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Development of an Adaptive Game-Based Diagnostic and Remedial Learning System Based on the Concept-Effect Model for Improving Learning Achievements in Mathematics

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ABSTRACT: Although game-based learning strategies have been used in mathematics education for a period of time, the potential for enhancing students' learning achievement and math self-efficacy is still being explored. Students need to face complex mathematics concepts and calculations in mathematics courses. Even though using games to learn mathematics may enhance students' motivation, without efficiently personalized learning guidance, students may not be able to learn well in games. Therefore, adaptive educational games provide opportunities to give students personalized learning content and guidance. The concept-effect relationship is an effective tool for the organization of learning material in developing adaptive diagnostic systems for detecting students' learning problems. In this study, a concept-effect relationship and an interactive game-based learning system were conducted as an effective tool for the organization of learning material in developing a diagnostic and remedial system for detecting students' learning problems. An experiment was conducted on an elementary school mathematics course to evaluate the effects of the proposed approach. The experimental results clearly show that the proposed approach not only improves the efficiency of learning achievement for students, but also enhances their learning attitudes and self-efficacy, and reduces their cognitive load in mathematics courses.

Keywords: Adaptive learning, Personalized learning, Mathematics education, Interactive learning environments, testing and diagnostic system

1. Introduction

In the past decades, several studies have indicated that students face difficulties when learning mathematics, especially elementary school students, who struggle with abstract and complex mathematics concepts such as fractions (Lai & Hwang, 2016; Pilli & Aksu, 2013; Yu et al., 2020). Although formulas taught by teachers could prompt students to solve fraction questions, researchers have indicated that this learning approach might not be sufficient for students to recognize the process of solving the problems (Chu, Hwang, & Huang, 2010). Moreover, it is difficult to attract students to learn boring formulas and correctly apply the fraction concepts to different problems (Chang, Wu, Weng, & Sung, 2012). Researchers have noticed that fractions are crucial for students to learn mathematics well (Zhang et al., 2019). Hence, it is important to consider not only enhancing students' learning interest and attitudes, but also improving their understanding of the complex relationships among concepts while developing their mathematics learning. Besides, researchers have pointed out the need to develop personalized learning guidance to assist students in learning with complex questions or learning scenarios to achieve the above purposes (Chang, Kao, Hwang, & Lin, 2020; Hwang, Chu, Lin, & Tsai, 2011; Hwang, Wang, & Lai, 2021).

With the rapid advancement of technological instruction, one of the well-studied strategies in teaching instruction and learning guidance, the concept-effect relationship (CER), has been proposed and has been widely applied in the domain of education diagnosis models (Hwang, 2003; Lin, Chang, Liew, & Chu, 2015). Structured learning guidance is regarded as an effective approach which promotes deeper understanding in conceptual-knowledge learning, especially for students who have difficulty with the learning material (Chu, Hwang, & Liang, 2014; Panjaburees, Triampo, Hwang, Chuedoung, & Triampo, 2013).

On the other hand, in order to enhance students' active engagement in learning activities, several studies have reported that game-based learning has benefits in terms of stimulating students' learning engagement and higher order thinking. Furthermore, many game-based learning systems have been applied to various educational applications. For example, researchers have noted the importance of the game-based learning approach as an effective technology-enhanced learning approach in language learning (Chiu, Kao, & Reynolds, 2012; Hwang, Shih, Shadiev, & Chen, 2016). Callaghan et al. (2013) reported the positive effect of simulation games on students' learning motivation in electronic and electrical engineering courses. However, researchers have also indicated that without properly incorporating learning supports or strategies, the effectiveness of the game-based learning approach could be limited, especially for the comprehension of mathematical concepts (Chang, Wu, Weng, & Sung, 2012). Hence, the development of an effective instructional approach for supporting game-based learning activities has become an important and challenging topic.

To cope with this problem, in this study, an adaptive concept-effect relationship (CER)-based mathematics game system was developed for conducting mathematics diagnostic and remedial learning activities. Furthermore, an experiment was conducted in the fraction unit of an elementary school mathematics course to evaluate the effectiveness of the proposed approach in terms of the students' learning achievement and learning attitudes.

2. Literature review

2.1. Concept-effect relationship

The idea of concept-effect relationships, or CER for short, was proposed by Hwang (2003). It means that when students learn concepts, the specific order of these concepts has to be considered. The CER model is oriented from the concept map theory which not only provides a tree structure but also defines the systematic learning paths based on those prerequisite relationships. Therefore, the CER model provides a systematic procedure for diagnosing students' learning problems and generating personalized learning guidance (Hwang, 2003). For example, there are two concepts, named C_i and C_j. If C_i is a prerequisite to effectively understanding the more complex and higher level concept C_j, then a concept effect relationship $C_i \rightarrow C_j$ is said to exist. For example, in a mathematics course, to learn the concept "subtraction of fractions," it is necessary to learn "addition of fractions" first, while learning "fractional multiples" first needs learning of "multiplication" and "multiplication of integers" (Chu, Hwang, & Huang, 2010).

Figure 1 demonstrates an illustrative example of the concept–effect relationships among "C_1 Addition of fractions," "C_2 Subtraction of fractions," "C_3 Multiplication of integers," and "C_4 Fractional multiples." This model considers the relationships between prior knowledge and posterior knowledge while planning personalized learning paths. For example, if a student fails to answer most of the test items concerning "C_4 Fractional multiples," the problem is likely that the student has not thoroughly understood "fractional multiples" or its prerequisite concepts (such as "subtraction of fractions" or "multiplication of integers").

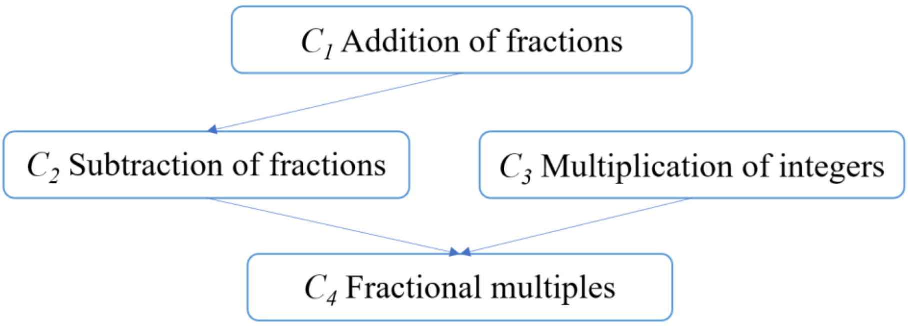

Figure 1. System structure

In the past decades, some researchers have focused on investigating the different applications of concept-effect models to enhance students' personalized learning (Chu, Hwang, & Huang, 2010; Hwang, Panjaburee, Triampo, & Shih, 2013; Wanichsan, Panjaburee, Laosinchai, Triampo, & Chookaew, 2012). For example, Chu et al. (2010) pointed out that students could benefit more if the learning system provided more precise learning guidance to individual students by considering multiple knowledge levels. Wanichsan et al. (2012) integrated test item–concept relationship opinions based on majority density of multiple experts. Their study provides a useful way to decrease inconsistencies in the weighting criteria of multiple experts.

