***	**.025**	GAGFS-PF > Random group
	Random group	28	50.93	35.16			
	Self-selection group	28	61.25	31.35			

[1]

[1] * indicates p＜.05

Table 3. Comparison of learning social network properties among the three learning groups using different group formation schemes

Group formation scheme	Number of students	Mean of Network density	Entire network distance		Entire network centrality		
			Mean of network diameter	Mean of clustering coefficient	Mean of degree centrality	Mean of closeness centrality	Mean of betweenness centrality
GAGFS-PF	27	0.18	2.38	0.51	0.18	0.43	0.06
Random group	26	0.08	2.69	0.21	0.08	0.07	0.03
Self-selection group	27	0.12	2.72	0.32	0.12	0.12	0.05

Table 4. Comparison of social network centrality of four learning stages for the three learning groups using different group formation schemes for CPBL

Centrality measure	Group formation scheme	Number of students	Mean	Std.	F	Sig.	Multiple comparison
Degree centrality	GAGFS-PF	27	0.18	0.08	11.49***	.000	GAGFS-PF > Random group; GAGFS-PF > Self-selection group
	Random group	26	0.09	0.05			
	Self-selection group	27	0.13	0.07			
Closeness centrality	GAGFS-PF	27	0.43	0.07	492.86***	.000	GAGFS-PF > Random group; GAGFS-PF > Self-selection group
	Random group	26	0.07	0.02			
	Self-selection group	27	0.12	0.04			
Betweenes s centrality	GAGFS-PF	27	0.06	0.05	.80	.454	---
	Random group	26	0.03	0.05			
	Self-selection group	27	0.05	0.10			

[2]

[2] *** indicates $p < .001$

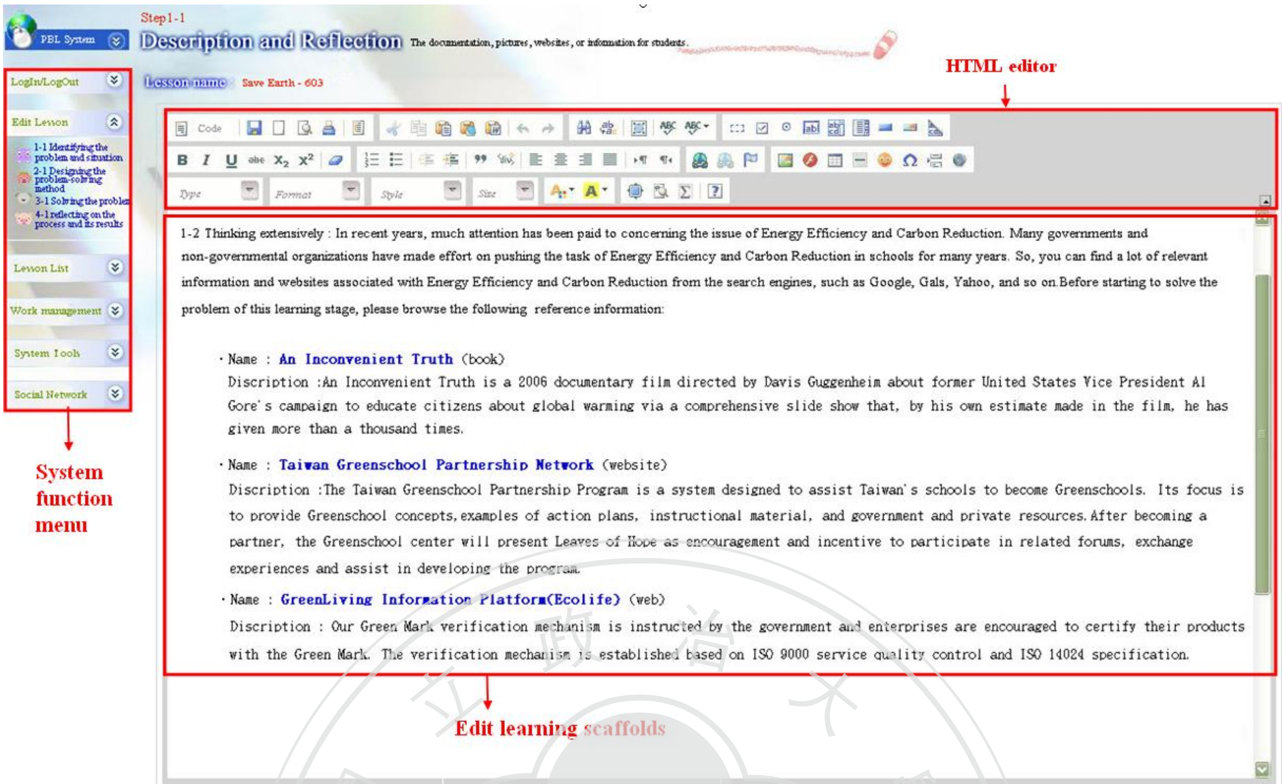

Figure 1. The user interface that the instructor can plan the learning scaffolds of the first learning stage

