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Applying game mechanics and student-generated questions to an online puzzle-based game learning system to promote algorithmic thinking skills

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ABSTRACT

Algorithmic thinking is a core skill for constructing algorithms to solve problems and for understanding computer science. The purpose of this study was to examine the effects of using game mechanics and a student-generated questions strategy to promote algorithmic thinking skills in an online puzzle-based game learning system. An online puzzle-based game learning system, TGTS (Turtle Graphics Tutorial System), was developed to help students learn algorithmic thinking skills by allowing them to solve puzzles. A quasi-experiment was conducted to examine the effectiveness of using game mechanics alone and using game mechanics plus a student-generated questions strategy. Nine fourth-grade elementary classes (n = 242) were used to form three treatment groups, including one without game mechanics, one using game mechanics, and one using game mechanics plus a student-generated questions strategy. The results indicate that TGTS with game mechanics significantly enhanced algorithmic thinking skills and puzzle-solving performance. Furthermore, although TGTS with game mechanics plus the student-generated questions strategy is less effective than TGTS with only game mechanics in puzzle solving, it is in fact more effective in enhancing the algorithmic thinking skills. Additionally, this study demonstrated that TGTS with game mechanics plus the student-generated questions strategy can enhance students' engagement experiences and willingness to participate. This study can be a reference for designing learning activities and developing an online puzzle-based game learning system to promote students' learning of algorithmic thinking skills.

1. Introduction

Being literate in information technology is increasingly essential in the digital age. Algorithmic thinking, one of the fundamental skills of working with information technology, has gradually increased in importance (Katai, 2015; National Research Council, 1999). Algorithmic thinking is not only a component of competence in information technology (Zsakó & Szlávi, 2012) but is also the key to understanding computer science (Futschek, 2006). Algorithmic thinking is a specialized problem-solving skill that uses several different abilities (Katai, 2015). The fundamental purpose of algorithmic thinking is to construct algorithms that can solve given problems (Futschek, 2006). This qualifies as puzzle-based learning, which seeks to engage students in thinking about how to scaffold and solve problems (Falkner, Sooriamurthi, & Michalewicz, 2010; Michalewicz, Falkner, & Sooriamurthi, 2011) and enhance students' critical analysis skills and problem-solving techniques (Merrick, 2010). The ultimate goal of puzzle-based learning is to help students become effective problem solvers in daily life (Falkner et al., 2010). Recognizing that learning algorithmic thinking is

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consistent with the nature of puzzle-based learning because both focus on critical analysis, logical reasoning and abstract reasoning to improve problem-solving skills, this study used puzzle-based learning as a fundamental strategy to develop an online learning system to help students learn algorithmic thinking skills.

Although puzzle-based learning can be used as a fundamental strategy when developing an online learning system, it remains essential to have a proper strategy or mechanism that can further increase students' motivation and engagement when they are solving and practicing puzzles. Engaging students in repeatedly solving a puzzle not only ensures that they truly understand how to solve that puzzle but also helps students practice the essential skills of puzzle solving. Integrating game-based learning with puzzle-based learning to create a puzzle-based game learning system that could make puzzle solving identical to game playing may help to fulfill the above requirements of repetition and practice.

Some researchers have suggested that game-based learning can support problem-based learning by enabling students to apply their own strategies and prior knowledge to solving problems (Cicchino, 2015; Kim, Park, & Baek, 2009; Papastergiou, 2009). In fact, Kim et al. (2009) indicated that engaging students to implement problem-solving strategies in a game-based learning environment may be the primary factor in promoting learning outcomes. This aspect provides support for integrating game-based learning into puzzle-based learning, which is regarded as a type of problem-based learning to engage students in solving and practicing puzzles. In addition, many researchers have suggested that digital game-based learning can promote students' engagement, motivation and learning outcomes (Chang, Huang, & Chien, 2014; Jong, 2015; Kim et al., 2009; Papastergiou, 2009; Su & Cheng, 2013; Tuzun, Yilmaz-Soylu, Karakus, Inal, & Kizilkaya, 2009). Engaging students to learn by games that embed educational objectives and learning materials not only raises students' learning motivation and outcomes (Chang et al., 2014; Gee, 2005; Prensky, 2003; Sung & Hwang, 2013) but also renders students' learning more interesting, enjoyable, learner-centered, and thus more effective (Kafai, 2001; Malone, 1980; Papastergiou, 2009; Prensky, 2001). These aspects provide support for integrating puzzle-based learning and game-based learning to create an online puzzle-based game learning system to enhance students' engagement and motivation.

