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An Effective Method for Incentivizing Groups Implemented in a Collaborative Problem-based Learning System to Enhance Positive Peer Interaction and Learning Performance

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Abstract

Many studies have verified that collaborative problem-based learning (CPBL) is an increasingly popular educational paradigm that has great potential to cultivate learners' collaborative learning and problem-solving abilities. The effective promotion of both positive interactions among group members and group accountability is a critical issue in CPBL. This work therefore proposes a group incentive mechanism (GIM) that is based on several important factors that influence peers' interactions and group accountability in collaborative learning to improve learning performance, interactive relationships, group efficacy, and the cohesiveness of groups of learners in a CPBL system. To evaluate the effectiveness of the proposed GIM, 48 Grade 4 students were recruited from an elementary school in Taoyuan City, Taiwan, to participate in an instruction experiment. The quasi-experimental design was used to evaluate differences in learning performance, interaction, group efficacy, and group cohesiveness between the experimental group of learners with the proposed GIM and a control group of learners with the individual incentive mechanism (IIM) while using the CPBL system to solve a target problem collaboratively. Analytical results reveal that although the control group of learners with the IIM exhibited greater social interactions than the experimental group of learners with the proposed GIM, the experimental group exhibited better learning performance, group efficacy, and positive interactive relationships than the control group. The CPBL system with novel GIM supports a more effective form of CPBL.

Keywords: Problem-based learning, Collaborative learning, Group incentive mechanism, Interactive relationships, Group efficacy, Group cohesiveness

1. Introduction

Problem-based learning (PBL) is a well-known and effective collaborative learning mode, which has already been widely used to help students cultivate collaborative learning and problem-solving skills. According to Barrows and Kelson (1995), the aim of PBL is to help students develop flexible knowledge, effective problem-solving skills, self-directed learning skills, effective collaboration skills, and intrinsic motivation. In PBL, learners focus on solving a complex problem that does not have an exact solution. To solve such a problem, learners must work collaboratively with other group members to determine what they need to learn based on self-directed learning, and then apply their newly acquired knowledge to solve the problem and to reflect on what they have

learned and the effectiveness of the strategies they have employed. In PBL, the teacher has the role of a guide, facilitating learning rather than directly providing knowledge. In other words, PBL not only provides learners with instructional mechanisms but also encourages learners to take part in social interactions and receive coaching from peers and teachers when solving authentic and ill-structured problems to increase higher-order thinking skills (Tseng, Chiang, & Hsu, 2008). The PBL activity is usually modified to support particular teaching goals, and technology frequently plays an important role in adapting PBL to particular disciplines (Hmelo-Silver, 2004). Therefore, the PBL model is being increasingly used with advanced information technology to facilitate learners' interactions with learning materials, peers, and their instructor.

Collaborative problem-solving group is a key feature of PBL (Hmelo-Silver, 2004). Zumbach, Schonemann and Reimann (2005) proposed various scaffolds that support collaborative learning, including task design, the distribution of learning resources, script design, and learner feedback. They found that providing feedback to learners significantly improved learning performance and collaborative behavior. Zumbach, Reimann and Koch (2006) developed a collaborative online learning environment that supported many functions, including tracking, analyzing, and feeding back parameters of participation, collaboration, motivation, and emotional state to group members. Their results suggested that appropriately distributing learning material can favor collaboration.

Deutsch (1949) and Slavin (1995) pointed out that the interdependence of individuals' academic goals and the collective reward of a team are essential to the success of collaborative learning. Johnson and Johnson (1994) indicated that common goals made group members interdependent. As members consider those goals, they experience a state of tension that motivates movement toward their accomplishment. Slavin (1980) presented the student team achievement division (STAD) that students with different levels of ability are assigned to four-member learning teams to work together to accomplish a shared learning goal as a collaborative learning strategy. However, it lacks a mechanism for promoting interdependence based on academic goals. Most of the research in collaborative learning focused on verifying the effectiveness of group rewards rather than the effectiveness of individual rewards (Dyson, Griffin, & Hastie, 2004).

Chen and Chang (2014) presented an individual incentive mechanism (IIM) that was based on social rank, determined by computing the social interaction score of each learner in a learning social network to encourage competition, with the purpose of improving social position in the CPBL system. To increase their social ranking by the IIM, learners must actively and frequently interact with their peers to help them solve target problems. This mechanism has been found to accelerate learning interaction among learning peers, improving learning performance in the CPBL system. However, the IIM, which is based on promoting social rank, easily causes learners to pay too much attention to individual accountability, while ignoring group accountability. Therefore, this work presents a novel group incentive mechanism (GIM) that is based on several important factors that influence peers' interactions and group accountability in the CPBL system. Whether the proposed GIM provides better learning performance, interactive relationships, group efficacy, and group cohesiveness than the IIM that was presented by Chen and Chang (2014) is examined.

2. Literature Review

2.1 Collaborative learning and problem-based learning

Collaborative learning has been regarded as effective in improving students' learning performance (Slavin, 1991; Davidson & Major, 2014) because of strong evidence that collaborative learning can improve students' academic achievement, thinking skills, social skills, and course satisfaction. Johnson and Johnson (1994) proposed five elements of collaborative learning, which are positive interdependence, face-to-face promotive interaction, individual accountability, interpersonal and small group skills, and group processing. Slavin (1995) proposed a three-element

theory of collaborative learning that considers team rewards, individual accountability, and equal opportunities. Team rewards have become a widely used means of motivating groups of learners to pursue a common collaborative goal. Moreover, individual accountability is important because the success of a group depends on learning by all of the team's members. Equal opportunities for success refer to the fact that all students can contribute to their teams by improving their own performance. This ensures that all the students, including those of high, average, and low ability strive to make their best individual contributions.