2.2. Personalized and adaptive digital game-based learning

With the rapid development of digital technology and the games industry, game-based learning has become popular in the digital learning field and has found abundant applications in several different disciplines (Chen, Xie, Zou, & Hwang, 2020). Researchers have indicated that digital games can provide complex learning content in its contextual learning environment; therefore, students can explore the learning concepts via interacting with games and adequate media (Ke, 2009; Chang, Kao, Hwang, & Lin, 2020). Previous research has pointed out that game-based learning might be successful because of particular features, such as automatically generated tests or exercises (Hwang, Sung, Hung, Huang, & Tsai, 2012), providing instant feedback (Hwang, Chien, & Li, 2020; Hwang, Xie, Wah, & Gašević, 2020), interaction between the elements in games and the learner, concrete representations (Hwang, Chien, & Li, 2020; Hung, Hwang, Lee, & Su, 2012), and an attractive narrative (Akman & Çakır, 2020).

Researchers have pointed out that effective teaching strategies should be integrated into game-based learning in order to correspond with those effective features and then improve students' learning motivation and learning achievements (Vanbecelaere, Cornillie, Sasanguie, Reynvoet, & Depaepe, 2021; Zhang et al., 2019). For example, Hwang, Sung, Hung, Huang, and Tsai (2012) proposed a cognitive analysis approach to develop a spatial game-based learning system. The spatial game is a kind of Mindtools. Students could learn the spatial concepts while performing different learning tasks such as matching games, treasure hunting, and recognizing different angles. The researchers conducted the cognitive component analysis to derive adequate cognitive components of the task for the students based on their learning performance in the game process. Finally, they found that the system did not just promote the students' learning achievement, but also their spatial sense. Moreover, Hwang, Chien, and Li (2020) found that students might have difficulties organizing what they have experienced in gaming contexts. They proposed a multidimensional repertory grid (MDRG) approach to give students instant feedback. Based on the behavioral analysis and interview results, they concluded that the MDRG approach could benefit students' learning achievement and promote their higher order thinking ability. Recently, Vanbecelaere et al. (2021) proposed an adaptive digital educational game named the Number Sense Game (NSG) to teach children their early numerical abilities. They found that the children in the adaptive condition learned more efficiently compared to those in the non-adaptive condition. Based on this finding, we can conclude that it is important to provide students with instant feedback and personalized learning content and to analyze students' learning process to give them personalized learning guidance while playing educational games (Komalawardhana, Panjaburee, & Srisawasdi, 2021; Xie, Chu, Hwang, & Wang, 2019; Zou, Huang, & Xie, 2019).

Currently, little research has provided instant feedback and diagnosis results to generate personalized learning paths in mathematics game-based environments. Ni and Zhou (2005) pointed out that the concept of fractions is the basis for learning decimals, percentages, and ratios. Moreover, the calculation of fractions is an important foundation for the formal symbolic calculation of rational numbers. Therefore, it is important to develop an adaptive game-based learning system to support individual students to learn according to personalized learning paths in order to match their mathematics ability, especially for the concepts of fractions.

3. Development of an adaptive concept-effect relationship (CER)-based mathematics game

In this study, we present an adaptive concept-effect relationship (CER)-based mathematics game for fractions to assist teachers in grasping students' learning status, and to provide adaptive learning guidance during the gaming learning process. Furthermore, this game incorporates concept-effect relationship learning strategies into the gaming scenarios to assist students in improving their learning attitudes and performance. Figure 2 represents the structure of the proposed adaptive CER-based mathematics game, which consists of the gaming module, the concept-effect relationship module, the learning behavior module, and the learning guidance module. The gaming module provides a scenario that includes scripts, materials, and problem-solving contexts for students. The concept-effect relationship module is in charge of defining the knowledge levels of each learning concept and relationship among the concepts through teachers. Moreover, this module could identify the poorly learned concepts for individual students by analyzing their learning portfolios. Next, the learning behavior module enables teachers to observe students engaged in tasks and their learning status based on the obtained CER results. Lastly, the learning guidance module is used to select appropriate learning material. This module enables students to grasp unfamiliar or poorly understood concepts more quickly, and helps them with concept consolidation and elaboration.

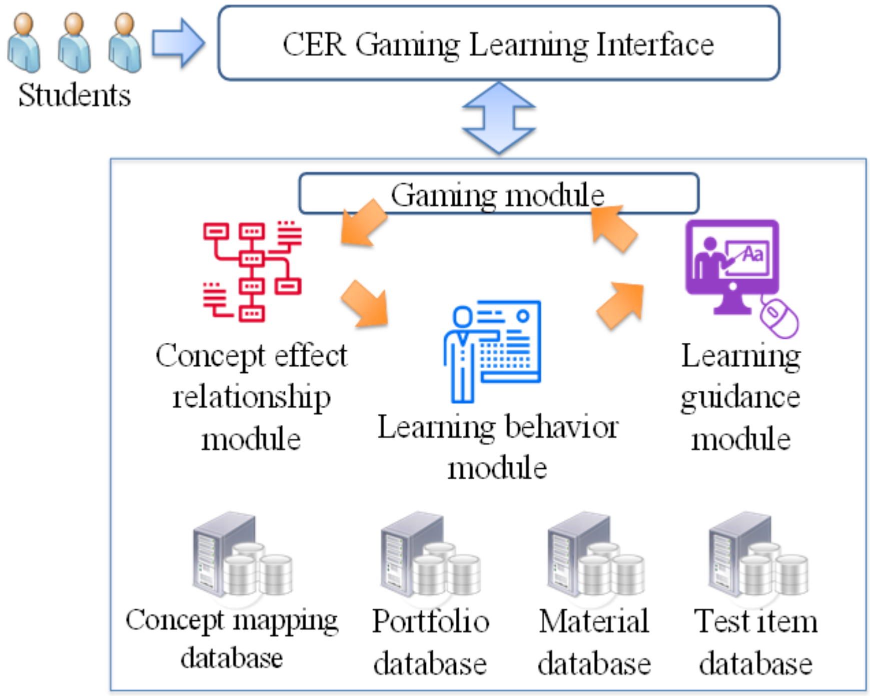

Figure 2. The structure of the proposed game

In this game, students (playing the role of the main character) are asked to find all of the treasures and complete tasks to pass each challenge; that is, the storyline provides students with an opportunity to accumulate knowledge of relevant fraction practices during the gaming process. The accumulated knowledge is recorded in the portfolio database for further learning behavior analysis.

3.1. Assessment model of an adaptive CER-based mathematics game

Recently, CER diagrams have gradually attracted more attention from researchers, and many studies have confirmed that the application of CER diagrams could help improve students' learning achievement by means of appropriate learning feedback (Chen, Chu, & Yang, 2016; Johnson & Johnson, 2002; Hwang, Yang, & Wang, 2013; Inaltun & Ateş, 2015; Nicase, Cogerino, Fairclough, Bcois, & Davis, 2007).