However, because enjoyment and entertainment are not the primary purposes of educational games, educational games generally are not as attractive or engaging as commercial games (Kim et al., 2009; Webb, Bunch, & Wallace, 2015). Although a puzzle-based learning game may engage students for several minutes at a time, it is essential to identify a manner in which to persistently maintain students' interest and motivation (Abdul Jabbar & Felicia, 2015; Csikszentmihalyi, 2008; Fullerton, 2008; Klopfer, Osterweil, & Salen, 2009). Many studies have indicated that in addition to designing a game with basic game characteristics, using game mechanics to maintain motivation and promote certain behaviors may be the critical strategy (Alaswad & Nadolny, 2015; Bunchball Inc., 2010; Figueroa Flores, 2015; Hull, Williams, & Griffiths, 2013). This study sought to integrate game-based learning and puzzle-based learning to create an online puzzle-based game learning system that would not only support puzzle solving but also use game mechanics to engage students in voluntarily attempting various puzzles and in repeatedly solving puzzles they had previously solved. By encouraging students to practice solving puzzles repeatedly, this system helps students master the basic concepts and problem-solving skills of algorithmic thinking.

To ensure that the puzzles in this online puzzle-based game learning system include the concepts and skills that students need to learn, the puzzles are traditionally generated by teachers. However, some studies have stressed the importance of allocating some of the responsibility for generating questions to students (Barak & Rafaeli, 2004; Brown & Walter, 2005; Dillon, 1990; English, 1997; Silver, 1994; Yu, 2009). Allowing students to produce questions for their peers to answer – that is, a student-generated questions strategy – would encourage students to reflect on what they have learned; this content could then be applied to the construction of personal knowledge (Bangert-Drowns, Hurley, & Wilkinson, 2004; Papinczak et al., 2012; Rosenshine, Meister, & Chapman, 1996; Yu, 2009). A student-generated questions strategy can promote improvements in comprehension, attitudes, motivation, problem-solving abilities, and flexible thinking (Abramovich & Cho, 2006; Barak & Rafaeli, 2004; Barlow & Cates, 2006; Brown & Walter, 2005; Dori & Herscovitz, 1999; Whitin, 2004; Yu & Liu, 2005; Yu, 2009). These effects, particularly on problem-solving abilities and flexible thinking, will be highly beneficial in promoting algorithmic thinking, which is considered to relate to problem-solving abilities (Futschek, 2006; Katai, 2015). Furthermore, a student-generated questions strategy not only enhances student performance but also diversifies the sources of questions (Brown & Walter, 2005; English, 1997; Silver, 1994; Yu, 2009). Thus, some studies have suggested that questions should be generated by both teachers and students (Barak & Rafaeli, 2004; Dillon, 1990). Based on the above, in addition to integrating game-based learning and puzzle-based learning, this study attempted to further integrate a student-generated questions strategy into an online puzzle-based game learning system that supports not only puzzle solving but also puzzle designing to promote algorithmic thinking skills.

1.1. Background

1.1.1. Algorithmic thinking skills

Algorithmic thinking has received increased attention in recent years. Many studies have indicated that algorithmic thinking is one of the most important competences in computer science (Cooper, Dann, & Pausch, 2000; Futschek, 2006; Sysło, 2015; Zsakó & Szlávi, 2012). An algorithm is a procedure or formula comprising a series of finite and implementable operations for solving a problem step-by-step (Futschek, 2006; Zsakó & Szlávi, 2012). Algorithmic thinking is considered to be associated with the skills of processing and creating algorithms (Katai, 2015). Futschek (2006) defined algorithmic thinking as the ability to construct new algorithms for solving given problems. Furthermore, the field of algorithmic thinking can be extended to daily life (Amorim, 2005; Hubalovsky & Korinek, 2015; Katai, 2015). Hubalovsky and Korinek (2015) indicated that algorithms arise in the common activities of daily living. Therefore, algorithmic thinking is not only an important part of computer science but also an important part of our daily lives (Amorim, 2005; Futschek, 2006; Katai, 2015; Zsakó & Szlávi, 2012). These arguments underscore the importance of promoting algorithmic thinking skills.

However, several factors render it difficult for students to develop algorithmic thinking skills (Katai, 2015). Algorithmic thinking incorporates many cognitive tasks, such as abstract thinking, logical thinking, structural thinking, and creative thinking (Futschek, 2006; Katai, 2015). The abstractions of computer algorithms generally render it difficult for students to relate algorithms to real-life experiences (Katai, 2015; Ramadhan, 2000). Futschek and Moschitz (2011) noted that novice learners of algorithmic thinking generally have trouble with the abstraction of a programming environment and with thinking through executive steps abstractly. Additionally, the differences between the ways computers work and the ways that humans think can increase students' difficulties. Computers enable algorithms designed for machines to execute limited sets of fundamental instructions sequentially; however, humans naturally process large sets of high-level instructions in parallel (Futschek & Moschitz, 2010; Katai, 2015). Students need more support in overcoming the difficulties of the abstraction of algorithmic thinking and in transforming the ways they think by problem solving.

