Building an asynchronous HTML5-related competency-based guided e-learning system

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Abstract. Improving learner behavior and attitude is one method for improving learning quality. However, every student has unique characteristics, which makes the prediction of how learning behavior alters learning effects challenging. Humans obtain knowledge through cognitive learning, which can be effectively taught using asynchronous e-learning systems. However, these systems require self-study and include tedious processes that can affect learner motivation and the overall learning effect. This study implemented an HTML5-related competency-based guided e-learning (CBGE) system with an embedded competency-based guided learning (CBGL) mechanism to implement a personalized learning environment. Moreover, learner behaviors were recorded in a log dataset for data mining. The results revealed that the participants were satisfied with the CBGL mechanism and e-course design. The cognitive ability of the participants significantly improved after the experiment. Moreover, the growth in cognitive ability of the participants who completed the guiding process was significantly higher than that of the participants who did not finish the guiding process. This indicates that cognitive ability was improved through the CBGE system and the completion of the CBGL process provided a significantly more pronounced learning effect. A decision tree technique was also employed to construct a predictive model of the learning effect that could help learners achieve the learning objective. The predictive model revealed that learners who used the CBGE system could not achieve the learning objective without passing the stage tests a minimum of 2.5 times. Thus, the number of times that the stage tests were passed was the critical factor in achieving the learning objective.

1. Introduction
Improving learners’ behavior and attitude is one method for improving learning quality [10]. However, every student has unique characteristics, which makes the prediction of how learning behavior alters learning effects challenging [9].

Humans obtain knowledge through cognitive learning. Currently, numerous online test systems exist for cognitive learning. Most of these systems involve asynchronous drills and include practice e-learning systems that employ cognitive question banks. These systems provide immediate feedback by using sequential training processes to determine the cognitive knowledge of the learner. Such systems are often used in education to assist in teaching. However, asynchronous e-learning without teacher assistance coupled with tedious learning processes negatively affects learner motivation and outcomes. This is a critical concern for many teachers; thus, studies that seek to overcome these problems are of clear importance.
In the 1970s, academicians determined that humans obtain cognitive abilities, such as knowledge and memory, according to the principles of the theory of behaviorism [2]. Cognitive development is the first stage of humans recognizing the world around them. Humans continuously gain knowledge through cognitive stimuli, cognitive responses, and experience feedbacks (S–R–F). A computer-assisted testing system is a digital drill and practice learning tool. Digital drill and practice learning is a type of e-learning method that integrates behaviorism and is usually used in cognitive ability learning. The cognitive stimulus and cognitive response (S–R) association model is formed from continuous stimuli and responses and is strengthened by feedback. The behaviorism model is illustrated in Figure 1. Appreciation and reward provide positive reinforcement and punishment restrains wrong behavior. The principle of contiguity emphasizes immediate feedback and states that events that occur together are likely to become associated. The principle of exercise emphasizes continuous practice as a route to attaining mastery. Therefore, applying the correct response in the shortest time through continuous exercise can be emphasized through a curriculum designed to strengthen the S–R association. In the drill and practice e-learning system, questions act as a stimulus and answers act as a response. The system adds points when the answer is correct and deducts points (negative feedback) when the answer is incorrect. The reward and punishment come from the immediate feedback (as in the principle of contiguity). Moreover, learners using this system must practice continuously (as in the principle of exercise). The drill and practice e-learning system can be a useful tool for accelerating the S–R–F process in cognitive knowledge learning. Li employed this process to propose an algorithm known as the proficiency-based learning algorithm. This algorithm is quite suitable for knowledge-oriented courses, which are designed to employ several items with standard answers [17]. However, because the system emphasizes continuous practice to increase efficacy, it can cause boredom among students and does not motivate learners or encourage self-study [7].

Figure 1. Behaviorism model.