Problem-based learning (PBL) is a well-known collaborative learning model in which group members frequently solve a target problem in a way that involves learning using the instructor's scaffolds and online resources (Chen & Yen, 2003). Many empirical evidences have shown the benefits of PBL over traditional teacher-centred pedagogy for different aged groups including primary school students (Li & Tsai, 2018). Barrows and Kelson (1995) proposed many important learning goals in PBL, including the acquisition of flexible knowledge, effective problem-solving skills, self-directed learning (SDL) skills, and effective collaboration skills, and intrinsic motivation. Many studies (Chen & Chen, 2010; Chen & Chang, 2014; Chen & You, 2018; Chen & Kuo, 2019) have proposed a collaborative PBL procedure with four major learning stages, which can be summarized as a "cognition-action-reflection" mental process, for solving target problems. Success in collaborative PBL is based on the interaction of learners, which is emphasized by the theory of collaborative learning. Therefore, many studies (Deutsch, 1949; Slavin, 1980; Farivar, 1985; Johnson & Johnson, 1994; Chen & Chang, 2014; Chen & You, 2018; Chen & Kuo, 2019) have examined factors that affect interactions among learners in collaborative PBL. For example, Deutsch (1949) found that if other members in a group reach their goals, particular individuals can reach theirs, so a situation of interdependence and mutual encouragement exists. Slavin (1980) proposed the student team achievement division (STAD) to point out that group reward is a core concept in collaborative learning and students must depend on each other to achieve their learning goals (Slavin, 1995). Farivar (1985) found that group rewards are more conducive to collaborative learning than are individual incentives. Johnson and Johnson (1994) found that collaborative learning involves positive interdependence and they emphasized the importance of individual responsibility for learning. Additionally, Chen and Kuo (2019) proposed 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 CPBL environment. Their study indicated 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. Chen and You (2018) presented the two-step flow of communication that employs the modularity Q function as the fitness function of genetic algorithm to optimally detect learning communities and uses PageRank measure to accurately find out community opinion leaders according to the social network interaction data of learners in the CPBL process to enhance web-based CPBL performance, social network interaction and group cohesion. Their study confirmed that using the two-step flow of communication instead of the one-step flow of communication traditionally used in web-based learning environments could significantly promote web-based CPBL performance, social network interaction, and group cohesion. In collaborative learning, a suitable learning partner can help a learner solve problems. Therefore, Chen and Chang (2014) proposed an individual incentive mechanism (IIM) that can show the social rank of each learner to improve the learning performance of learners in a CPBL system. However, the IIM that is based on improving social rank easily causes learners to focus on individual accountability, while ignoring group accountability. This work thus proposes a group incentive mechanism (GIM) that is based on the simultaneous consideration of individual and group accountabilities to improve the

learning performance, interactive relationships, group efficacy, and group cohesiveness of learners in a CPBL system.

2.2 Group efficacy and group cohesiveness

Self-efficacy is the extent or strength of one's belief in one's own ability to complete tasks and reach goals. One's self-efficacy can play a major role in how one approaches goals, tasks, and challenges. Williams and Williams (2010) indicated that individuals with high levels of self-efficacy see difficult tasks as challenges to be overcome rather than as threats to be avoided. Bandura (1986) suggested that the sources of self-efficacy are experiences of mastery, vicarious experiences, social persuasion, and somatic and emotional states. These sources help individuals determine whether they believe they have the capability to accomplish specific tasks. Bandura (1997) noted that the most effective way to develop a strong sense of efficacy is through mastery experiences. Success establishes a robust belief in one's personal efficacy. As discussed by Bandura (1997), seeing people similar to oneself succeed by sustained effort raises an observer's beliefs that he or she has the capabilities to master comparable activities. Somatic and emotional states also provide information about efficacy beliefs. When people are under stress and anxiety, they tend to have lower self-efficacy.

Bandura's (1996) concept of group efficacy builds on his concept of self-efficacy. Group efficacy is defined as a group's shared belief, which emerges from an aggregation of individual group members' perceptions of the group's ability to succeed at a given task (Bandura, 1986). Marks (1999) found that group efficacy was positively related to group performance in a routine task environment. The influence of group leaders or coaches on learning may also provide insight into group efficacy and performance (George & Feltz, 1995). Bandura (1990) has suggested that coaches may structure mastery experiences in practical and game situations to improve group efficacy. Group efficacy is an important topic in group research (Chen & Bliese, 2002), and a positive relationship exists between it and groups' performance (Knight, Durham & Locke, 2001), so group efficacy can be regarded as an important predictor of group performance. Gully, Incalcaterra, and Beauien (2002) used meta-analytic techniques to study the level of analysis and the interdependence of learners as moderators of observed relationships among task-specific group-efficacy, generalized potency, and performance. Their results indicated that both group-efficacy and potency had positive relationships with performance.

People define group cohesiveness differently. One of its common definitions is commitment to task and interpersonal attraction to the group. Beal, Cohen, Burke, and McLendon (2003) used meta-analytic scheme to study the relationship between group cohesiveness and group performance. Their results revealed a strong correlation between group cohesiveness and performance. Peterson (2007) carried out a study of 672 students in 48 groups and found empirical evidence of a positive relationship between group cohesiveness and group performance. González, Burke, Santuzzi, and Bradley (2003) tested competing models of the effectiveness of a group of 200 Mexican business students. Their results revealed that group cohesiveness mediated the relationship between group efficacy and group effectiveness, and that group behavioral performance directly affected group effectiveness. Group efficacy and group cohesiveness have been found to motivate group members to behave in a manner that favors the group (Hogg & Vaughan, 2005) and the same work identified effective interaction factors that had been mentioned in related research into collaborative learning and PBL. These were then used to develop a GIM to promote interactions among group members and to help group members improve their group efficacy, group cohesiveness, and learning performance.

3. Proposed CPBL System with Individual and Group Incentive Mechanisms

3.1 System learning functions in CPBL system

The proposed CPBL system involves the following four major learning stages in the solving of a target problem (Chen & Chen, 2010); (1) cognition - identifying the problem; (2) action 1 - designing a method for solving the problem; (3) action 2 - solving the problem; and (4) reflection - reflecting on the process and result. The four learning stages are summarized as a "cognition-action-reflection" mental process, and each involves one task. The CPBL system guides learners in solving the target problem using proposed problem-solving procedures, and provides a friendly user interface that can help course instructors design learning scaffolding for solving the target problem. Based on the designed learning scaffolding, the CPBL system asks learners to solve a semi-structured problem using higher-order thinking. Specifically, a problem-solving report regarding a target problem is completed from individual task reports. The components of the CPBL system are briefly described below.

Figure 1 shows an example of the instructor interface that can be used by the course instructor to plan learning scaffolds in the first learning stage of a task that concerns 'global warming, to assist learning by both the control and the experimental groups. Figure 2 shows an example of a learner interface that can be used by the learner to write up a task report in the first learning stage of a task on global warming, based on the learning scaffolds that are designed by the course instructor. The learning scaffolds provide students with well-organized basic knowledge, a learning guideline, reference websites, reference videos, and predesigned forms that can be easily filled in. The purpose of the learning scaffolds is to guide the learning of students in solving complex problems that would be beyond their current abilities. On the left-hand side of the student interface is a system function menu that supports the CPBL system in the first learning stage. The student 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 also provide corresponding user interfaces to support CPBL.