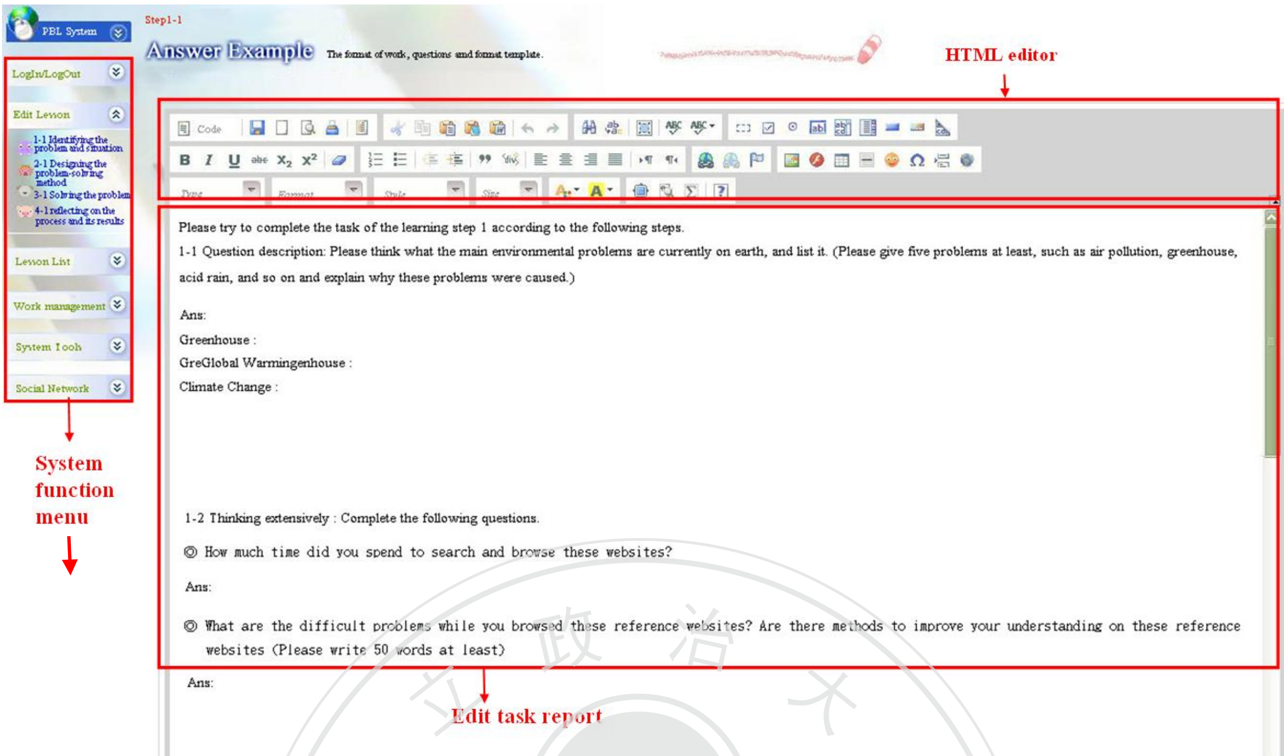

Figure 2. The user interface that the learner can write the task report of the first learning stage according to the learning scaffolds designed by the course instructor