Thus, in order to provide students with appropriate learning feedback by the diagnosis of the CER diagrams, the following steps describe how to use the CER to establish a game-based learning assessment model with guidance and feedback functions, which applies the concept relationship algorithm to figure out students' degree of understanding of the concepts, and the relevance between the students' answers and the correct concepts, to assist educators in providing them with appropriate learning strategies.

3.1.1. Step 1: Establish the concept-effect relationship (CER)

First of all, the learning concepts of mathematics have to be constructed by domain experts, then the relationship among the learning concepts must be described, as well as the sequence of these concepts by using a two-dimensional concept table, as can be seen in Figure 3, in which the fraction unit of mathematics is illustrated as a concept-effect relationship (CER) diagram. Through this diagram, the mathematics teacher can clearly design the instructional plan, learning content and assessments for learning achievement. Accordingly, students are able to learn the critical concepts and the relevance and sequence among these concepts. For example, if students need to understand the meaning of fraction concept (C_4), they must first understand addition and subtraction of integers (C_1), the concept of integers (C_2), and the meaning of equal measures (C_3), and then finally proceed to the unit of fraction meaning (C_4).

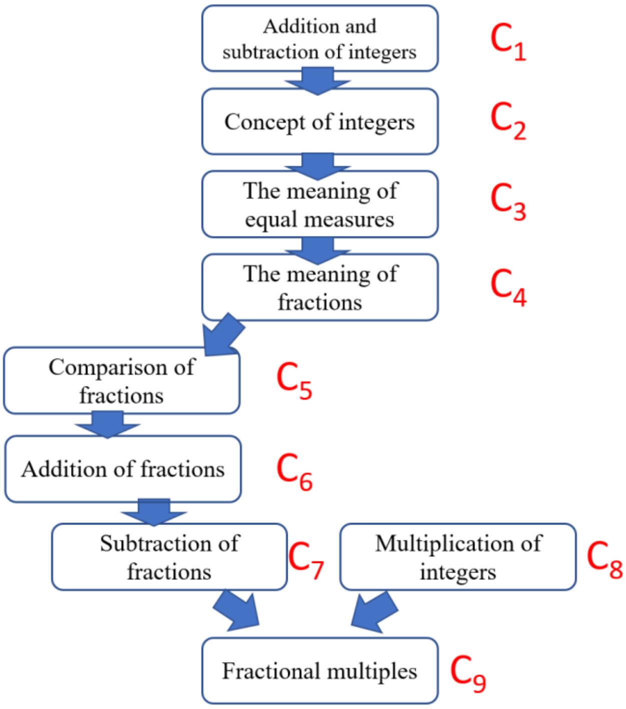

Figure 3. Diagram of CER for the mathematics fraction unit

3.1.2. Step 2: Calculate the student's understanding of different concepts

In order to grasp a student's span of comprehension for each concept, the relationship between learning concepts and test questions is developed by domain experts based on the CER diagram and test questions, as shown in Table 1. The numbers in the table represent the degree of relevance between the test questions and concepts, where the value "0" means not relevant and "9" means highly relevant. For example, C_1 has a weight of "1" in question Q_1 and C_2 has a weight of "3" in question Q_1, which means that question Q_1 contains the concepts of C_1 and C_2 simultaneously, and the weight of this question is 1:3. Accordingly, the weights for all of the concepts are calculated below:

$Sum(C_1)=1+5+3+1=10$; $Sum(C_2)=3+2+2+2=9$; $Sum(C_3)=3+2+2=7$
$Sum(C_4)=1+2+4+2=9$; $Sum(C_5)=4+5=9$; $Sum(C_6)=3+3+4=10$
$Sum(C_7)=1+2=3$; $Sum(C_8)=1+2=3$; $Sum(C_9)=4+1=5$

Table 1. Relevance between concepts and test questions

Q_i	C_j								
	C_1	C_2	C_3	C_4	C_5	C_6	C_7	C_8	C_9
Q_1	1	3	0	0	0	0	0	0	0
Q_2	5	2	3	0	4	3	0	0	0
Q_3	3	2	2	0	5	3	0	0	0
Q_4	0	0	2	1	0	4	0	0	0
Q_5	0	0	0	2	0	0	1	1	0
Q_6	0	0	0	4	0	0	0	0	0
Q_7	1	2	0	0	0	0	2	0	0
Q_8	0	0	0	2	0	0	0	2	0
Q_9	0	0	0	0	0	0	0	0	4
Q_{10}	0	0	0	0	0	0	0	0	1
Sum	10	9	7	9	9	10	3	3	5
$Error(C_j)$	3	3	1	2	4	7	2	1	2
$ER(C_j)$	0.3	0.33	0.14	0.22	0.44	0.7	0.66	0.33	0.4

In order to grasp a student's misconceptions from questions that are answered incorrectly, and then to give them the relevant learning concepts that need to be enhanced, each student's answers to the test items in the mathematics game are collected, and the individual student's answering status table is established, as shown in

Table 2. In the table, the value "0" represents a wrong answer, and the value "1" represents a correct answer. Therefore, Table 2 reflects the number of errors of concept C_j for the student in the test, Error (C_j), and the error rate of the student's answer for each concept C_j, shown with the formula $ER(C_j) = Error(C_j)/Sum$. Thus, Table 1 shows Error(C_j) for each concept below,

$Error(C_1)=3$; $Error(C_2)=3$; $Error(C_3)=1$; $Error(C_4)=2$; $Error(C_5)=4$;
$Error(C_6)=7$; $Error(C_7)=2$; $Error(C_8)=1$; $Error(C_9)=2$;

and shows ER(C_j), error rate of each concept as below:

$ER(C_1)=3/10=0.3$; $ER(C_2)=3/9=0.33$; $ER(C_3)=1/7=0.14$; $ER(C_4)=2/9=0.22$;
$ER(C_5)=4/9=0.44$; $ER(C_6)=7/10=0.7$; $ER(C_7)=2/3=0.66$; $ER(C_8)=1/3=0.33$;
$ER(C_9)=2/5=0.4$

Table 2. Individual students' answering status

Student S_i	Test item Q_k									
	Q_1	Q_2	Q_3	Q_4	Q_5	Q_6	Q_7	Q_8	Q_9	Q_{10}
S_1	1	1	1	0	1	1	0	1	1	1
S_2	1	0	1	0	1	0	1	1	0	1
S_3	1	0	1	1	1	1	0	1	1	1
S_4	0	1	1	1	0	0	1	1	0	1
S_5	1	0	0	0	1	1	1	1	1	1
S_6	1	1	1	1	1	1	1	0	1	1
S_7	0	1	1	1	0	1	0	1	0	0
S_8	1	0	0	0	1	0	1	1	1	1
S_9	1	1	1	1	1	1	1	0	1	0
S_{10}	1	1	1	1	1	0	1	1	1	1

Finally, individual students' span of comprehension for each concept is calculated on the basis of the CER diagram with error rate, as shown in Figure 4.