To address the problem of abstraction, Futschek and Moschitz (2011) suggested that providing a manipulation and visualization tool was appropriate for helping students connect the real world to a programming environment. This study uses Logo, which meets the requirements mentioned above, as the medium for learning algorithmic thinking skills. Logo is a well-known educational programming language that uses a turtle (an on-screen cursor) to produce line graphics (turtle graphics) by giving the turtle movement commands and drawing instructions. Many studies confirm that Logo may benefit students in not only fostering programming skills but also providing experiential learning, enhancing geometric concepts, developing spatial abilities, and promoting other higher-order thinking skills (e.g., critical thinking skills, problem-solving skills, reflection and self-monitoring) (Clements & Sarama, 1997; Clements, 2002; McAllister, 1991; Miller, 1998; Papert, 1980; Ratcliff & Anderson, 2011; Vasu & Tyler, 1997; Yeh & Chandra, 2015). Logo provides a programming environment in which abstract ideas can be expressed, handled, and dynamically tested to help students internalize the transformation between abstract ideas and concrete models in cognitive processes (Papert, 1980; Swan & Black, 1990). In the interactive programming environment, students can test, observe, and correct their strategies and then learn from trials and mistakes (Miller, 1998; Ratcliff & Anderson, 2011; Sharp, 1993). By providing a constructivist learning environment, Logo promotes the development of reasoning, logic, and procedural and debugging skills that are essential to algorithmic thinking skills (Miller, 1998; Poulin-Dubois, McGilly, & Shultz, 1989). In addition to using Logo to address the problem of transformation, Futschek (2006) suggested that the fundamental and practical strategy for teaching algorithmic thinking skills was allowing students to solve multiple problems. Therefore, this study used puzzle-based learning as its fundamental strategy to help students learn algorithmic thinking skills. By the arrangement of moderate and progressively more difficult problems, students can be guided to solve problems step-by-step.

To teach algorithmic thinking skills, it is first necessary to determine what concepts should be included in algorithmic thinking. Many studies have proposed various concepts that should be included (Futschek & Moschitz, 2011; Futschek, 2006; National Research Council, 1999). Cooper et al. (2000) proposed that the general algorithmic concepts include functional decomposition, repetition, basic data organizations, generalization and parameterization, top-down design, and refinement. Futschek and Moschitz (2011) proposed that the basic algorithmic concepts include basic commands, sequence commands, iteration commands, alternative commands, and abstraction commands. This study followed the suggestion of Cooper et al. (2000) and Futschek and Moschitz (2011) to incorporate basic algorithmic concepts into the online learning system developed by this study for young learners.

Although several studies have sought to teach algorithmic thinking skills to students (Cooper et al., 2000; Futschek & Moschitz, 2011; Katai, 2015), some have noted the need for more research before conclusions can be drawn regarding how best to help students learn algorithmic thinking skills (Cooper et al., 2000; Katai, 2015). In investigating the issue of teaching algorithmic thinking skills to elementary school students, this study attempted to develop an online puzzle-based learning system that can support students in learning algorithmic thinking skills at any time and in any location.

1.1.2. Game-based learning

In recent years, game-based learning has attracted increasing attention because of its positive effectiveness in promoting students' engagement, motivation, and learning outcomes (Games & Squire, 2011; Jong, 2015; Kebritchi & Hirumi, 2008). Game-based learning is generally defined as engaging students in a type of game to play with distinct learning goals that seek to develop their cognitive abilities (Erhel & Jamet, 2013; Plass, Homer, & Kinzer, 2015; Shaffer, Squire, Halverson, & Gee, 2005; Webb et al., 2015). Game-based learning considered to have potential in the learning environment is based on several central aspects: providing students with challenges or difficulties to overcome, enabling students to combine prior knowledge from different aspects to make meaningful decisions, and encouraging students to predict what will result from their decisions and actions (Bouras et al., 2004; Cicchino, 2015; Kim et al., 2009; McCall, 2012). These aspects are consistent with the essential elements of constructing a puzzle-based learning environment and provide support for integrating game-based learning into puzzle-based learning to create a puzzle-based game learning system (Connolly, Boyle, MacArthur, Hainey, & Boyle, 2012; Klymchuk, 2017).

With the wide application of technology in education, digital games holding the inherent characteristics of goals, interaction, feedback, and entertainment have been given distinct educational purpose and developed to promote students' cognitive and intelligent abilities (Abdul Jabbar & Felicia, 2015; Alaswad & Nadolny, 2015; Kim et al., 2009; Su & Cheng, 2013; Webb et al., 2015). However, it is not sufficient to simply transform puzzle-solving into the form of a puzzle-solving game that only possesses the inherent characteristics of digital games. Kim et al. (2009) indicate that because they are developed specifically to achieve learning objectives, educational games are usually not as attractive or engaging for students as commercial games. Moreover, puzzle-based learning games are usually not as entertaining as other types of games. Although puzzle-based learning games can be played for some minutes at a time because they invoke the concept of flow, puzzle-based learning games still require game mechanics to persistently maintain students' interest and motivation (Abdul Jabbar & Felicia, 2015; Csikszentmihalyi, 2008; Fullerton, 2008; Klopfer et al., 2009). How to drive and maintain the students' engagement and attempts to solve puzzles is an important issue when designing a game-based learning environment for puzzle solving.