Computer-assisted instruction (CAI) is generally used in interactive functions to introduce learning materials and provide an individual or individualized teaching environment. The benefits of CAI include increased interaction opportunities, individualized instructional requirements, immediate feedback, study motivation, and easy-to-monitor learning. Personalized learning is widely used in education [5]. In the out-of-classroom learning process of online learning systems, students can select personalized activities. These systems progressively increase the difficulty of activities and provide a personalized learning schedule. As students progress through their schedule, they experience a feeling of satisfaction and increased motivation. This is a form of personalized purpose that enables learners
to have a more favorable learning experience and outcome [8]. The inclusion of stages allows a personalized design that is similar to a computer game, which gradually promotes users through different levels [3, 6]. Competency-based guided learning (CBGL) theory emphasizes that students be the masters of the learning process and also emphasize individual differences among students. CBGL theory involves stages. The cognitive learning material is usually always presented in a fixed question bank. When the learning material is in a fixed range and can be separated into several units, e-learning systems using CBGL can be based on the different levels of every unit to schedule a personalized learning path and effectively guide learners through their study [4]. The stimuli and building methods in e-learning environments directly affect students’ learning, and students’ attitudes to learn clearly affect the learning effects in such environments [1]. When e-learning environments record users’ behaviors, a large, logged dataset is available to researchers for analysis for exploring users’ behavior models [11, 16].

Therefore, this study used Internet technologies to develop a web-based asynchronous drill and practice e-learning system employing an HTML5-related cognitive course. The system embedded a CBGL mechanism to develop a personalized learning environment that guided learners to study in stages to promote positive learning effects. The logged dataset recorded learners’ learning behaviors. Then, a decision tree technique was employed to analyze the logged dataset to explore why the boring and lengthy learning processes of asynchronous drill and practice e-learning systems result in poor learning effects. Finally, based on the findings, a predictive model was developed to determine successful learning among learners using such systems.

2. Related work
To tutor technicians, teachers use the test to check the performance of students’ study. Testing methods have changed from traditional paper tests to computer-aided testing. By using the system, teachers can provide results instantly and be unrestricted vis-à-vis time and place. In this study, the discipline of level C technician for computer software application was used to the experimental material. This study proposed a proficiency-based learning algorithm by observing the training processes of technicians. The proposed algorithm was embedded in the computer-aided testing system. The newly developed system contained a proficient learning mechanism. This system is quite suitable for question-based knowledge-oriented courses. However, the system only provides a fixed sequence of activities in the learning path for every learner and repeats this sequence until learners are proficient. The learning material is not adaptive. Moreover, because the system emphasizes continuous practice to increase learning efficacy, boredom can be caused among learners and their motivation can be affected [17].

Hsu and Li revealed that when the learning material is in a fixed range and can be separated into several units, e-learning systems using the CBGL algorithm can be based on different levels of every unit to schedule a personalized learning path and effectively guide learners through their study. Before study, a learner is guided to a pretest, and the learner’s cognitive ability for each unit is analyzed. The algorithm then generates an adaptive learning path according to the cognitive abilities of the learner. The system guides the learner to learn proficiently with the learning path. The question bank interface is also redesigned for open and closed answers so that learners do not memorize answers when they study and they can internalize and absorb. If the cognitive abilities of some units tested in the pretest already attain the expected goal, then the system does not guide learners to study. By using this method, the study period can be reduced without affecting the learning outcomes [4].

Predictive studies have been widely used in education to provide strategic information related to teaching, learning, and researching which variables predict certain educational outcomes [23, 24, 25]. Data mining allows the discovery and abstraction of knowledge from one or many large-scale databases, data warehouses, and other information sources [11, 12, 13, 21]. A typical procedure of knowledge data discovery includes five stages: data preprocessing, data transformation, data mining, data visualization, and data interpretation [15]. Data mining has been applied to web-based educational systems to discover unique data patterns [11, 14, 19, 22]. The gradual increase in the
availability and quality of educational datasets and data mining algorithms indicates that educational data mining has become a crucial research domain that combines the fields of education and information or computer sciences [10, 14, 18, 20, 21]. The decision tree method is a well-known and standard approach in data mining and has been widely used in data science since the 1980s. The decision tree method has been widely used in many studies pertaining to education [26, 27, 28, 29, 30].

3. Proposed methods
This section introduces the system model, cognitive e-course design, the design of the adaptive, personalized learning cognitive e-course, and the method used to record user behavior logs. This study employed PHP6, HTML5, CSS3, JavaScript, and MySQL to implement an HTML5-related competency-based guided e-learning (CBGE) system. The system website can be found at http://lcs.dk.ntc.edu.tw/~lcs/mtahtml5etask_ng/.

3.1. System model
The system model is illustrated in Figure 2. The system contains four major elements: a user, asynchronous HTML5-related CBGE system, webpage server, and database server. The system was based on an asynchronous drill and practice e-learning system. The e-learning course was focused on HTML5-related cognitive knowledge by using a question bank. The CBGL algorithm was integrated into the cognitive e-course so that the system could arrange the learning stages according to learners’ cognitive abilities. This method guided the learners in a self-study mode without any assistance from a teacher.