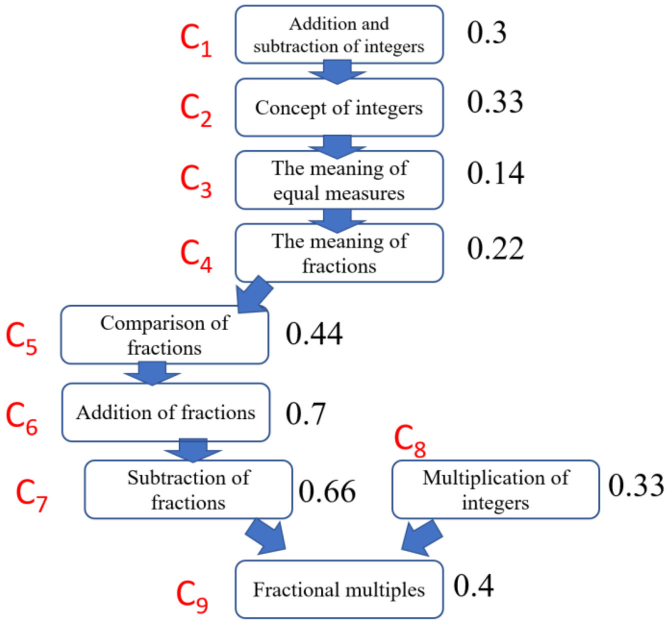

Figure 4. Diagram of weighted CER for fractions with the error rate

3.1.3. Step 3: Learning diagnosis and feedback

Based on the CER diagram with error rate established in step 2, the system finds out the error rate of the student's answer for each concept, and the relationship among concepts. Accordingly, a concept diagnosis and remedial learning path for the student's learning status is conducted.

Suppose that the mathematics teacher sets up the threshold for wrong answers to each concept as $\alpha = 0.28$, which means that the error rates of concepts exceed the threshold, and the system will provide the student with a remedial course for the wrong concepts. Therefore, the system could calculate the student's learning problems through the learning diagnosis mechanism based on the student's formative assessment in the game. From the CER diagram of the student in this example, it is known that the student failed to comprehend the given learning content involving the concepts C_1, C_2, C_5, C_6, C_7, C_8, and C_9. Thus, a follow-up remedial course should be given based on the following results:

$ER(C_1) = 0.30 > \alpha(=0.28)$
$ER(C_2) = 0.33 > \alpha(=0.28)$
$ER(C_3) = 0.14 < \alpha(=0.28)$
$ER(C_4) = 0.22 < \alpha(=0.28)$
$ER(C_5) = 0.44 > \alpha(=0.28)$
$ER(C_6) = 0.70 > \alpha(=0.28)$
$ER(C_7) = 0.66 > \alpha(=0.28)$
$ER(C_8) = 0.33 > \alpha(=0.28)$
$ER(C_9) = 0.40 > \alpha(=0.28)$

It derives three learning paths from the CER diagram for the sequence of concepts below:

Path 1: $C_1 \rightarrow C_2$
Path 2: $C_5 \rightarrow C_6 \rightarrow C_7 \rightarrow C_9$
Path 3: $C_8 \rightarrow C_9$

Therefore, when students have not reached the expected learning concepts, the system performs diagnosis through the concept-effect relationship (CER) and remedial learning paths for the student's learning status, and then recommends suitable learning content and offers additional learning contexts, levels and evaluations for the student's wrong and unfamiliar concepts in the next round of the game.

3.2. System interface and game content

The game flowchart designed in the study is shown in Figure 5. The game is played by students who adopt the role of the protagonist to pass through the different levels by continuously accumulating energy and collecting treasures in the game, in order to obtain the qualification to defeat the Devil. During the learning activities in the game, the events and treasures encountered by students are derived from the learning content of the elementary school third-grade mathematics curriculum. The learning content of the game primarily contains nine units according to the game plot and story, including addition and subtraction of integers, equal measures, integers, unit quantity, the meaning of fractions, subtraction of fractions, comparison of fractions, and fractional multiples. By trying to defeat enemies and gathering treasure in the game, students unknowingly and systematically construct the learning concepts of integers and fractions based on the CER diagram and remedial learning diagnosis. Such a learning model not only increases students' motivation in the game, but also helps them enhance their weaker concepts.

The guidance of the concept-effect relationship (CER) diagram proposed in the study is described as follows.

Once students log into the game, the system will guide them to the starting point to learn the content of each unit, and then assess their learning performance. If students pass the threshold that is set up by the mathematics teachers, they are allowed to enter the next level of the game. For instance, in Figure 6, students start to learn addition of integers at the beginning of the game, and then enter the next level to learn subtraction of integers until they complete the nine concepts and the final test. The test is regarded as a formative assessment to diagnose students' potential errors of nine concepts for the CER remedial learning stage. Students who are given suitable learning content in the remedial process will be required to assess the concept after learning immediately. Finally, the system checks whether the error rate of each concept exceeds the threshold. If not, the course is over; otherwise, the remedial course will be organized and conducted thereafter. The system will provide students with relevant learning content based on the wrong concepts.