When implementing game-based learning, many studies have attempted to introduce systematic mechanisms for designing a game-based learning environment, including game characteristics (the common characteristics that most games have) or game mechanics (the control mechanisms that are used to initiate and maintain interest in gaming activities) (Alaswad & Nadolny, 2015; Bunchball Inc., 2010; Figueroa Flores, 2015; Hull et al., 2013). Hamari, Koivisto, and Sarsa (2014) reviewed several studies and proposed ten of the most popular mechanisms that can promote engagement: providing clear goals, providing challenges, arranging a story or theme, providing feedback, using levels, allotting points, displaying progress, awarding rewards, granting badges, and showing leaders on leaderboards. Providing clear goals, providing challenges, arranging a story or theme, and providing feedback are game characteristics that may apply to creating a puzzle-based learning game; using levels, allotting points, displaying progress, awarding rewards, granting badges, and showing leaders on leaderboards are game mechanics that may engage students when they are playing the puzzle-based learning game. Cugelman (2013) suggested that these systematic mechanisms might be used to interact with students in online learning systems to increase engagement. However, how to apply not only game characteristics to transform puzzle solving into a type of game playing but also game mechanics to design an online puzzle-based game learning system to engage students in learning algorithmic thinking skills is an issue that is worth exploring.

1.1.3. Student-generated questions strategy

A student-generated questions strategy is regarded as an important cognitive strategy that may contribute to fostering and monitoring comprehension and to self-regulatory cognitive development (Abramovich & Cho, 2006; Barlow & Cates, 2006; Brown & Walter, 2005; Palinscar & Brown, 1984; Papinczak et al., 2012; Rosenshine et al., 1996; Yu, 2009). Generating questions does not directly guide students to comprehension in a step-by-step manner, but rather engages students in analyzing learning content, identifying main concepts, and combining this information during the process of generating questions (Craik & Lockhart, 1972; Rosenshine et al., 1996). By requiring students to recall learning content, become aware of the key points of learning content, generate answers to self-designed questions, and reflect on what they have learned, the student-generated questions strategy allows students to identify and resolve incomplete or inadequate comprehension and monitor the state of their own comprehension (King, 1994; Palinscar & Brown, 1984; Wong, 1985). Furthermore, students may benefit from generating the questions that will be answered by their peers. Psychological studies have noted that having an audience affects the effort and interest of students, who will then view tasks as more meaningful and relevant, thus promoting better performance (Cohen & Riel, 1989; Redd-Boyd & Slater, 1989; Ward, 2008; Yu & Chen, 2014). For the above reasons, this study hypothesizes that integrating a student-generated questions strategy into an online puzzle-based game learning system that could support puzzles designed by students will further engage students in a deeper understanding and processing of the basic concepts and problem-solving skills of algorithmic thinking.

Several studies have provided empirical evidence to support the hypothesis that a student-generated questions strategy could contribute to the learning process (Rosenshine et al., 1996; Yu & Chen, 2014; Yu, 2009). In addition to enhancing the cognitive learning process (Drake & Barlow, 2008; Yu & Liu, 2009; Zohar & Dori, 2003), student-generated questions also help students in the affective domain by enhancing learning motivation (Chin & Brown, 2002), promoting active learning (Liu & Yu, 2004), and encouraging positive attitudes toward learning new content (Keil, 1965; Perez, 1985). Nevertheless, most studies of the student-generated questions strategy have focused on inquiring about the effect of text-based questions, and few empirical studies have been conducted on using this strategy to promote algorithmic thinking. Allowing students to construct questions using a form of turtle graphics to promote algorithmic thinking is an issue that must be addressed.

1.2. Purpose and questions

This study used an online puzzle-based game learning system that integrates puzzle-based learning, game-based learning and a student-generated question strategy to promote algorithmic thinking skills. However, how to use the game mechanics to maintain students' engagement and motivation rather than creating a puzzle-solving game that only possesses game characteristics requires further investigation. Furthermore, the effect of using a student-generated questions strategy to allow students to design puzzles on a puzzle-based game learning system is another important issue. To examine the effect of using game mechanics and a student-generated questions strategy, three types of system mechanisms – using a puzzle-based game learning system that only possesses game characteristics as a fundamental strategy – were developed to encourage students to engage in puzzle-solving activities to learn algorithmic thinking skills: without game mechanics, with game mechanics, and with game mechanics plus the student-generated questions strategy.

The research questions for this study were as follows:

- Are there differences among students who use the three types of system mechanisms with regard to algorithmic thinking skills?
- Are there differences among students who use the three types of system mechanisms with regard to puzzle-solving performance?
- Are there differences among students who use the three types of system mechanisms with regard to attitudes toward learning activities?

2. Method

A quasi-experimental design was adopted with pretests and posttests for the evaluation. The independent variable was whether game mechanics or the student-generated questions strategy was used during the learning activity. Three treatment groups were developed: the puzzle-based game learning group (PBL, control group), the puzzle-based game learning plus game mechanics group (PGM, Experimental Group I) and the puzzle-based game learning plus game mechanics and a student-generated questions strategy group (PGS, Experimental Group II). The dependent variables included the assessment of algorithmic thinking skills, performances of solving puzzles, and attitudes toward learning activities. Four learning activities, including a series of tasks supported by the Turtle Graphics Tutorial System (TGTS), were arranged.