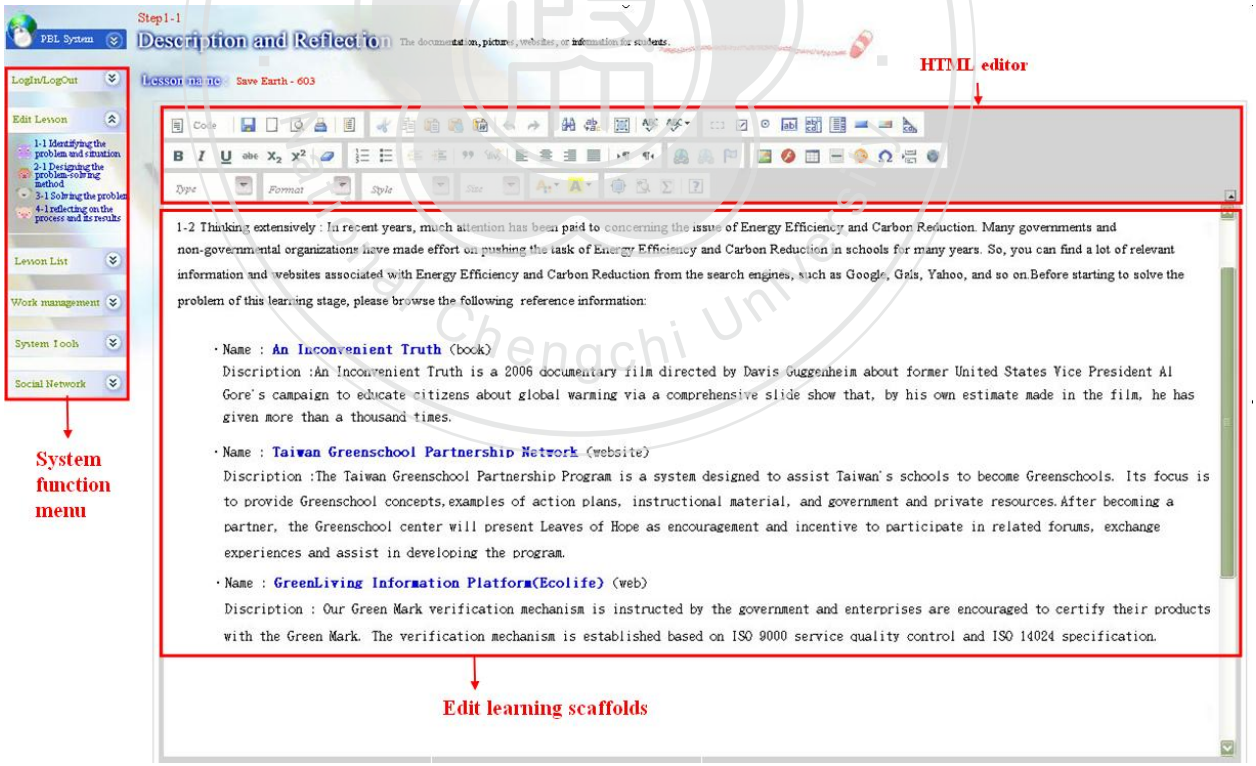


Figure 1. Teacher scaffolding design interface in the CPBL system

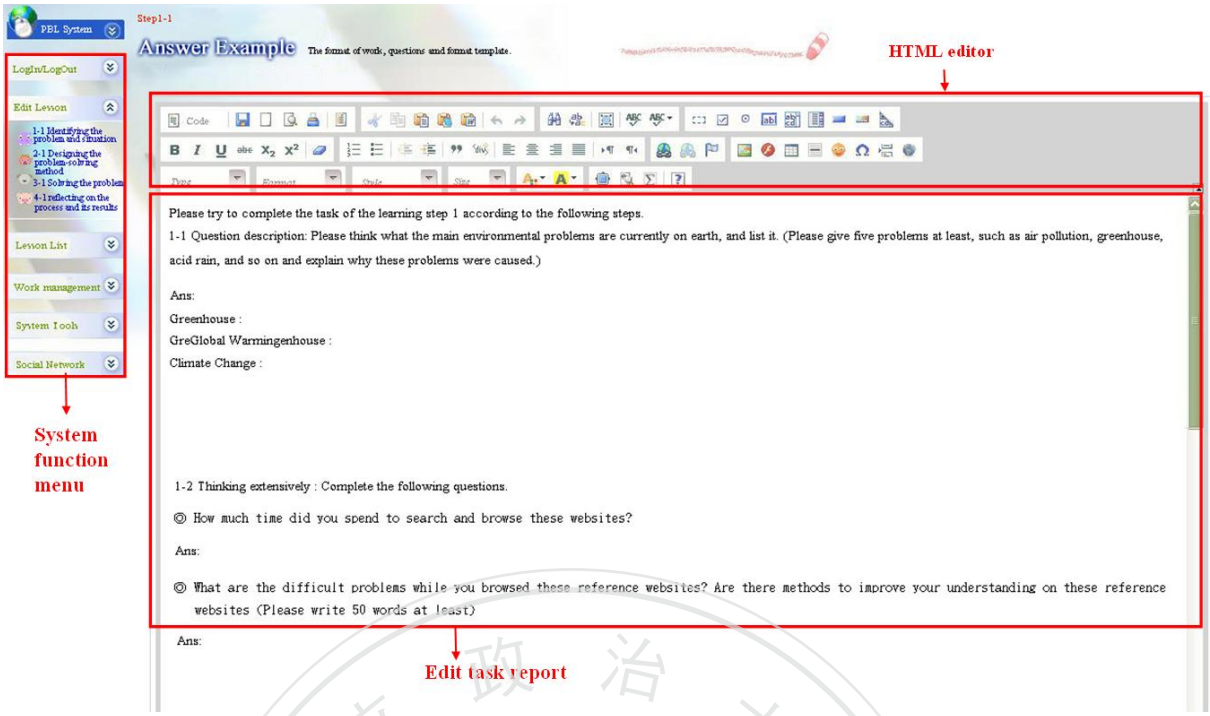


Figure 2. Learner answer scaffolding interface in the CPBL system

3.2 Individual incentive mechanism (IIM) in CPBL system

The IIM that was developed by Chen and Chang (2014) shows the social position of a learner based on interactive value and a social score that is computed from records of the learner's interactions with peers. With reference to Fig. 3, for example, suppose that the interactive scores of learners A, B, C, and D are 3, 2, 4, 1 (indicated in parentheses), respectively. The social score of learner A is 2 because learner A only exits the bidirectional interaction with learner B. Therefore, learner A receives the interactive score of learners B. The social score of learner B is 7 because learner B simultaneously exits bidirectional interactions with learners A and C. Therefore, learner B receives the interactive scores of learners A and C. Similarly, the social scores of learners C and D are 3 and 4, respectively. Therefore, the social ranks in this social network, based on the social scores, are in the order B, D, C, and A. Learners obtain low social scores if they only interact frequently with peers who have low interactive scores but obtain high social scores if they interact frequently with peers with high interactive scores.