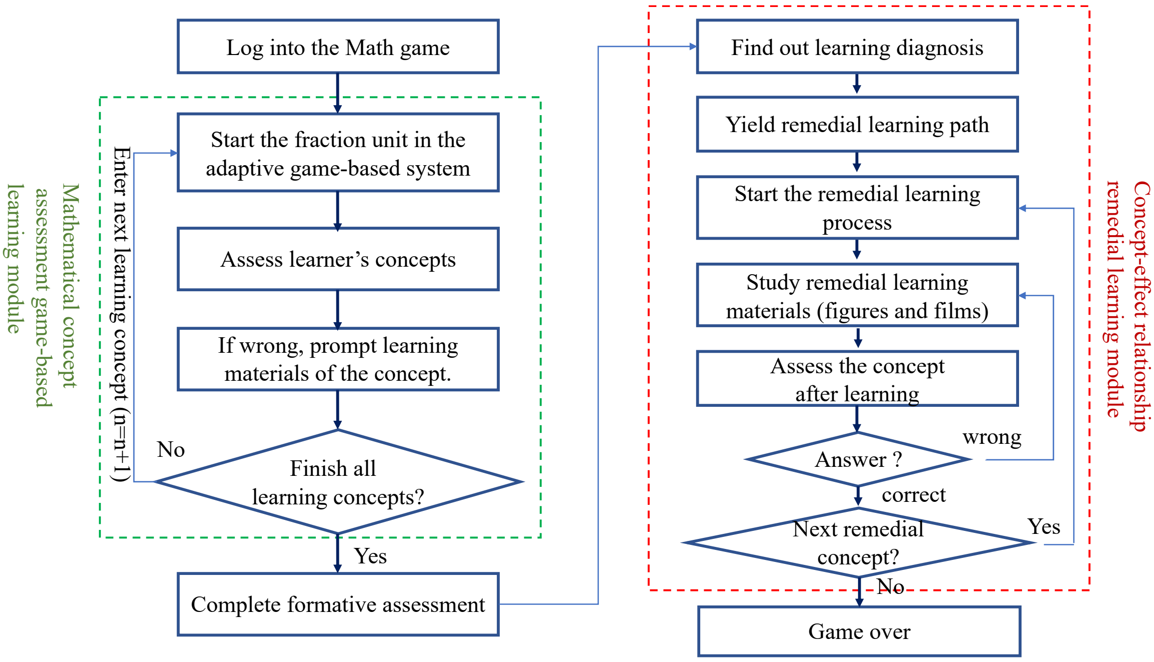

Figure 5. Flowchart based on the CER diagram of the game

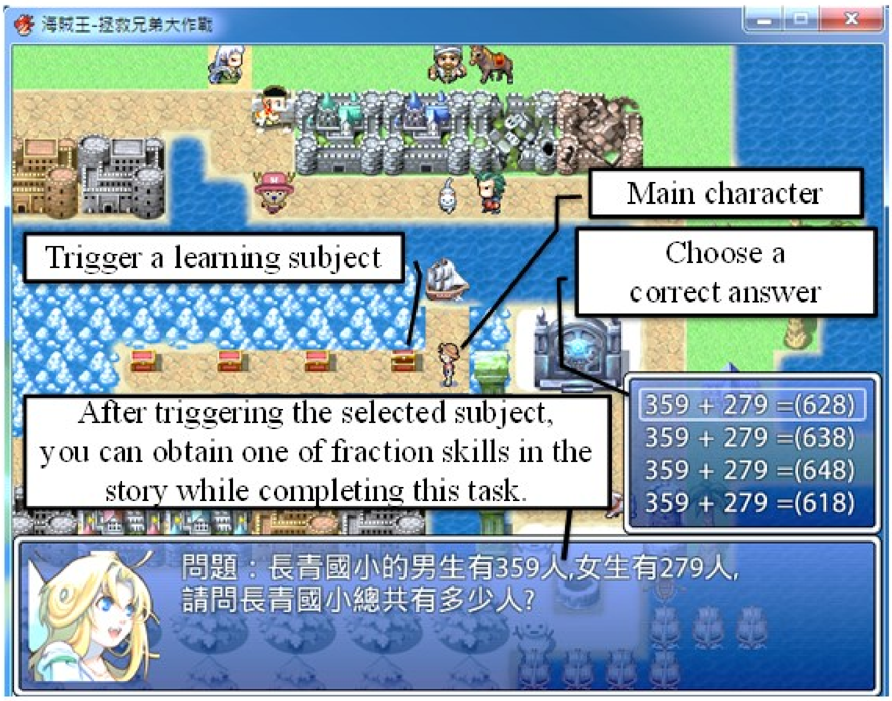

Figure 6. Gaming scenario of triggering the fraction task

After completing the collected treasures and tasks, an adaptive game process is customized by analyzing the students' learning behavior to generate learning guidance for individual students. Moreover, this way provides students with an engaging way to select appropriate learning material, as shown in Figure 7. Meanwhile, if students answer the question incorrectly, the system will give the correct answer and provide the problem-solving steps to address the problem for the student. Figure 7 shows that when the student answers the question correctly, the student will get the energy and treasures in the game, and the system will provide the correct answer for the student to confirm.

By collecting treasures and gaining the ability to defeat the devil, the students can constantly solve problems and make decisions in the game via integrating what they have learned during the game. When students reply to a test item with the correct answer, the system checks and shows a successful message of reward, as shown in Figure 8.

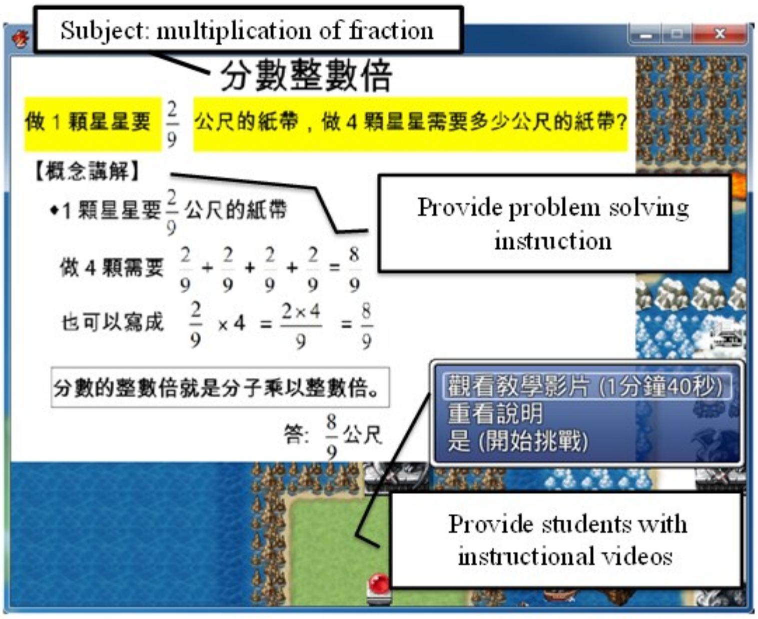

Figure 7. Illustrative example of learning guidance

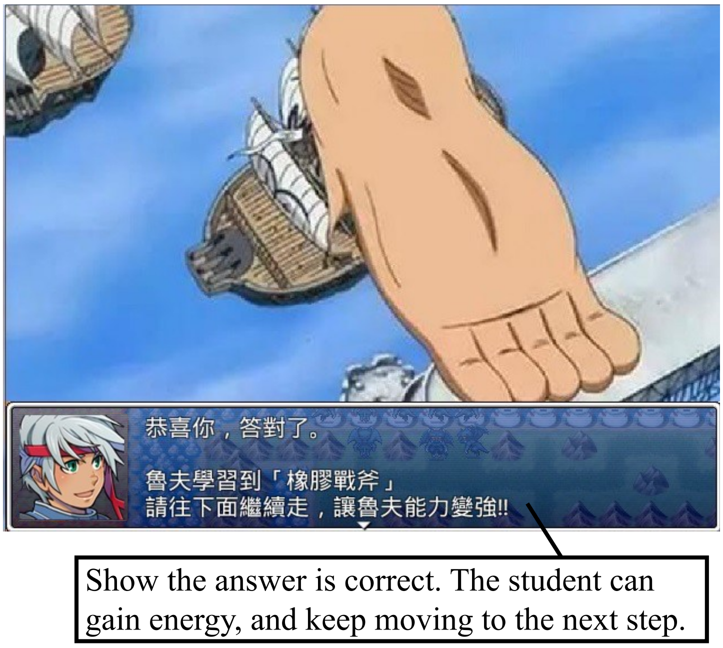

Figure 8. Screenshot of a student's correct answer

Students are asked to go through the learning content with nine concepts and then complete the formative assessment, as shown in Figure 9. The assessment mainly consists of nine concepts with 18 questions, and the system confirms whether the student's answer is right or wrong. After the formative assessment is finished, the system calculates whether the error rate of conceptual questions exceeds the threshold, and if it exceeds the threshold, a remedial course will be conducted, as shown in Figure 10.