For studying, users were permitted to use any device, such as notebook personal computers, tablets, and smartphones, that was capable of accessing the webpage. Because the system was accessed through the Internet, users were able to log into the system to study at any location with Internet access.

![Figure 2. System model.](image)

3.2. Design of the cognitive e-course and personalized learning
Online test systems are often used to verify learning effects by using question banks as the learning material.

Programming is a standard course in the departments of information engineering and information management and is also becoming a common subject in many other areas. Numerous programming languages exist. HTML5 is the newest front-end programming language for website development. This study employed a cognitive question bank based on HTML5 as the learning material and the CBGL algorithm to categorize the content into five learning units that included 257 questions. The system then developed the e-course interface based on the question bank. Training courses for
HTML5 programming include two parts—cognitive knowledge and practical technique. These parts cover HTML5, CSS3, JavaScript, and jQuery. Cognitive knowledge can be learned using an e-learning system to increase teaching efficiency; this allows teachers to focus on teaching practical techniques.

Students and teachers rarely access e-learning systems simultaneously during asynchronous e-learning. Therefore, the system must explain the meaning of its answers and assist the students as a teacher might do. Constructivism theory was employed to design a system interface that clearly indicated the meaning of the answers. Two types of interfaces were designed—closed and open solutions (Figure 3). The closed solution interface sought to directly explain the reason behind the answer. By contrast, the open solution interface used hyperlinks connected to learning resources on the Internet to provide students with their own space to think about and comprehend the related information. Through this method, students could come to understand the answer rather than simply memorizing the answer. This learning method enabled them to realize a cognitive link through their personal experience.

Figure 3. Design of the cognitive learning interface.

Figure 4. Algorithmic process of the CBGL system (Hsu and Li, 2015).
If the cognitive learning material is contained within a question bank, which has a fixed range and is separated into five units, then the CBGL algorithm can be used to generate personalized learning paths according to the different cognitive abilities of its users, with the system guiding users to study in stages [4]. The CBGL algorithm was the basis of the proposed system design. Every learner was assigned a pretest to gauge their HTML5 cognitive abilities before learning, and the system generated a personalized learning path based on the pretest results.

Hsu and Li proposed an algorithmic process for a CBGL system (Figure 4) [4]. Upon completing registration, their system guides learners directly to the pretest stage. The system randomly displays questions from the question bank, and learners proceed through the test. The result of every unit is recorded in the system database. The obtained test result is then computed, and the learning path is generated using Equation (1), which then proceeds to the proficiency-based learning process. The learners proceed to the next unit after they attain a required level of cognitive ability. Otherwise, learners have to repeatedly practice the unit until they attain the necessary standard.

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\text{Personal learning path} := \text{Bubble sort rank}(\text{Score}(i))_{1 \leq i \leq N}
\]  

(1)

3.3. Design of recording user behavior logs

In this study, the learners’ learning behaviors were recorded into a log dataset. Subsequently, educational data mining technology was used to analyze the reasons why the learners may have found the learning process to be lengthy or boring. From this analysis, a predictive model was constructed for successful learning.

The algorithmic process of the CBGE system (Figure 4) was analyzed, and the users’ behaviors were coded to rules for exploring the learning effect through data mining. Sixteen learning behavior styles were summarized, and the coded rules of users’ behaviors are listed in Table 1.

The system used the MySQL database to record users’ behaviors while studying. The database first constructed a log table with ID, user, time, and catalog columns. To record the users’ behaviors, a function was designed (Figure 5) and embedded into every webpage in the system. Users’ behaviors could be written into the columns of a table for analysis through data mining by using this function.

| Behavior Style                                      | Coded Rule                                      |
|-----------------------------------------------------|-------------------------------------------------|
| Proceeding to login the guided learning process     | Guided-learning Login                           |
| Proceeding to do the pre-test 1                     | Pre-test1 testing                               |
| Proceeding to do the pre-test 2                     | Pre-test2 testing                               |
| Proceeding to do the pre-test 3                     | Pre-test3 testing                               |
| Proceeding to do the pre-test 4                     | Pre-test4 testing                               |
| Proceeding to do the pre-test 5                     | Pre-test5 testing                               |
| Proceeding to browser the guided learning progress  | Browser the Guided-learning Progress            |
| To be confident for question N                      | Reading Guided-learning QuestionN               |
| To read again for question N                        | Re-reading Guided-learning QuestionN            |
| Proceeding to the stage test of current unit        | Stage-test Testing                              |
| Finishing the stage test                            | Stage Success                                   |
| Failing in the stage test and guide to learn the unit again | Fail the Stage-test and Go Back to Guided-learning |
| Passing through the stage test                      | Pass the Post-test1 Test                        |
| Proceeding to the final test                        | Post-ending-test testing                        |
| Finishing the final test and calculate the result   | Finishing Post-ending-test and Calculating the Result |
| Browsing the result of final test                   | Post-ending-test Result Browsing                |