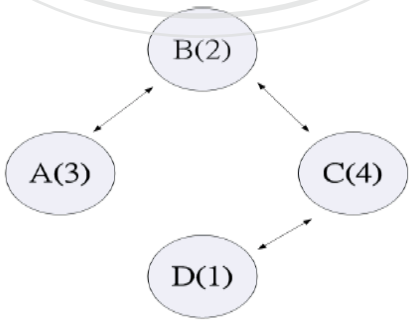


Figure 3. An example for illustrating how to compute social score in the CPBL system, where the number in the brackets represents the interactive score

The social ranking of each learner can be regarded as a measure of individual accountability. This information is displayed to encourage competition for social rank in the CPBL system. To

improve their social positions, learners must actively and frequently interact with their peers to help them solve a target problem that is assigned by the instructor. This mechanism increases learning interactions between learning peers, improving problem-based learning performance. Figure 4 shows individual accountability ranking, based on the IIM.

Figure 4. The ranking display of the individual accountability based on IIM

3.3 Proposed group incentive mechanism (GIM) in CPBL system

Theories of collaborative learning are reviewed and the factors that can affect the effectiveness of peers' interactions with each other are summarized. These factors are then integrated into the CPBL system to develop the group incentive mechanism (GIM). The formula for the score that is used in the GIM of the CPBL system consists of two parts, as shown in Eq. (1). The first part represents individual responsibility in a collaborative learning group while the second represents interdependence among group members and the pardon mechanism.

$$S_n = 100 \times \frac{P_n}{T} - (T - P_n) \sum_{K=n-2}^{n-1} \frac{200R_k}{(n-k)T} \tag{1}$$

where S_n is the GIM score in the nth learning stage; P_n is the number of learners who have passed the nth learning stage before the deadline; T is the total number of members in a collaborative group, and R_k is the number of learners who fail to pass the kth learning stage.

Individual accountability in a learning group importantly affects the success of collaborative learning. Therefore, the learning performance of each learner in a learning group must be evaluated. From part 1 of Eq. (1), if a collaborative learning group has four members of whom only one passes the first collaborative assignment in the four learning stages in CPBL system, then the GIM score is calculated as follows:

$$S_1 = 100 \times \frac{P_1}{4} \tag{2}$$

Consequently, S_1 = 25 when one member of a collaborative learning group submits an assignment to the CPBL system, and the assignment is passed by the instructor. Similarly, if two members of a collaborative learning group pass the instructor's review, then S_1 = 50; if three members pass the instructor's review, then S_1 = 75, and finally, if all four by default members pass the instructor's review, then S_1 = 100. Restated, the GIM score for the first assignment is based on the proportion of homework that is done by the group members. Hence, any individual assignment score for each learner that exceeds 60 will be considered to indicate a completed task in the learning stage, allowing the learner to move to the next learning stage. Everyone can gain up to one fourth of the total score (25 points) of the group, so everyone has the same opportunity to succeed to contribute to the group's success. The immediate feedback to each learner in the CPBL system favors the self-efficacy of the leaner.

Generally, the objectives of collaborative learning fall into two sets, which are academic objectives and social skill objectives (Goodsell, Maher, & Tinto, 1992). The achievement of positive interdependence of group members in pursuit of academic objectives must result in all members' receiving the same reward to enable learners to understand that to achieve common goals with other members is to achieve their own goals. Learners with the strongest ability thus help and encourage others to learn, to the benefit of not only the mentee but also the mentor. Moreover, encouraging members of the group to achieve their social skill objectives helps them achieve their academic objectives. The positive interdependence of group members' academic goals motivates learners to achieve their social skills objectives. Part 2 of Eq. (1) can be regarded as a cumulative penalty term.

$$-(T - P_n) \sum_{K=n-2}^{n-1} \frac{200R_k}{(n-k)T} \tag{3}$$

For example, if only three of the four members of a group pass assignment 3 in the four learning stages in CPBL, and all group members pass assignment 1. If one member cannot pass assignment 2 by the deadline, then the GIM score is computed as follows.

$$S_3 = 100 \times \frac{P_3}{T} - (T - P_3) \sum_{k=1}^{2} \frac{200R_k}{(3-k)T} = 100 \times \frac{3}{4} - (4-3) \sum_{k=1}^{2} \frac{200R_k}{(3-k)T} = 100 \times \frac{3}{4} - (4-3) \left\{ \frac{0}{4} \times \frac{200}{3-1} + \frac{1}{4} \times \frac{200}{3-2} \right\} = 25$$

Since only three of the four members pass assignment 3, the first part of the score S_3 is reduced from 100 to 75 (S_3 = 100 × (3/4) = 75); this part evaluates individual responsibility for individual performance. The second part of the score S_3 can be regarded as a cumulative penalty term because it decreases the GIM score when anyone fails to pass both assignment 2 and assignment 1. Therefore, a higher proportion of unfinished assignments corresponds to a lower GIM score. This is, this cumulative penalty term is designed to promote the interdependence of group members since if a group member fails to complete the assignment, then the group's score will be significantly reduced. Accordingly, the score formula that is proposed in this study, simultaneously including the individual's and group's responsibility to perform in a collaborative group, captures how the individual's performance affects the group's performance. A member who wants to receive a higher GIM score has to work with other members to achieve their common goal. Therefore, working with other members and helping them to complete the learning task is critical to increasing GIM score. After the completion of assignment 2 in learning stage 3 in CPBL, the CPBL system implements a mechanism for suspending the promotion of highly performing individuals to the next stage (assignment 3) to prevent highly performing individuals from completing all stages of the alone without helping other group members. If the GIM score is less than or equal to zero, then the progress of the learner with the fastest progress will be held up until all members catch up with that learner. After approval by the instructor, the group members can proceed to the final stage of the

task.