Students answer the questions based on their knowledge of mathematics, and the system gives them information about correct or incorrect answers based on the results of their answers. At the same time, the answers that students give are recorded in the system.

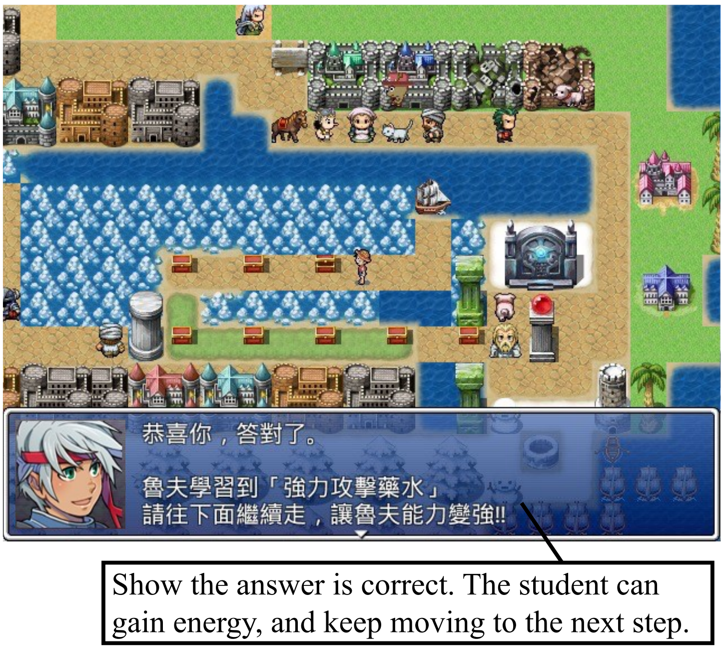

Figure 9. Process of formative assessment

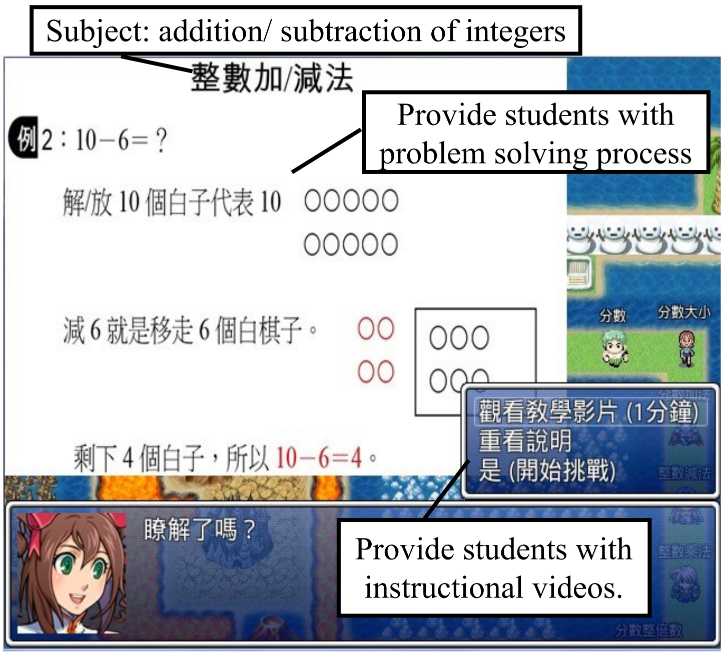

Figure 10. Process of a remedial course

4. Experimental design

This study aimed to evaluate the effectiveness of the proposed adaptive concept-effect relationship (CER)-based mathematics game on the students' learning achievement, attributes, self-efficacy, cognitive load, and mathematics anxiety. A quasi-experimental design was conducted in an elementary school mathematics course in Taiwan. The activity engaged and motivated students to grasp unfamiliar or poorly comprehended concepts related to the curriculum during the gaming learning process. It was expected that the adaptive CER-based mathematics game would be used by the students to more quickly grasp the concepts and the relationships between the learning targets. The experiment is described in more detail in the following.

4.1. Participants

The participants of this study were 116 third-grade students in two classes of an elementary school in northern Taiwan. The average age of the students was 9. Each class consisted of 58 students. A quasi-experiment was designed by assigning the students in one class to the experimental group (26 males and 32 females), while the other class was assigned to the control group (30 males and 28 females). The experimental group learned with the adaptive concept-effect relationship (CER)-based game-based learning (short for adaptive CER-based mathematics game), while the control group learned with the conventional digital game without the concept-effect relationship. In this study, the students in both groups were asked to study the same difficulty level of the assigned materials and learning tasks. All of the students were taught by the same teacher who had more than 10 years' experience of teaching mathematics courses, as shown in Figure 11.

Figure 11. CER game-based learning scenarios for students

4.2. Experiment procedure

Figure 12 shows the procedure of the experiment, indicating that before the learning activity, the two groups of students took a 2-week mathematics course on the basic knowledge of fractions. Moreover, the students took the pre-test and completed the questionnaire of learning attitude and self-efficacy.

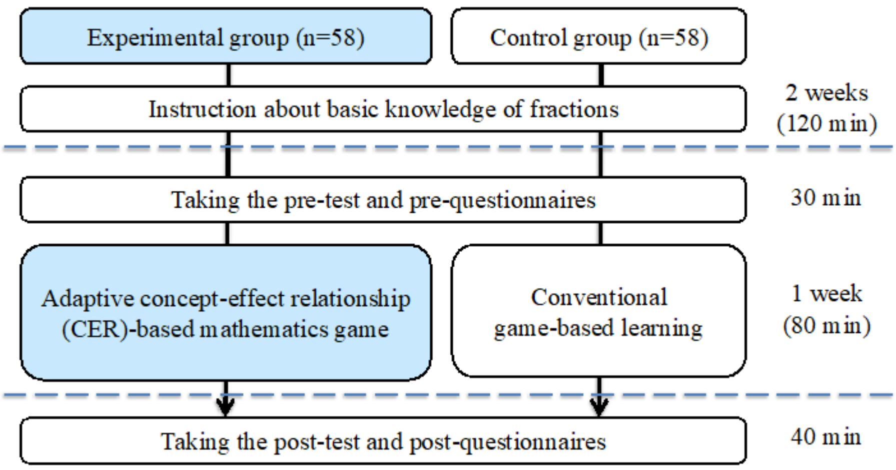

Figure 12. Experiment procedure

During the learning activity, the students in the experimental group learned with the adaptive CER-based mathematics game, while the students in the control group learned with the conventional digital educational game without any CER guidance. The students in both groups were scheduled to learn by playing the educational digital games and were asked to complete all learning tasks based on the same gaming scenarios, learning missions and learning content.