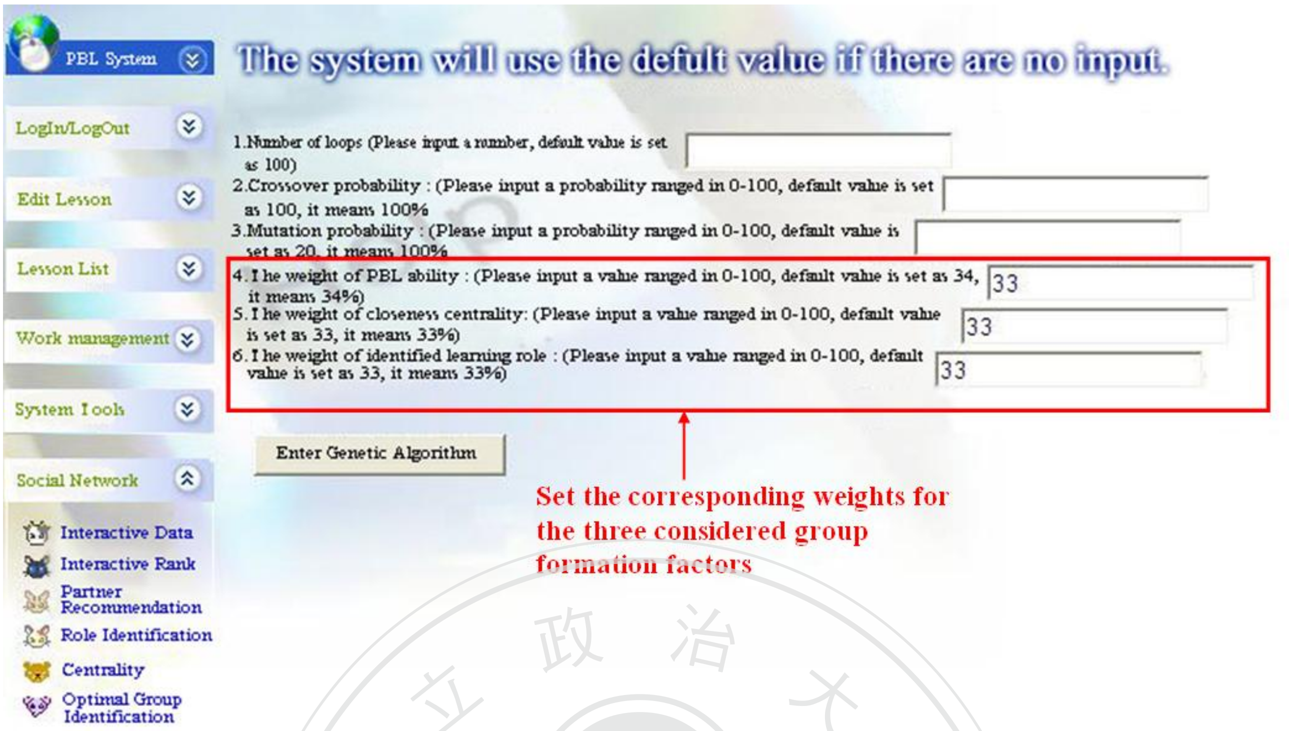

Figure 3. The teacher interface that can automatically generate optimized learning groups by the proposed GAGFS-PF through adjusting the corresponding weights of each considered group formation factor