Table 1. Rules of users’ learning behaviors.
4. Experimental results and analysis
SPSS was used to analyze the results of system satisfaction and the teaching experiment. Moreover, the decision tree of Rattle GUI for R was used to analyze the learners’ learning behaviors and construct a predictive reference model of the learning effect.

4.1. Conceptual framework of teaching experiment
This study employed Internet technologies to implement a web-based HTML5-related CBGE system. This system embedded a CBGL mechanism to adaptively guide learners to study more efficiently. However, because the learning process of asynchronous drill and practice e-learning systems can be lengthy and tedious, the overall learning effect is often negatively affected. Therefore, the present study focused on whether the completeness of the guiding procedure is related to the learning effect.

This study conducted a teaching experiment to evaluate the difference between the learning effects of the participants who completed the guiding process (finished guided learning group) and the participants who did not complete the guiding process (unfinished guided learning group). The teaching experiment analyzed system satisfaction and learning effects. The learning effect analysis included two dimensions: the whole learning effect and the learning effect related to the completeness of the CBGL guiding procedure. Thus, a null hypothesis was created. The conceptual framework of the teaching experiment is displayed in Figure 6.

H1: In the HTML5-related CBGE system, there is no difference between the learning effects of the finished and unfinished guided learning groups.

4.2. Scheme of the teaching experiment
The overview of the study is as follows:
A. Experimental period
   The teaching experiment was conducted from September 20, 2017 to November 15, 2017.
B. Experimental participants
   The participants were 39 first-year students studying computer programming at National Taitung Junior College.
C. Experimental course
   The learning material in the experiment was an HTML5-related cognitive knowledge e-course.
D. Experimental design
   (A) All the participants used the asynchronous HTML5-related CBGE system to study online.
   (B) All the participants proceeded through the learning process without any teacher assistance and continued their study according to the system’s adaptive guidance.
(C) After finishing the experiment, the participants completed a system satisfaction survey. Then, the learning effect was analyzed, and educational data mining was conducted to examine the learners’ behaviors.

4.3. Teaching experiment analysis

1. System satisfaction analysis

A system satisfaction survey was conducted to determine the learners’ perception after using the system and whether the system fulfilled the research objectives. The adaptively guided learning system satisfaction questionnaire designed by Hsu and Li was selected [4], and a 5-point Likert scale was used to examine the learners’ satisfaction. The system design focused on the CBGL algorithm and the interface of the HTML5 cognitive e-course. Therefore, the questionnaire focused on these two dimensions. The total number of valid responses to the questionnaire was 37 for an effective response rate of 94.9%. The content of the questionnaire is presented in Table 2.

| Dimension                  | Question                                                                 | Mean  | Standard deviation | Average dimension score |
|----------------------------|--------------------------------------------------------------------------|-------|--------------------|-------------------------|
| Design of CBGL guided learning | I can use the system to study positively.                                | 4.03  | .645               |                         |
| Design of CBGL guided learning | The system enables me to learn.                                          | 3.81  | .776               |                         |
| Design of CBGL guided learning | I feel the learning process is fun.                                      | 3.59  | .762               |                         |
| Design of CBGL guided learning | I feel the learning process is too lengthy.                              | 3.30  | .878               |                         |
| Design of CBGL guided learning | I feel the system can guide me to learn effectively.                    | 4.08  | .640               | 3.76                    |
| Design of e-Course          | When I do not understand the meaning of a question, I check the explanation of the solution. | 4.11  | .699               |                         |
| Design of e-Course          | The explanation of the solution completely solves my confusion pertaining to the question. | 3.92  | .722               | 4.02                    |

Note: $n = 37$.

According to the result of the system satisfaction survey, the total average score was higher than 3.89. This value indicates that the participants were satisfied with the system design. The average score of the CBGL guided learning design was 3.76. This value indicates that the participants were satisfied with the CBGL guided learning mechanism. They used the system to study positively and felt that the guidance of the system enabled them to learn effectively. However, they also felt that the learning process was slightly fun and lengthy. These problems occurred very often in the drill and practice learning process, and they affected learners’ learning performance. These problems will be considered in a future study.