As mentioned above in relation assignment 2 (in learning stage 3), when a group member cannot finish the task before its due date, the penalty term in the formula is applied. However, if the group members help each other to complete all tasks of a certain learning stage within the time limit, then the ($T-P_n$) value in the penalty term is calculated as (4-4) = 0. Thus, the term of ($T-P_n$) is called as a pardon mechanism because it will let the value of cumulative penalty term become zero when T is equal to P_n. This pardon mechanism design aims to motivate the "hope" that the high-performance learners who have passed a higher learning stage help their group members with low-performance who have still not passed the learning stage as the high-performance learners. Cohen-Chen & Zomeren (2018) indicated that group efficacy beliefs motivate collective action when these are enabled by hope for social change. Namely, the pardon mechanism encourages group members to help each other whenever possible.

The group performance score encourages learners to collaborate to achieve better results. The CPBL system automatically calculates the GIM scores in each CPBL stage. Short-term group feedback supports learners' personal reflection, motivating them to learn and encouraging participation to improve their learning. Figure 5 shows an image that is displayed on the user interface to provide friendly feedback in real time.

Figure 5. The ranking display of the group accountability based on GIM

4. Research Methodology

4.1 Experimental design

Each learner had to follow a mental process of "cognition", "action 1", "action 2", and "reflection" to solve a target problem that was associated with global warming, using the CPBL system for problem-based learning. The course instructor designed suitable learning scaffolds for

each learning stage to support learning in pursuit of problem-solving. For both the experimental and control groups, the learning activity in the first stage did not include collaborative learning because this learning stage involves assessing the prior knowledge of the learners that is relevant to solving the target problem from the instructor, the social interactions of the learners to each other, and learning roles of individual learners for optimally determining collaborative learning groups. From the second to the fourth learning stages, learners in the experimental and control groups performed collaborative learning activities with GIM and IIM support, respectively. The learning activity in each learning stage lasted for a week. The instruction experiment involved the following three stages.

(A) Pre-test stage
Before the experiment was performed, basic concepts related to experimental design and experimental processes were introduced to the research participants. The research participants then logged in to the CPBL system and practiced basic operations.

(B) Collaboratively learning stage with the support of two incentive mechanisms
The experimental and control groups, with different incentive mechanisms, performed problem-based collaborative learning tasks in the CPBL system. Each learning stage took one week, for a total of four weeks.

In the first learning stage, the learners read the learning scaffolds and the information relating to the target PBL tasks of global warming that was provided by the instructor in the CPBL system. They then were asked to explain what the problem of global warming is. If a learner is unfamiliar with the problem or her/his answer submitted to the instructor is rejected due to incorrect or imperfect, then the learner can search the web for getting more useful information associated with global warming problem that enables the learner to describe the problem accurately, and shares relevant search results with peers. In the process of learning, learners can interact with their peers to solve the target problem by using an instant message function provided by the CPBL system. If learners are not satisfied with the assignment score in this stage, they can modify their submission and upload it again. This approach provides a positive learning experience.

The learning partners of an individual learner in a collaborative learning environment significantly affect interaction and learning performance. In the beginning of the second learning stage, a default optimal grouping method that considers the heterogeneity of learners' knowledge levels and learning roles, and the homogeneity of social interactions, as measured by a social network analysis of the members of the learning group, which was proposed by Liu, Chen and Kuo (2016), is used in the CPBL system automatically to divide students into learning groups of at least four members. The research participants were randomly divided into the experimental group using the GIM and the control group using IIM in the second to fourth stages. In the second to fourth stages, involving a total of three weeks of learning activities, both groups had the same learning conditions except for their incentive mechanisms.

The learners of both the groups have to complete the learning tasks of each learning stage in the CPBL system designed by the instructor within one week. A special function provided by the GIM and IIM is that the due date countdown of submitting an assignment for a certain learning stage begins when the first learner of both the groups submits his/her assignment to the CPBL system for the instructor's evaluation. At that time, all other group members in both the groups will see that they only still have six days to complete their task. Before the due date, a learner can submit his/her assignment at any time. Thereafter, the instructor can determine whether the assignment is accepted or not. The instructor provides a score and feedback for the learners in both the groups by text message. The CPBL system automatically increases the GIM score of a group in the experimental group if one member of the group has submitted the assignment and receives a score of higher than a threshold score set by instructor, while the CPBL system automatically updates the ranking of

social position of a learner in the control group based on the IIM score of the learner getting from helping other peers to solve the target PBL tasks. The purpose of the feedback from the GIM and IIM is to improve the self-awareness and self-regulation of learners and to enable group members to help each other and discuss problems that are encountered.

(C) Post-test stage
At the end of the experiment, the learners in both the groups were asked to evaluate their group efficacy and group cohesiveness by using appropriate scales.

When the last assignment in the learning stage 4 has been completed, the learners in both the groups can integrate all assignments from the learning stages 1 to 4 into a single report as well as the CPBL system automatically summarizes the learning score of each learner in each PBL stage.

4.2 Research participants

The research participants randomly recruited were Grade 4 students aged 10-11 in two classes at a primary school in Taoyuan City, Taiwan. Each class had 24 students. One of the two classes was randomly selected as the experimental group, which comprised ten males and 14 females; this group used the proposed GIM in support of CPBL. The other class formed the control group, which comprised 11 males and 13 females; this group used the IIM in support of CPBL. During the experiment, both groups carried out the four-stage problem-solving learning process in the CPBLS. In the first stage, the learning conditions of the two groups were the same. In the second to the fourth stages, the experimental and control groups used a CPBLS with GIM support and IIM support, respectively, to solve the target problem that was set by the instructor.

4.3 Research instruments

The self-efficacy scale for learning and performance in the motivated strategies for learning questionnaire (MSLQ) (Pintrich, Smith, García, & McKeachie, 1991) was used to design a group efficacy scale with a total of eight items, for the purpose of identifying the participants' group efficacy toward using the CPBLS with the IIM or GIM support to solve a target problem collaboratively. The reliability of the questionnaire was confirmed using Cronbach's alpha (Cronbach's alpha=.884, N=76). The group cohesiveness scale comprised 13 items, and was modified from Zaccaro (1991), Seibold and Kelly's (1988) questionnaires. The reliability of the questionnaire was confirmed using Cronbach's alpha (Cronbach's alpha=.919, N=76). Analytical results confirm that both scales had satisfactory reliability with Cronbach's alpha values in excess of 0.7.

5. Experimental Results

5.1 Analysis of difference between prior knowledge levels of both groups

To determine whether the prior knowledge levels of both groups differed significantly, the independent sample *t*-test was performed on the mean scores of both the groups in the first learning stage of the CPBL system. In the first learning stage, all students in both groups completed the task on time. The result indicates that the prior knowledge levels of both groups did not differ significantly ($t = 0.667$, $p = .502 > .05$), as shown in Table 1.