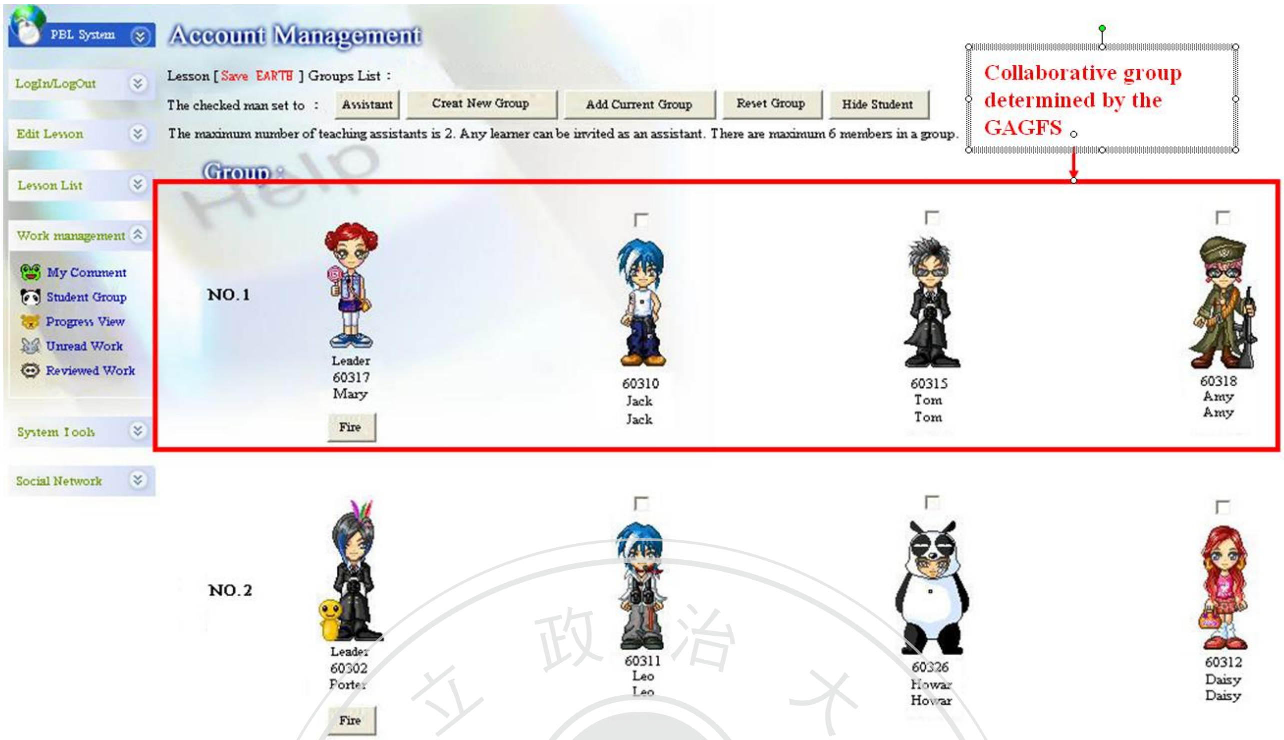

Figure 4. The user interface of the collaborative learning groups determined by the proposed GAGFS-PF under the considered group formation factors

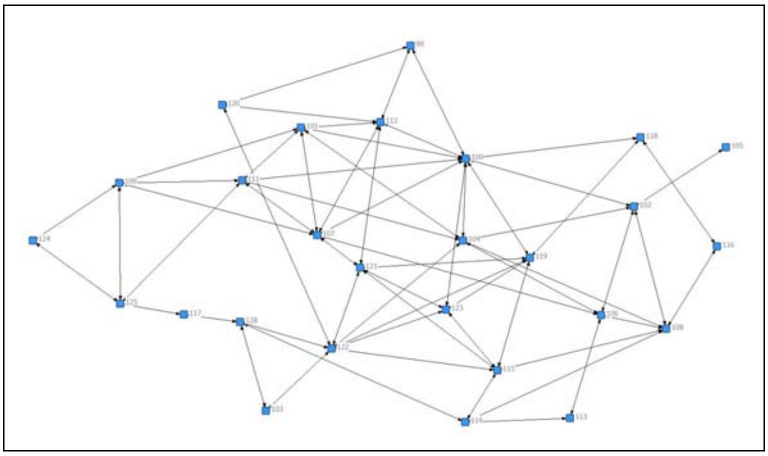

Figure 5. The global structure of social networks of the GAGFS-PF group

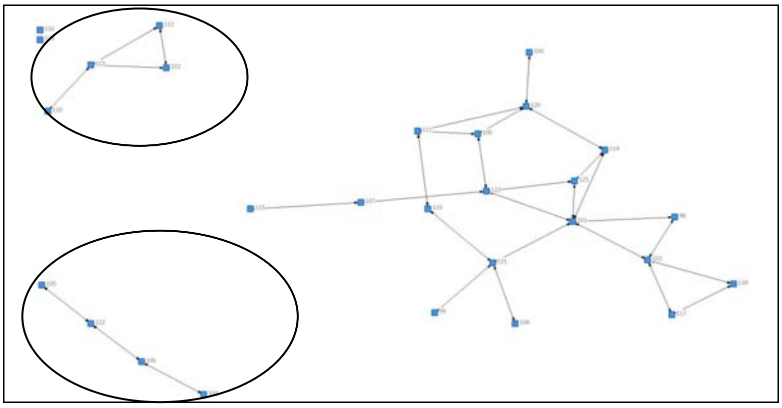

Figure 6. The global structure of social networks of the random group, where circle indicates a clique

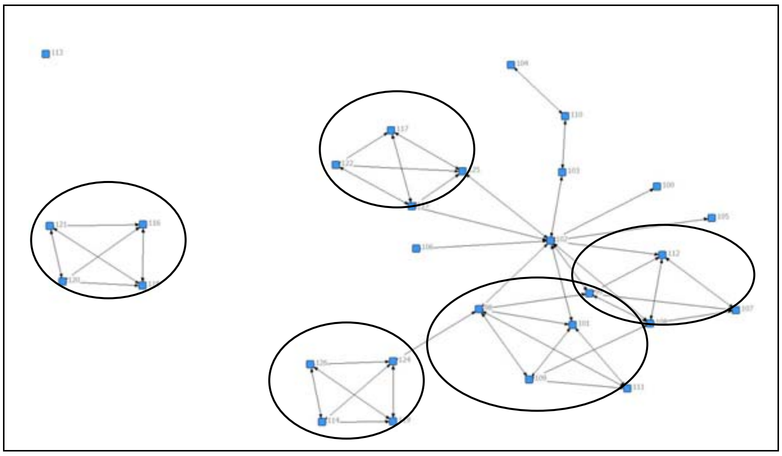

Figure 7. The global structure of social networks of the self-selection group, where circle indicates a clique