The average score of the e-course design was 4.02. This value indicates that the participants were very satisfied with this type of e-course interface. The participants checked the explanations of the solutions when they did not understand the meaning of the questions, and the solutions could completely solve the confusion of the questions.

2. Learning effect analysis

The study focused on verifying whether the completeness of the guiding procedure is related to the learning effect and whether finding the guided learning process made any difference to the learning effect. Thus, two dimensions of the learning effects were examined: the whole learning effect and the learning effect related to the completeness of the CBGL guiding procedure. Moreover, the learning effect of unfinished guided learning, the learning effect of finished guided learning, and the difference
between the learning effect of finished and unfinished guided learning were analyzed for the learning effect related to the completeness of the CBGL guiding procedure.

A. Whole learning effect

Repeated measures were conducted on the results obtained from the 39 participants who completed the learning process, and the significance of mean posttest and pretest scores was examined using the t-test results of paired samples. Then, an evaluation was conducted to determine whether the learning effect was improved using the CBGE system.

The results presented in Table 3 reveal that the mean posttest and pretest scores were 58.64 and 25.54, respectively. Thus, the average score increased by 33.1 after using the e-course system. This reflects an increased score distribution. Paired sample t-test yielded a t value of 8.442 and a significance of .000. Differential t test analysis results indicated that the experimental group attained a significantly higher posttest score (p < .001). Therefore, the cognitive abilities of the experimental group were significantly improved after the experiment.

| Variable            | N  | Mean | SD  | t     |
|---------------------|----|------|-----|-------|
| Experimental group  |    |      |     |       |
| Post-test scores    | 39 | 58.64| 25.71| 8.442*** |
| Pre-test scores     | 39 | 25.54| 6.20 |

Note: ***p < .001

B. Analyzing the learning effect related to the completeness of the CBGL guiding procedure

(A) Learning effect of unfinished guided learning

Repeated measures were conducted on the results of the 24 participants who did not finish the guided learning process, and the mean posttest and pretest scores were also tested to determine their significance by using the paired sample t test. Then, an evaluation was conducted to determine whether the learning effect was improved in the CBGE system when the guiding process was not completed.

The results listed in Table 4 reveal that the mean posttest and pretest scores were 44.46 and 25.33, respectively. Thus, the average score increased by 19.13 after using the e-course system. This reflects an increased score distribution. The paired sample t test yielded a t value of 4.748 and a significance of .000. Differential t test analysis results revealed that the unfinished guided learning group attained a significantly higher posttest score (p < .001). Therefore, the cognitive abilities of the unfinished guided learning group significantly improved after the experiment.

| Variable                  | N  | Mean  | SD  | t     |
|---------------------------|----|-------|-----|-------|
| Unfinished guided learning group |    |       |     |       |
| Post-test scores          | 24 | 44.46 | 21.66| 4.748*** |
| Pre-test scores           | 24 | 25.33 | 6.66 |

Note: ***p < .001

(B) Learning effect of finished guided learning

Repeated measures were conducted on the results of the 15 participants who finished the guided learning process, and the mean posttest and pretest scores were also tested to determine significance by using the paired sample t test. Then, an evaluation was conducted to determine whether the learning effect was improved in the CBGE system when the guiding process was completed.

The results listed in Table 5 reveal that the mean posttest and pretest scores were 81.33 and 25.87, respectively. Thus, the average score increased by 55.46 after using the e-course system. This reflects an increased score distribution. The paired sample t test yielded a t value of 19.850 and a significance of .000. Differential t test analysis results revealed that the finished guided learning experimental
group attained a significantly higher posttest score ($p < .001$). Therefore, the cognitive abilities of the finished guided learning group significantly improved after the experiment.

Table 5. Analysis of the posttest and pretest scores of the finished guided learning group.

| Variable                        | N  | Mean | SD  | $t$  |
|---------------------------------|----|------|-----|------|
| Finished guided learning group  | 15 | 81.33| 11.28| 19.850*** |
| Post-test scores                |    |      |     |      |
| Pre-test scores                 | 15 | 25.87| 5.58 |      |

Note: ***$p < .001$

(C) Learning effect differences between finished and unfinished guided learning groups

The study used grade growths to verify the learning effect differences. An independent sample $t$ test was conducted to test the significance in grade growth (posttest scores minus pretest scores) among the 15 participants who completed the learning process and 24 participants who did not complete the learning process. Then, an evaluation was conducted to determine whether the learning effect was significant between the two groups.