Table 1. The differences of prior knowledge for the experimental and control groups

The first learning stage score	Number of learners	Mean score	Standard deviation	*t* test for equality of means		
				t	Degrees of freedom	Two-tailed test of significance
Experimental group	24	84.88	8.002	0.667	46	.502
Control group	24	83.29	8.206			

5.2 Analysis of difference in learning performance between groups

In this study, the PBL processes are divided into four learning stages, which are "cognition", "action 1", "action 2" and "reflection." The overall learning process lasts for four weeks. Both groups of learners used the "instant message" functions in the CPBL system to communicate with their peers and help them solve their learning problems. Table 2 shows the number of learners and the pass rates in the experimental and control groups in the four learning stages. In the first learning stage, the pass rates of both groups were 100%. In the second and third stages, the pass rate of the experimental group was still 100%, but it fell to 83.3% in the fourth stage. The pass rates of the control group in the second and third stages were 87.5% and 66.7%, respectively; its pass rate in the fourth stage was only 45.8%.

Table 2. The number of passed learners and passed rate of both groups for the four learning stages

Stage / Group	1st stage		2nd stage		3rd stage		4th stage	
	Number of passed learners	Passed rate	Number of passed learners	Passed rate	Number of passed learners	Passed rate	Number of passed learners	Passed rate
Experimental group	24	100%	24	100%	24	100%	20	83.3%
Control group	24	100%	21	87.5%	16	66.7%	11	45.8%

Whether the learning performance differed significantly between two groups was assessed. Table 3 shows independent sample *t*-test results concerning the learning performance of the two groups. The results demonstrate that the learning performance of the experimental group in the third and fourth learning stages differed significantly from that of the control group (t=3.051, p=.005<.05, t=3.891, p=.001<.05) and that of the experimental group exceeded that of the control group. Table 4 also shows the analytical results that are based on the mean scores from the second to the fourth stage. The results reveal that the learning performance differed significantly between two groups (t = 3.715, p = .001 <.05). The mean score of the experimental group in the second to fourth stages (M = 83.154) significantly exceeded that of the control group (M = 62.742), indicating that the experimental group with the GIM support exhibited better learning performance than the control group with the IIM support. Clearly, the proposed GIM in the CPBL system was more effective than the IIM in improving PBL performance.

Table 3. The independent sample *t*-test results of the learning performance for both groups

Learning stage	Group	Number	Mean score	Standard deviation	t	Two-tailed test of significance
The 2nd stage score	Experimental group	24	84.67	7.993	1.998	.053
	Control group	24	79.29	10.56		
The 3rd stage score	Experimental group	24	86.83	7.4990	3.051**	.005
	Control group	24	65.83	32.872		
The 4th stage score	Experimental group	24	77.96	14.094	3.891**	.001
	Control group	24	43.08	41.586		
Average score from the 2nd to 4th stage	Experimental group	24	83.154	7.6698	3.715**	.001
	Control group	24	62.742	25.8004		

**indicates p<.01

5.3 Analysis of social networks in both groups

The attributes of network density, network diameter, cohesion, and centrality are calculated to analyze the properties of the social networks that were formed in the CPBL process. UCINET software (Borgatti, Everett, and Freeman, 2002) was used to analyze the social network data.

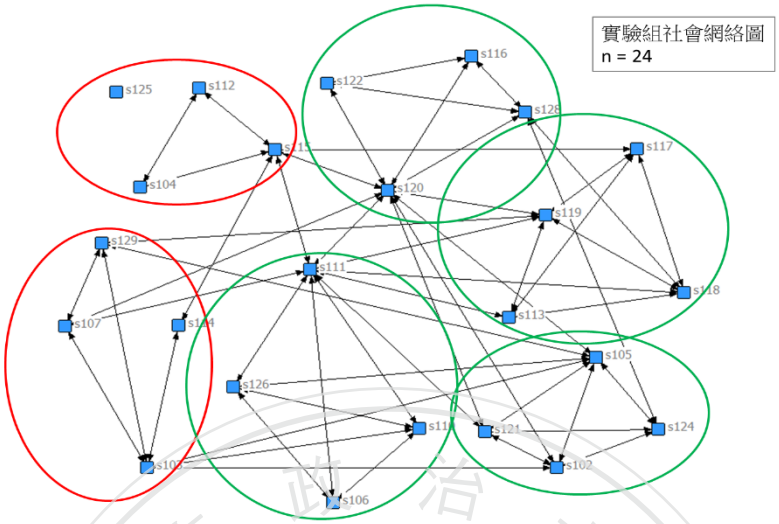
5.3.1 Interaction matrix of learners in both groups

Data concerning the interactions of learners were collected for social network analysis from the instant message application in the CPBL system. An interaction matrix was constructed for the learners based on these data. Whenever a learner responded to an instant message from a peer (such as when A sends a message to B and B responds), then the corresponding (matrix relationship value is 1). If a learner does not respond (as when A sends a message to B, but B does not respond to A), then the corresponding matrix relationship value is 0. The interaction relationships can be expressed as an N × N binary interaction matrix. To normalize the distribution of the abilities of learners in each learning group, the first learning stage in the CPBL system was used to classify learners into collaborative groups of four members that considers the heterogeneity of learners' knowledge levels and learning roles and the homogeneity of their social interactions as determined by social network analysis. In the first learning stage, no incentive mechanism is used, but in the second to fourth learning stages, different incentive mechanisms are used. Therefore, the interaction matrix that is used in UCINET for the social network analyses of both groups is divided into two parts. The first part of the interaction matrix does not have incentive mechanism, corresponding to the first learning stage, and the second part of the interaction matrix has the incentive mechanism that is used in the second to the fourth learning stages in the CPBL system.