2.1. Participants

Nine fourth-grade elementary classes (N = 242, ages 9–10) formed the PBL group (82 total, 38 boys and 44 girls), the PGM group (79 total, 39 boys and 40 girls), and the PGS group (81 total, 39 boys and 42 girls). The academic performances of students in these classes were similar. The students had taken mathematics lessons in fundamental geometrical concepts and computer lessons in basic computer operations and applications. Thus, the students had the basic skills to operate computers and use a browser to surf the Internet. However, they had no experience in algorithmic thinking or programming.

2.2. Instrumentation and measurement

2.2.1. Turtle Graphics Tutorial System (TGTS)

A web-based Turtle Graphics Tutorial System (TGTS) was utilized to help students learn turtle graphics. TGTS was modified and extended based on the turtle game of Blockly Games (Google Inc., 2015), which is a series of educational games for teaching turtle graphics. Blockly Games uses visual block programming editors by linking the blocks of program commands together to make writing code easier, helping students learn the general concepts and skills of algorithmic thinking. The turtle game of Blockly Games is an aggregation of a series of puzzles that use command blocks to draw turtle graphics. This study modified and extended Blockly Games' turtle game to a complete web-based learning system that could manage learning activities, provide a tutorial mechanism with an interactive guide, record the learning processes of students, and integrate game mechanics and a student-generated question strategy. TGTS provides a series of puzzle-solving activities that guide students to learn the general concepts of algorithmic thinking. Each activity contains a series of puzzles that comprise line graphics that students must solve by moving and drawing the same graphics to complete the tasks.

2.2.1.1. Puzzle based game learning in TGTS. In this study, every student who used TGTS played the role of a novice wizard whose goal was to complete all wizard learning activities. To achieve their goals, novice wizards were required to solve all of the puzzles in the learning activities. Each puzzle was a line graphics task that relied on the concepts and problem-solving skills of algorithmic thinking and met the criteria for good educational puzzles. Falkner et al. (2010) proposed that educational puzzles satisfy the criteria as follows: independence, generality, simplicity, eureka factor, and entertainment factor. Two content experts, computer science teachers with a master degree in computer science education, reviewed and revised the Blockly Games puzzles to match the criteria. When a novice wizard was challenged to solve a puzzle, he/she was required to use incantation blocks (command blocks) to move a mysterious statue (the turtle in turtle graphics) to draw a line graphic that was identical to the line graphic of the puzzle. The interface observed when solving a puzzle is shown in Fig. 1. A novice wizard was not only required to draw a line graphic that was identical to the line graphic of the puzzle but also to do so using the smallest number of blocks. If a novice wizard drew the same graphic and used the fewest blocks, he/she solved the puzzle. Every time a novice wizard solved a puzzle, he/she received from 0 to 3 points according to the number of blocks and whether he/she had solved the puzzle. After each try, TGTS displayed feedback containing the score for the student's solution, possible causes of mistakes, requirements that were not yet met, or hints about puzzle-solving strategies. Providing real-time feedback not only immediately informed students of the results of their challenges and what mistakes they had made but also tutored students in solving puzzles according to the mistakes they had made.

TGTS, applying puzzle-based game learning as described above, implemented several basic game characteristics, such as providing a story or theme, providing a clear goal, offering challenges, and providing feedback.

2.2.1.2. Game mechanics. To advance student engagement and promote desirable learning behaviors, this study integrates several game mechanics in TGTS. The popular game mechanics applied in TGTS are shown in Table 1, which includes points, leaderboards, levels and badges. Allocating points is one of the most popular game mechanics, showing how the students' rank by leaderboards and levels can encourage a sense of competition, and changing badges can trigger more fun and motivation. This study also demonstrates the progress that indicates the point at which a student challenges each puzzle during all activities on both personal and activities web pages to help each novice wizard learn the progression of challenging every puzzle.

2.2.1.3. Student-generated questions with peer assessment strategy. To evaluate students on what they have learned, this study used a student-generated questions strategy, which is to allow the students to design their own turtle graphic puzzles using restricted types of blocks. Other students in addition to the puzzle designer can solve the puzzles under identical conditions. However, the challenger must attempt not only to draw a graphic that is identical to the puzzle but also to use fewer blocks than the designer used. If a