After the game-based learning activity, the students took the post-test and post-questionnaires including learning attitude, self-efficacy, cognitive load, and mathematics anxiety, in order to compare the learning achievements and the improvements of the two groups.

4.3. Measuring tools

In this study, the measuring tools included a pre-test, a post-test, and the questionnaire for measuring the students' learning achievements, attitudes, self-efficacy, cognitive load, and mathematics anxiety.

To evaluate the effectiveness of the students' performance, a pre- and post-test were implemented by two teachers at the Taiwanese elementary school. The pre-test aimed to identify any differences in the students' prior knowledge of learning the course unit. It consisted of eight mathematics word problems, giving a perfect score of 100. The post-test consisted of four matching problems and 20 mathematics word problems for assessing the students' knowledge of the fraction unit in mathematics. The perfect score of the post-test was 100.

The questionnaire of learning attitude and self-efficacy was modified from the measure developed by Wang, Chu, and Hwang (2010). It contains seven items using a 5-point Likert scale rating scheme. The Cronbach's alpha value of the questionnaire reaches 0.91, which shows the high internal consistency and reliability of the scale (Cohen, 1988; Bryman & Cramer, 1997).

The cognitive load scale was modified by Hwang, Yang, and Wang (2013) based on the cognitive load measures proposed by Sweller, Van Merriënboer, and Paas (1998). It consists of two dimensions, mental load and mental effort. Mental load is regarded as the intrinsic cognition load which represents the difficulty level of the interaction between the subject materials and learning tasks. Mental effort is referred to as the extraneous cognitive load which is associated with the pressure of the instructional design, teaching methods and learning strategies; that is, the mental effort refers to the degree of difficulty and suitability of the instructional materials. There are eight items with a 5-point Likert rating scheme, including five items for mental load and three for mental effort. The Cronbach's alpha values of the two dimensions are 0.92 and 0.90, respectively, which shows high internal consistency and reliability of the scale (Cohen, 1988; Bryman & Cramer, 1997).

To realize the influence of the students' mathematical anxiety during the learning process, the questionnaire of mathematical anxiety was modified from the measure developed by Lim and Chapman (2012). It contains five items using a 5-point Likert scale rating scheme. The Cronbach's alpha value of the questionnaire reaches 0.91, which shows the high internal consistency and reliability of the scale (Cohen, 1988; Bryman & Cramer, 1997).

5. Experimental results

5.1. Analysis of learning achievement

To evaluate the effectiveness of the proposed approach, an experiment was conducted on a mathematics course taught at an elementary school in Taiwan. The results show that the mean values and standard deviations of the pre-test scores were 72.10 and 16.37 for the control group, and 70.31 and 17.19 for the experimental group. Here, the t-test result (t = -0.575, p > .05) reveals that the control and experimental groups were not significantly different.

After the learning activity, this study performed a one-way independent-samples analysis of covariance (ANCOVA) to examine the difference between the two groups on the students' fraction performance. Moreover, this analysis used the pre-test scores as the covariate and the post-test scores of learning achievement as dependent variables, as shown in Table 3. The adjusted mean value and standard error of the post-test scores were 69.48 and 1.49 for the control group, and 78.37 and 1.49 for the experimental group. According to the results (F = 17.85, p < .001), there was a significant difference between the two groups, implying that the students who learned with the adaptive CER-based mathematics game showed significantly better learning achievements than those who learned with the mathematics game without the concept-effect relationship (CER) approach. Furthermore, in terms of η^2 described by Howell (2002), with large (η^2 > 0.138), moderate (η^2 > 0.059), and small ($\eta^2 > 0.01$) effects, the ANCOVA results of the proposed learning model gave a large effect size, with $\eta^2 = 0.14$.

Table 3. ANCOVA results of the post-test scores

Groups	*N*	Mean	*S.D.*	Adjusted mean	Std. error	*F*	η^2
Experimental group	58	78.03	11.46	78.37	1.49	17.85^{***}	0.14
Control group	58	69.81	14.15	69.48	1.49		

Note. $^{***}p < .001$.

5.2. Analysis of mathematics self-efficacy

To realize the effect of the proposed approach on the students' learning self-efficacy, a pre-questionnaire was used to measure their self-efficacy before the experiment. The results show that the mean values and standard deviations of the self-efficacy degrees were 3.94 and 0.56 for the control group, and 3.97 and 0.48 for the experimental group; meanwhile, the *t*-test result ($t = 0.358$, $p > .05$) revealed that the difference in the control and experimental groups' learning self-efficacy was not significant.

After completing the game-based learning activity, ANCOVA was used to compare group differences in mean self-efficacy ratings by excluding the impacts of the pre-questionnaire ratings. Table 4 shows the ANCOVA result of the post-questionnaire ratings of the two groups. The adjusted means of the experimental group and the control group were 4.44 and 4.09. Moreover, it was found that the experimental group had significant differences on the self-efficacy ratings, with F = 14.25 ($p < .001$). In addition, ANCOVA results of self-efficacy represented a moderate effect size ($\eta^2 < 0.059$) for the experimental group (Howell, 2002). The results indicate that the game-based learning system based on the concept-effect relationship approach could enhance the students' self-efficacy more than the conventional game-based learning in mathematics.

Table 4. ANCOVA results of self-efficacy of the two groups

Groups	*N*	Mean	*S.D.*	Adjusted mean	Std. error	*F*	η^2
Experimental group	58	4.44	0.48	4.44	0.66	14.25^{***}	0.11
Control group	58	4.09	0.52	4.09	0.66		

Note. $^{***}p < .001$.

5.3. Analysis of learning attitudes

Table 5 shows the independent t-test result of the students' learning attitudes. According to the results ($t = -0.74$, $p > .05$), before the learning activity, the t-test result showed no significant difference between the pre-tests of the two groups.

After the learning activity, the mean values and standard deviations of the post-test scores were 4.55 and 0.57 for the experimental group, and 4.15 and 0.54 for the control group. In addition, the independent t-test results of learning attitudes represented a moderate to large effect size ($d = 0.73$) for the post-test level between two groups (Cohen, 1988). In Cohen's criteria, if the Cohen's d value is greater than 0.8, it is considered as a large effect. The results showed that the learning attitudes of the students in the experimental group were significantly more positive than those of the students who learned with the game without the concept-effect relationship approach.

Table 5. The independent *t*-test results of learning attitudes for the two groups

	Group	*N*	Mean	*S.D.*	*t*	*d*
Pre-test	Experimental Group	58	3.93	0.55	-0.74	0.13
	Control Group	58	4.00	0.49		
Post-test	Experimental Group	58	4.55	0.57	3.79^{***}	0.72
	Control Group	58	4.15	0.54		

Note. $^{***}p < .001$.

5.4. Analysis of cognitive load

In this study, the cognitive loads of the two groups of students were measured by investigating the effect of mental effort and mental load. As shown in Table 6, the total scores of both mental effort and mental load range from 1 to 5, with a median of 3.