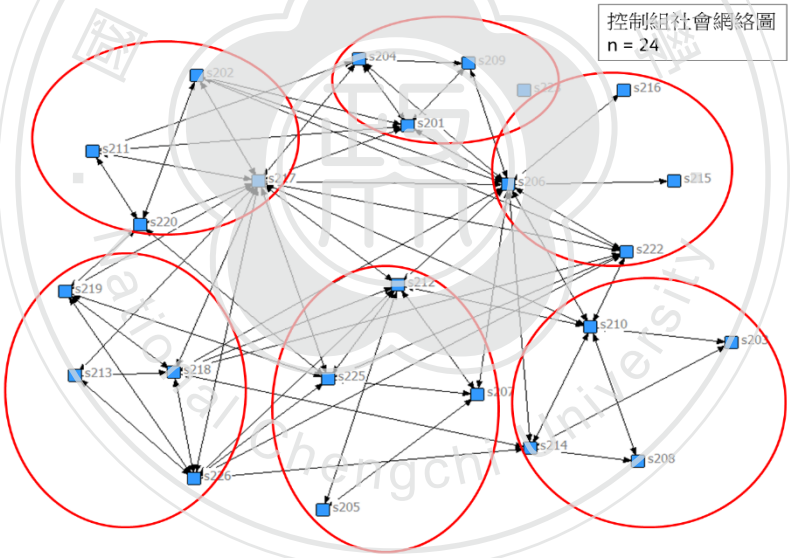
5.3.2 Analysis of structures of social networks in both groups

To study the social network relationships within the experimental and control groups, UCINET software is used to draw diagrams of the social networks of the two groups in the second to fourth stages in the CPBL system, as shown in Fig. 6. In each social network interaction diagram, a double arrow indicates that the learners respond to each other and form an interacting pair. Figure 6 indicates that the network of the control group has more links than that of the experimental group, but 4 of 6 groups in the experimental group form a complete connected network. That is, a link

exists between any group member and other members. In contrast, the control group does not have any group to form a complete connected network. It means that the experimental group using the GIM carried out better collaborative learning in the 4-member group in terms of the information transmission, communication, and collaboration than the control group using the IIM.



(a) The interaction relationship diagram of the experimental group



(b) The interaction relationship diagram of the control group

Figure 6. The interaction relationship diagram of both groups from the second to fourth stages in the CPBL system

5.3.3 Analysis of social network measures in both groups

If learners in a social network do not interact with other learners, then no social network analysis can be performed. Therefore, this study excludes two isolated learners that do not interact with peers, as identified by the social network analysis. One is in the experimental group and the other is in the control group. Then, social network structures of both groups were analyzed. Table 4 presents the results of the analysis of the differences between the social networks of the experimental group and the control group with different incentive mechanisms.

Table 4. The differences of social networks analysis in both groups

Learning stage from the 2nd to 4th stage	Network density	Overall network distance		Degree centrality	Closeness centrality	Betweenness centrality
		Network diameter	Cohesion	Mean	Mean	Mean
Experimental group (n=23)	0.213	2.138	0.360	0.2641	0.3645	0.2477
Control group (n=23)	0.249	1.984	0.428	0.4242	0.4596	0.3039

Network density is social network-related metric that quantifies relationships in collaborative learning. A larger network density indicates more great interaction among the learners. The results of Table 4 indicate that the network density of the control group with the IIM is 0.249, which exceeds the 0.213 of the experimental group with the GIM. Therefore, the IIM is more effective than the GIM in promoting interaction and the willingness of learners. Network diameter is average distance, which is given by the number of learners who pass through one node to another. In this study, the network diameter of the control group is 1.984, which is less than that, 2.138, of the experiment group. The results indicate that the members of the control group with the IIM deliver messages to each other over shorter distances, so the learners receive the information more quickly. The cohesion of the control group is 0.428, which is higher than the 0.360 of the experimental group, indicating that the control group with the IIM is more cohesive than the experimental group with the GIM.

The degree centrality is an individual's capacity to develop relationships with other peers in a CPBL social network. The mean degree centrality of the control group is 0.4242, which is higher than that, 0.2641, of the experimental group, indicating that the control group learners with the IIM were more willing to interact with their peers than were those in the experimental group with the GIM. The mean closeness centrality of the control group is 0.4596, which is lower than that, 0.3645, of the experimental group. Therefore, the overall cohesion of control group learners exceeds that of the experimental group learners. Finally, the mean betweenness centrality in the control group is 0.3039, which exceeds that, 0.2477, of the experimental group, indicating that the network intermediary of the control group with the IIM is higher than that of the experimental group with the GIM.

Although the interaction among the control group learners is superior to that of the experimental group learners, the former is remarkably ineffective in helping peers solve the target problem because the learning performance of the control group is significantly poorer than that of the experimental group. The stronger motivation of the control group learners to interact with their peers is actually to improve their ranking of social position.

5.4 Analysis of differences in group efficacy and cohesiveness between groups

This section assesses whether the group efficacy differed significantly between both groups. Table 5 shows the result of the independent sample t-test. The group efficacy differed significantly between both groups ($t = 2.138$, $p = .038 < .05$). The group efficacy of the experimental group ($M = 29.50$) with GIM significantly exceeded that of the control group ($M = 24.38$) with IIM.

Table 5. Statistical analysis of group efficacy of both groups

Item	Group	Number of learners	Mean	Standard deviation	*t*	Sig. (two-tailed)
Group efficacy	Experimental group	24	29.50	8.787	2.138*	.038
	Control group	24	24.38	7.790		

*indicates p<.05

The cohesiveness of both groups was also evaluated. The result of the independent sample t-test, presented in Table 6, indicates that the mean cohesion (M = 49.54) in the experimental group exceeds that of the control group (M = 43.83), but does not reach significant level (t=1.642, p=.107<.05).

Table 6. Statistical analysis of group cohesiveness of both groups

Item	Group	Number of learners	Mean	Standard deviation	*t*	Sig. (two-tailed)
Group cohesiveness	Experimental group	24	49.54	14.037	1.642	.107
	Control group	24	43.83	9.644		

6. Discussion

The analytical results herein indicate that the learners in the control group with the IIM interacted with their peers remarkably more than did those in the experimental group with the GIM, but the learning performance of the latter was significantly better than that of the former. The reasons warrant discussion. Chen and Chang (2014) demonstrated that a learning group with more interaction exhibits better learning performance in a web-based CPBL environment. Although the social network-related interactions of the experimental group were less than those of the control group, the former was more focused on helping poorly performing group members to solve the target problem and so supported more mutual aid, favoring overall learning performance. Clearly, the interactions of learners in the control group with their peers were more motivated by getting social rank than by helping peers to solve the target problem. Akinbobola (2009) noted that positive interdependence is one of the most important factors that affects the effectiveness of collaborative learning. Tsay and Brady (2010) indicated that designing a learning context that favors the formation of strong collaborative relationships as a common goal can favor collaborative learning performance, because each member of a collaborative learning group must actively help the others to achieve a common learning goal and improve learning. The use of the GIM favors the formation of strong collaborative relationships among members of a group, enabling them to compensate for each other's strengths and weaknesses.