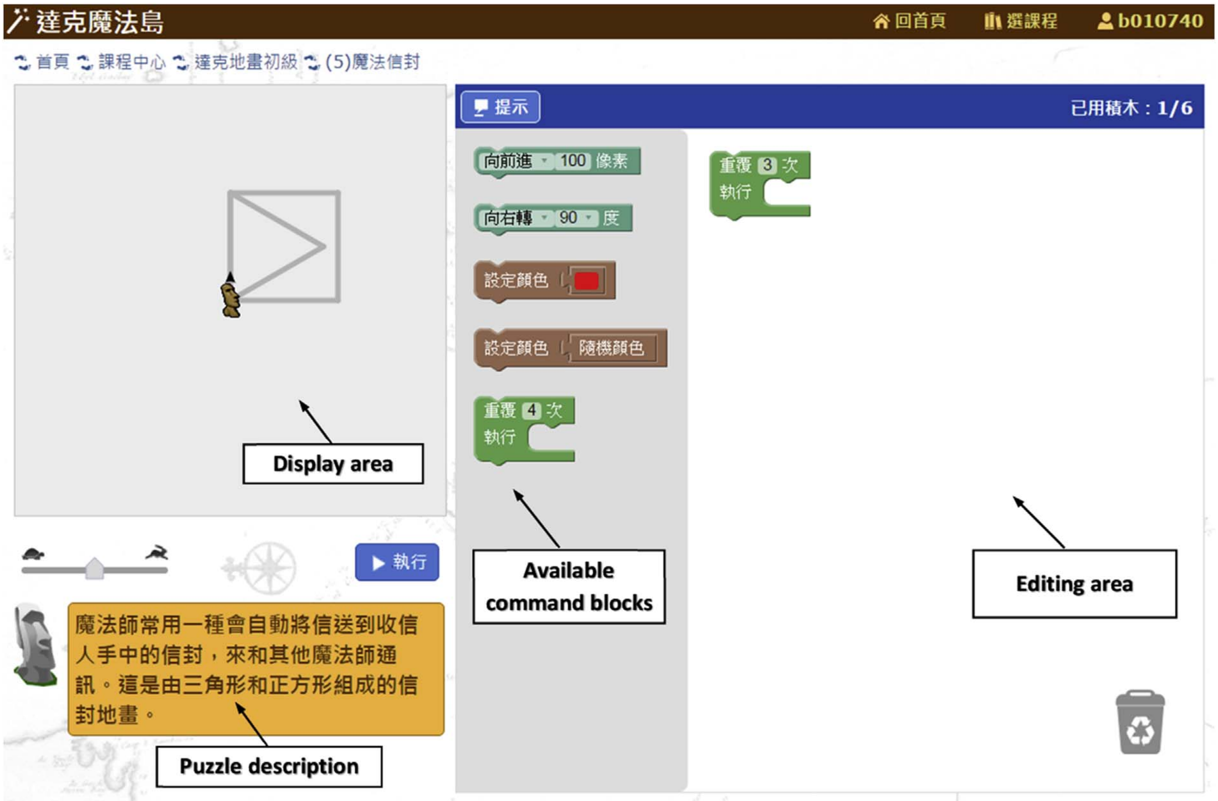

Fig. 1. The interface of solving a puzzle.

Table 1
The game mechanics used in TGTS.

Game mechanics	The implementation of TGTS
Points	TGTS uses “magic points” to represent the power of novice wizards. Every time a novice wizard tries to solve a puzzle, he/she can win 0 to 3 points according to the result of his/her solution. These points will transform into “experience points” and “skill points,” which, when weighted and calculated become “magic points”. The more times a novice wizard completes challenges and the better the results he/she gets, the more magic points he/she can win.
Leaderboards	This study shows the TGTS leaders in terms of magic points, experience points, skill points, wizard levels, and stars.
Levels	The levels mechanism of TGTS includes grading courses and wizards. TGTS grades courses to two levels. However, following the suggestion of allowing students to choose a different sequence of sub-tasks (Simões et al., 2013) TGTS does not limit students to solving puzzles one by one. TGTS grades wizards to fourteen levels. The novice wizards are level 0 wizards when they are just beginning to learn. When students have completed a course or their magic points have been accumulated up to upgrade criteria, they can level up.
Progress	The information on the challenge state includes challenge times, top scores, and average scores for each player on every puzzle. In addition to the above-mentioned information, to help each novice wizard compare his/her challenge state with that of all players, TGTS also shows information about total challenge times, top scores of all players, and average scores of players on every puzzle.
Badges	The badges mechanism of TGTS includes displaying the wizard's hat, symbolizing the wizard's level and recording stars representing the level of his/her breakthrough. TGTS will display a different color wizard's hat according to the level of the wizard. The number of stars represents the number of students who use a better strategy to than the standard for solving the puzzle.

challenger can draw the same graphic and use fewer blocks than the designer, the challenger can win a “star,” indicating that he or she has made a breakthrough in the solution of the designer. To avoid a puzzle being solved and even to avoid breakthroughs by challengers, the designer of the puzzle must think about not only how to design the graphic but also how to increase the difficulty of the puzzle and reduce the number of blocks used. To do this, the puzzle designers must analyze the components of the graphics that they have solved, master the solving strategies that they have learned, and then apply, vary, and reorganize those skills to construct a new algorithm to draw the graphics that they want to design. They must try to use the fewest number of blocks and try other possible solutions that can draw the same graphics but use fewer blocks than the solution has required so far. Thus, allowing students to design puzzles can reflect their learning status and give them a deeper comprehension of the basic concepts and problem-solving skills of algorithmic thinking. The interface of designing a turtle graphic question and saving it as a puzzle for peers to solve is shown in Fig. 2.