In terms of mental effort, there is no significant difference between the two groups of students (t = -1.01; p > .05). The result showed that the mean values of the two groups of students showed relatively lower values considering that the questionnaire uses a 5-point Likert scale (i.e., corresponding to a low workload level or higher effort). That is, it can be seen that suitable mental effort might be good for students to enhance their learning achievement, implying that the proposed game-supported educational scenario and friendly game interface might facilitate the reduction of the learning pressure in the mathematics learning process.

On the other hand, mental load is concerned with intrinsic cognitive load, which represents the degree to which students need to engage in cognitive processing in order to handle the challenging tasks. The students in both groups were asked to study assigned materials and learning tasks with the same level of difficulty. From the experimental results in Table 6, the means and standard deviations were 2.21 and 1.11 for the experimental group, and 2.74 and 1.23 for the control group, showing that there was a significant difference in the mental load of the two groups (t = -2.46; p < .05; d = 0.45). In addition, the independent t-test results of cognitive load reached a moderate effect size for mental load between the two groups (Cohen, 1988). This implies that, owing to using the concept-effect relationship approach, the students could engage in deeper understanding in conceptual-knowledge learning, especially those who had difficulty with the learning material, and it reduced their burden in the learning process. As a result, the experimental group did not have a higher mental load.

Table 6. The independent *t*-test result of the cognitive load of the two groups

	Group	*N*	Mean	*S.D.*	*t*	*d*
Mental effort	Experimental Group	58	2.89	1.31	-1.01	0.19
	Control Group	58	3.12	1.06		
Mental load	Experimental Group	58	2.21	1.11	-2.46*	0.45
	Control Group	58	2.74	1.23		

Note. $^{*}p$ < .05.

5.5. Analysis of mathematics anxiety

Reducing students' mathematical anxiety has been recognized as an important and challenging issue. Moreover, studies have indicated that lower learning anxiety has a more positive effect on learning achievement while engaged in mathematics learning (Fast et al., 2010; Maloney et al., 2015; Vukovic et al., 2013). In this study, a post-questionnaire was used to measure the participants' mathematical anxiety after the experiment. Table 7 illustrates the independent t-test result of the mathematical anxiety of the two groups. The results showed no significant difference in the mean score for mathematical anxiety between the two groups (t = -1.16, p > .05, d = 0.22). In addition, the independent t-test results of mathematics anxiety represented a small effect size (d < 0.5) for the mental effort and mental load between the two groups (Cohen, 1988), implying that the proposed game-based learning approach based on the concept-effect model may lower anxiety and have a positive effect on depression.

Table 7. *t*-test result of mathematics anxiety of the two groups

Group	*N*	Mean	*S.D.*	*t*	*d*
Experimental Group	58	2.10	0.86	-1.16	0.22
Control Group	58	2.33	1.19		

6. Discussion and conclusions

In this study, an adaptive concept-effect relationship (CER)-based mathematics game was developed for conducting mathematics learning activities. An experiment was conducted in a fraction learning activity to evaluate the performance of the proposed approach.

The experimental results demonstrated that, in comparison with the adaptive CER-based mathematics game with conventional game-based learning, the proposed approach significantly improved the students' learning achievements. That is, students in the experimental group conducted the adaptive CER-based mathematics game approach to learn the mathematical concept of fractions. The system could diagnose whether students comprehended concepts for each learning task. Based on the learning diagnosis, the system would offer additional learning tasks for students to remedy the poorly understood concepts. The research findings are consistent with previous studies, indicating that the learning achievement of learners could be enhanced via learning diagnosis after regular learning activities (Chu, Hwang, & Huang, 2010; Panjaburees, Triampo, Hwang, Chuedoung, & Triampo, 2013; Wongwatkit, Srisawasdi, Hwang, & Panjaburee, 2017; Wang, Lin, Hwang, Kung, & Chen, 2017).

As for the learning attitudes of the two groups, the experimental group students had significantly better learning attitudes than those who learned with the game without the concept-effect relationship approach. From this finding it could be inferred that the adaptive CER-based mathematics game approach diagnoses students' learning concepts, and strengthens their weaker concepts by offering remedial courses in fractions. Generally, students thought their mathematics learning performance was enhanced via the proposed approach, and were willing to continually learn the content with the adaptive CER-based mathematics game approach. This finding is consistent with previous studies, showing that improvement in learning achievement for learners could positively change their learning attitudes (Hwang, Wu, Chen, & Tu, 2016; Chuang, Hwang, & Tsai, 2018).

As for the mathematics self-efficacy of the two groups, although the finding shows no significant difference between the two group, students in the experimental group expressed higher positive confidence than those in the control group. This implies that students who adopted the adaptive CER-based mathematics game approach could learn better than students who learned with the conventional game-based learning approach. Thus, students in the experimental group were willing to put more effort into fraction learning and learn more important concepts about fractions. This finding is consistent with previous research, indicating that a good learning approach could motivate learners' self-efficacy as well as enhance their learning performance (Lai, Hwang, & Tu, 2018; Hsia & Hwang, 2020).

As for the two groups' cognitive load, although the finding shows no significant difference between them in terms of mental effort, students in the experimental group expressed lower mental load than those in the control group. From this it can be inferred that the adaptive CER-based mathematics game approach can enable students to engage in further training in conceptual-knowledge learning, especially those who have poor comprehension of the learning material, and thus it reduces their burden in the learning process, and then reduces their mental load. This implies that a good learning approach could facilitate learners' critical thinking and deep understanding of the important concepts, and finally enhance their learning achievements (Hwang, Kuo, Chen, & Ho, 2014; Wu, Hwang, Yang, & Chen, 2018).

As for the mathematics anxiety of the two groups, although the finding shows no significant difference between them, students in both groups expressed low mathematics anxiety, indicating that the game-based learning approach can motivate students' learning and reduce their anxiety during mathematics learning tasks. This finding is consistent with previous studies, showing that a learning approach with playfulness and joyfulness could raise learners' learning motivation and lower their anxiety, especially in complex courses (Hwang, Hung, & Huang, 2014; Yang, Chang, & Hwang, 2020).

In the near future, several extended studies can be considered; for example, the investigation of the proposed approach combined with a cooperative learning strategy, Team Assisted Individualization (TAI), can be probed to determine the effectiveness of team-based learning support in mathematics. It is expected that such a social learning setting could help low-achieving students in mathematics in an interactive way more than individual approaches. Moreover, we plan to develop other interactive and tutoring tools by using Artificial Intelligence (AI) technologies, which provide students with an engaging way to increase the effectiveness of tutorial interactions and diagnose students' learning obstacles.

Besides, it is necessary to strengthen the system function for teachers to construct CER diagrams quickly and properly. Currently, it is time-consuming for teachers to construct accurate concepts of subjects during the preparation of the instruction plan. Thus, if domain experts could construct domain concepts collaboratively via the learning system, the subject teachers would be able to easily and quickly complete the CER for the course.

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