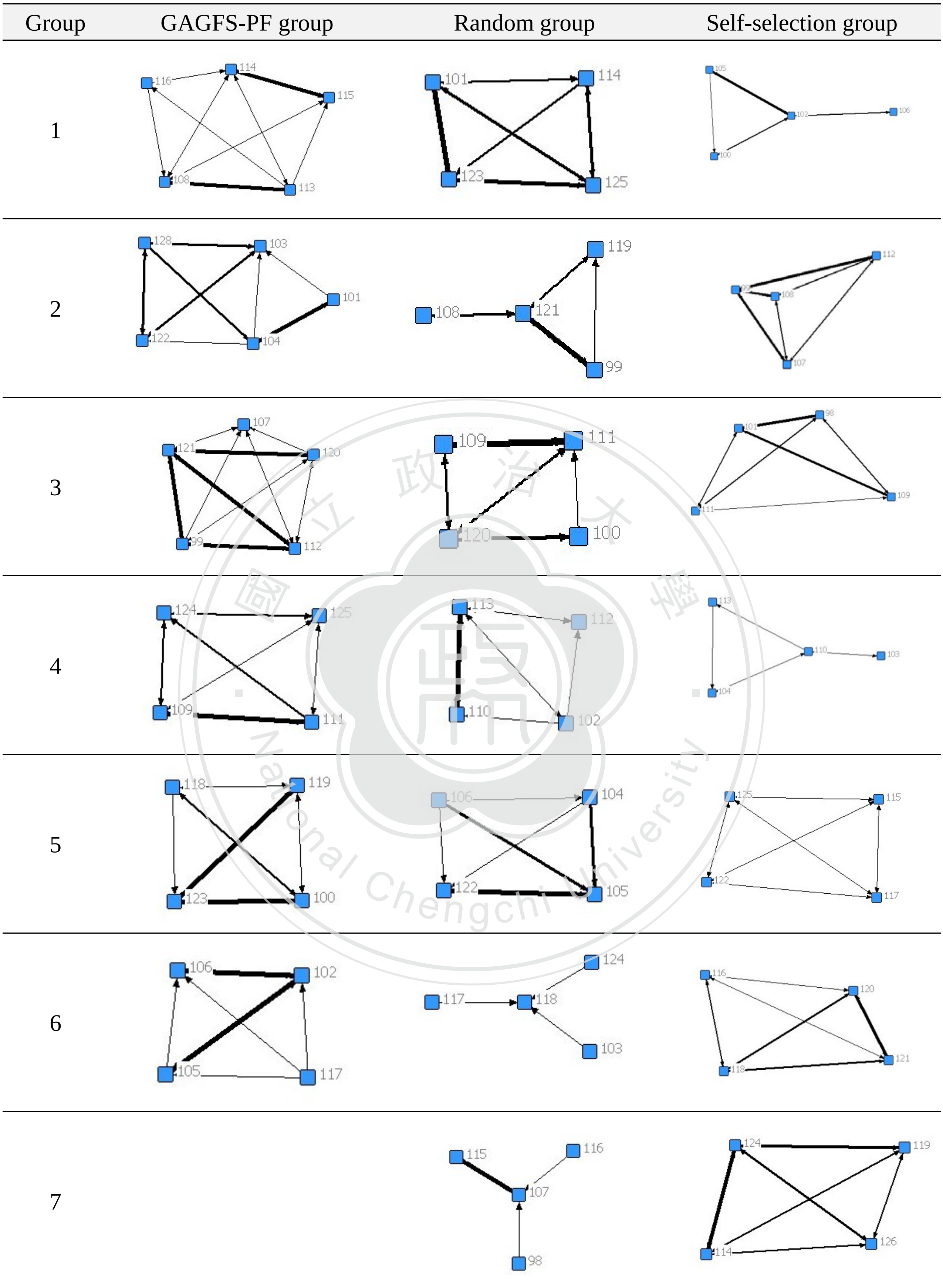

Figure 8. The local structure of social networks of the collaborative groups determined by different group formation schemes