Schimmel (2008) indicated that the most effective collaborative learning involves meaningful interactions among learners, such as the sharing of useful information or knowledge, helping solve problems, or clarifying concepts. Therefore, collaborative learning depends on not only interactions but also and more importantly the quality of the discussions that involve those interactions, on which mutual benefit depends. The GIM that was proposed herein motivates most learners in a collaborative learning group actively to contact other members of the group, improving group effectiveness. Active roles in a collaborative learning group are regarded as contributing to discussions because they facilitate positive group discussions (Gasson & Waters, 2011). Overall, this study demonstrated that the use of the GIM enables individuals to interact more actively and meaningfully with other group members and to balance quality and quantity of discussion, yielding better learning performance than can be achieved using the IIM. Duxbury and Tsai (2010) emphasized that social skills, such as basic etiquette, building a sense of trust, effective communication, and conflict resolution, should be cultivated to achieve highly effective collaborative learning. When learners participate in a discussion without adequate social skills, friction may be generated, thus reducing the effectiveness of the group. In this study, the optimal group formation scheme, based on a genetic algorithm that considers the heterogeneity of learners' knowledge levels and learning roles and the homogeneity of their social interactions as determined by social network analysis, is used to generate collaborative learning groups with balanced learning characteristics (Liu, Chen, & Kuo 2016). The ultimate purpose is to improve students' learning

performance and facilitate their interactions in a collaborative problem-based learning (CPBL) environment (Liu, Chen, & Kuo 2016). Therefore, when the GIM is used to support CPBL, the members of each collaborative learning group with a high knowledge level were expected to help members with a low knowledge level to improve group performance. Hence, high-performance learners were motivated to change their learning habits in CPBL as a result of GIM support. They had to pay much more attention to their group members with low performance for improve group performance. In doing so, high-performance learners may become frustrated by the results achieved by low-performance learners. However, appropriate frustration and stress can remind high-performance learners' responsibilities in a collaborative learning group. Ifamuyiwa and Akinsola (2008) pointed out that a heterogeneous collaborative learning group that considers group members with various learning abilities can improve the self expectation of learners with a low ability, causing them to make even better progress than learners with high or moderate abilities.

This study found that the GIM causes learners with high or low performance to better meet their responsibilities, improving the satisfaction and performance of the learning group, resulting in significantly higher group efficacy than can be achieved using the IIM. This result is consistent with the results of Bandura (1997), who found that learner's experience of success can improve the efficacy of the group. Moreover, Cohen-Chen & Zomeren (2018) indicated that group efficacy beliefs only predicted collective action when hope was high. Remarkably, the pardon mechanism design in the proposed GIM motivated the "hope" that the high-performance learners who had passed a higher learning stage helped their group members with low-performance who had still not passed the learning stage as the high-performance learners make a success of finishing CPBL tasks. This study inferred that this leads to the group efficacy belief of the experimental group with GIM significantly exceeded that of the control group with IIM.

Compared to western learners, Taiwanese students are traditionally shy or passive toward interacting with group members to express their opinions (Chen, Hsu, & Caropreso, 2006). In addition, most Taiwanese students are accustomed to working or studying alone and they rarely have opportunities to collaborate with their peers in doing projects in their schools due to the examination and competition cultures in teaching and learning. Therefore, they easily become passive learners and do not know how to share their feelings or negotiate with others. In other words, most Taiwanese students lack collaborative learning experiences and skills. To develop an effective computer-based collaborative learning system to support students' collaborative learning, Economides (2008) claimed that the system should offer to the learners communication and collaboration tools tailored to their social and cultural characteristics. For example, if a learner is shy, quiet and reserved, then the system may push him to participate in online discussion more actively. Also, if a learner has strong relationships with only few other learners, then the system may try to introduce him to some others and encourage his acceptance. Obviously, the proposed CPBL system with GIM is an effective computer-based collaborative learning system that can facilitate Taiwanese students' collaborative learning processes while solving a target problem together based on considering their culture components. Moreover, collaborative learning groups may co-create a "new learning culture" as well as the cultural co-creation may occur in a computer supported collaborative learning environment that can support diversified cultures (Michailidou & Economides, 2007). Therefore, developing a culture-aware computer-based collaborative learning system would support learners facilitating communication and collaborative learning. But more importantly, at the beginning of a course, instructors should teach collaborative learning skills and encourage learners to familiarize themselves with the instant message function in the CPBLS for group communication mechanism. Since optimized group formation scheme, based on a genetic algorithm, was used by default to form automatically collaborative learning groups based on learners' knowledge levels, learning roles, and social interactions in the first learning stage in the CPBLS, the learning design for solving a target problem in the first learning stage had to encourage sufficient interactions among learners. The experimental time should be appropriately increased to

collect more learning records of learners in the first learning stage of the CPBLS to generate better grouping results.

Despite its important contributions, this study has some limitations. First, instruction time was limited and only a four week-long experiment was performed. The effects of the proposed GIM on web-based CPBL over a much longer period, such as a semester, may differ from those herein. Second, Grade 4 students in an elementary school in Taoyuan City were selected for this study. Whether the research results can be generalized to learners of different ages requires further study. Third, the problem-based learning in the instruction experiment involved proposing solutions to the problem of global warming and the results herein cannot be assumed to apply to other problem-based learning mission.

7. Conclusions and Future Works

This study examines the effects of the proposed GIM, which was applied to the four stages of a CPBL task involved in the CPBLS, on learning performance, interactive relationships, group efficacy, and group cohesiveness of Grade 4 students from an elementary school in Taiwan. Statistical analyses supported the following major findings. First, the experimental group with the GIM exhibited better learning performance than the control group with the IIM in the third and fourth learning stages of the CPBL system. The experimental group also exhibited better overall learning performance than the control group in the second to the fourth stages. A social network analysis was performed for both the experimental and the control groups with their different incentive mechanisms. The control group had a higher social network density, a shorter network distance, a more centralized power distribution, and a higher social network centrality than the experimental group. The group efficacy of the experimental group with the GIM was significantly higher than that of the control group with the IIM. In contrast, the groups did not differ significantly in group cohesiveness. Remarkably, the CPBL system with novel GIM supports a more effective form of CPBL and brings CPBL mode into a new ground.

Finally, the experimental results and participant responses suggest several directions for future work. First, this study involved Grade 4 students. The ability of Grade 4 primary school students is generally not high enough to enable them to take full advantage of the interactive functions in the CPBL system. Therefore, future research can study how the proposed GIM influences the collaborative learning results of learners of other ages. Second, in this study, the three characteristics of interest - students' knowledge levels, learning roles, and social interactions among the members of a learning group – were equally weighted in the formation of collaborative learning groups using a genetic algorithm. Future research should consider how varying these weights influences collaborative learning performance and peers' interactions when using CPBL system with GIM to support PBL.

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