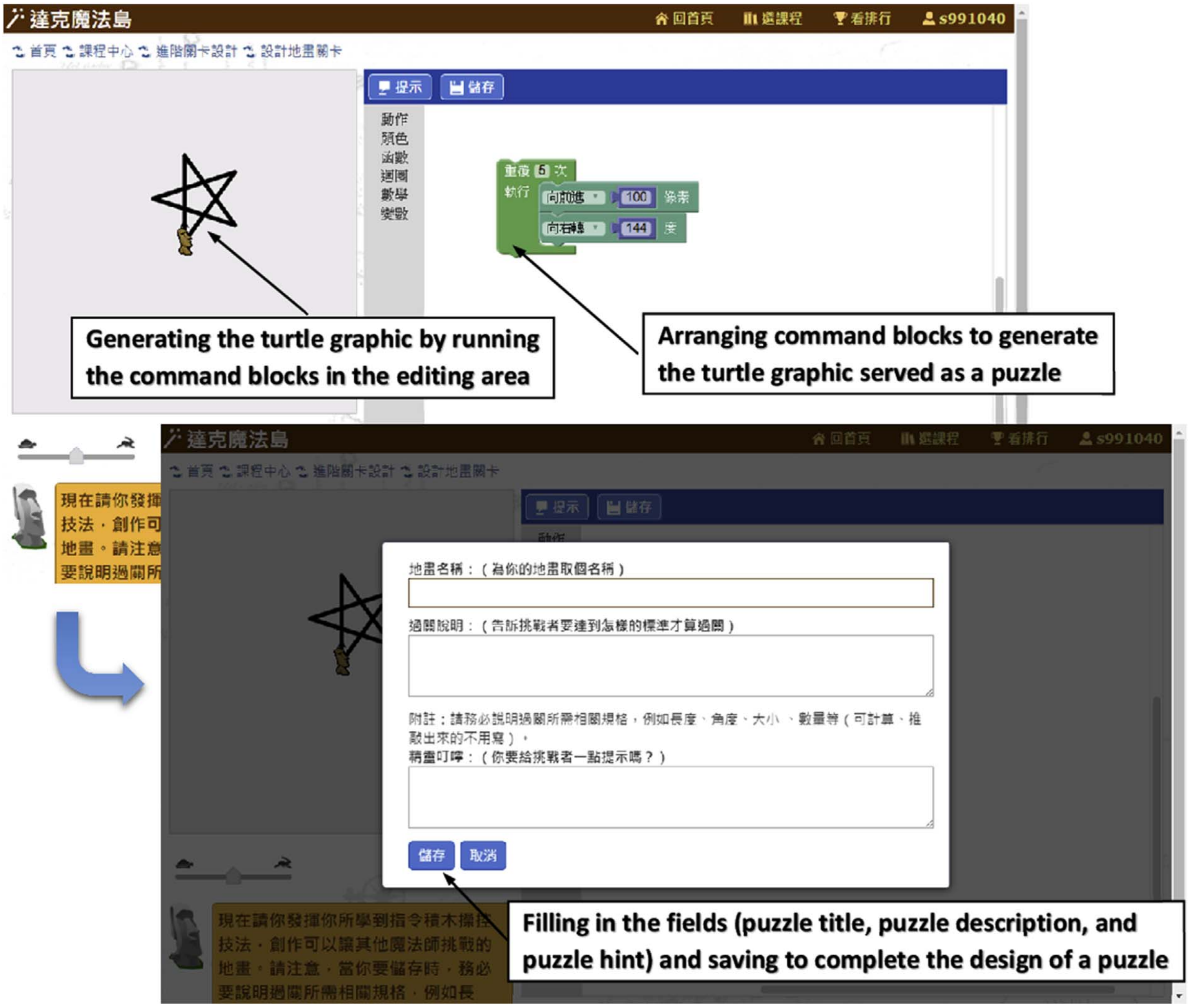

Fig. 2. The interface of designing a turtle graphic and saving it as a puzzle.

2.2.2. *Assessing algorithmic thinking skills*

The pretest and posttest, compiled by a computer science teacher with a master degree in computer science education, were used to measure algorithmic thinking skills (see Fig. 3). Two other content experts, computer science teachers with a master degrees in computer science education and with 22 and 26 years of teaching experience, respectively, reviewed and revised the questions of the pretest and posttest to ensure content validity. The pretest comprised 4 multiple-choice questions, an ordering question, 12 fill-in-the-blank questions, and 2 free-response questions (Cronbach's $\alpha = 0.808$). The total score of the pretest was 27 points. Because drawing the turtle graphic requires concepts of space and geometric shapes, in addition to the basic concepts of algorithmic thinking such as decomposition, sequencing, and repetition, the topics covered in the pretest included basic geometric concepts and geometric problems too. An example question set from the pretest is presented below:

The criteria of assessing free-response questions are as follows:

- 3 points: Solve the puzzle that uses a minimum number of commands or execution times.
- 2 points: Solve the puzzle that uses more commands or longer execution times than the answer's.
- 1 point: Do not solve the puzzle but the sub procedure is correct
- 0 points: Do not solve the puzzle at all.