The results listed in Table 6 reveal that the mean grade growths of the finished and unfinished guided learning groups were 55.47 and 19.13, respectively. An independent sample $t$ test yielded a $t$ value of 7.414 and a significance of .000. Differential $t$ test analysis results revealed that the grade increase between the finished and unfinished guided learning groups attained a significantly higher score ($p < .001$). Therefore, the increase in the cognitive ability between the finished and unfinished guided learning groups was significantly different after the experiment. This indicates that participants’ cognitive ability was improved using the CBGE system and that completing the CBGL learning process yielded a more significantly pronounced learning effect.

Table 6. Analysis of the grade growth in finished and unfinished guided learning groups.

| Variable                        | N  | Mean | SD  | $t$  |
|---------------------------------|----|------|-----|------|
| Grade growths                   |    |      |     |      |
| Finished guided learning group  | 15 | 55.47| 10.82| 7.414*** |
| Unfinished guided learning group| 24 | 19.13| 19.73|      |

Note: ***$p < .001$

4.4. Predictive reference model of learning effect

According to the experimental design, the learning behaviors of the participants in the CBGL learning process were recorded in the system’s log tables. Then, the dataset was analyzed to develop a predictive reference model of the learning effect. The model can be used as a reference for other learners to help them achieve the learning objectives in the CBGE system.

The learners’ learning behaviors are defined in Table 1. Therefore, the test conditions were explicit. A decision tree was employed using the data mining tool. This technique used an ID3 algorithm to choose the selected attribute nodes and obtain the classified information of the nodes by using information gain.

After the experiment, the log table contained 13,443 records of learning behaviors. The table of recorded log data of behaviors is presented in Figure 7. According to the CBGL guided process, the study selected seven coded rules for the test conditions: browse the guided learning progress, stage success, fail the stage test and go back to the guided learning, pass posttest 1, read the guided learning questions, reread the guided learning questions, and finish the posttest and calculate the result.

The Rattle GUI for R was used to analyze the learners’ learning behaviors and construct a predictive reference model of the learning effect. The predictive reference model of the learning effect was built by using the decision tree and is illustrated in Figure 8. The analysis results revealed that the information gained from “stage success” was the highest. The optimized decision tree was constructed by only selecting this condition for the test node—whether learners can achieve the learning objective (a mark of 60) can be predicted by monitoring only one condition.
The predictive reference model revealed that when the learners studied in the CBGE system, they could not achieve the learning objective without passing the stage tests 2.5 times. Thus, the number of times the stage tests were passed was the crucial factor in determining whether the learning objective was achieved. According to these findings, learners using such a system attempt five learning stages and should pass stage tests at least 2.5 times to achieve their learning objective.

**Figure 8.** Predictive reference model of the learning effect.
5. Conclusions
This study used the following Internet technologies to implement a CBGE system with an HTML5-related cognitive e-course: PHP6, HTML5, CSS3, JavaScript, and MySQL. The system embedded a CBGL mechanism to implement a personalized learning environment that guided learners to study in stages while recording their learning behaviors in a log dataset for data mining.

The results of the system satisfaction survey revealed that the participants were satisfied with the designed system. The participants actively used the system to study, and they felt that the system provided effective guidance. Moreover, although they found the learning process to be lengthy, they felt the guiding procedure was interesting and could engage learners. They were also very satisfied with the e-course design, which provided guidance through closed and open solutions whenever the participants could not understand the questions.

According to the learning effect analysis, the cognitive abilities of the participants significantly improved after the experiment. Moreover, the increase in the cognitive ability of those who finished the guided learning process was significantly higher than that of those who did not finish the guided learning process. This indicated that the participants’ cognitive abilities improved after the guided learning process. The learning effect was significantly more pronounced if the process was completed entirely.

A decision tree technique was used to construct a predictive model of the learning effect to help the learners achieve the learning objective. The predictive model revealed that the learners who used the CBGL system could not achieve the learning objective without passing the stage tests a minimum of 2.5 times. Thus, the number of times that stage tests were passed was the critical factor in achieving the learning objective.

Because the completion of the CBGL learning process was the key factor that affected the learning effect, future studies can focus on improving the tedious and lengthy learning process that is typical of the asynchronous drill and practice e-learning systems. A gamified design may be successful for this purpose.

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