The posttest comprised an ordering question, 2 matching questions, 5 multiple-choice questions, 6 fill-in-the-blank questions, and 12 free-response questions (Cronbach's $\alpha = 0.86$). The total score of the posttest was 72 points. The topics covered in the posttest for assessing the concepts and skills of algorithmic thinking included sequence concept, iteration concept, geometric concepts, decomposition, pattern recognition, variable operation, reading code, debugging, and refinement.

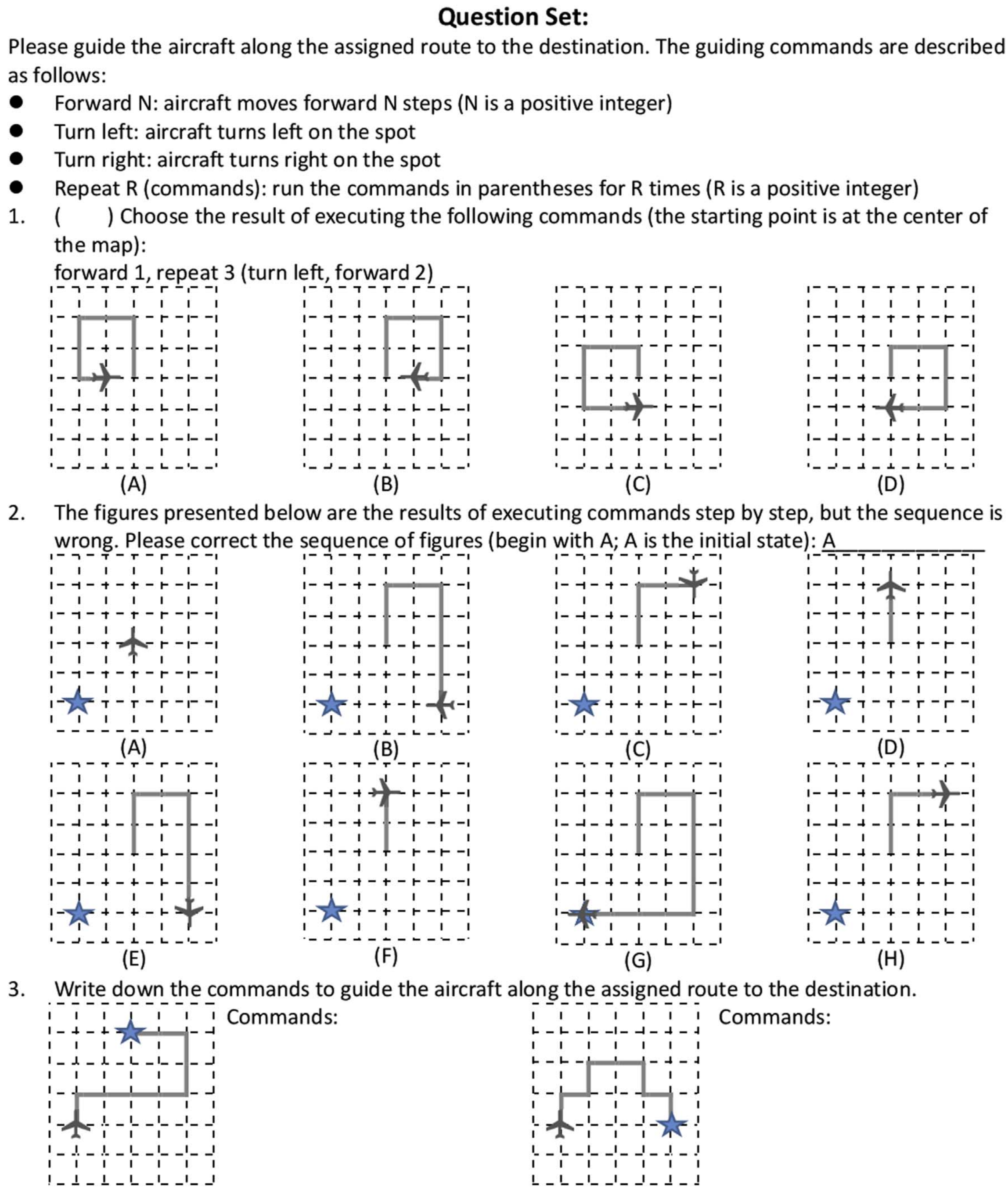

Fig. 3. An example question set from the pretest.

2.2.3. *Comparing puzzle-solving performances and attitudes toward learning activities*

To compare participants' performance in solving puzzles when using the learning activities of TGTS, the following performances were compared:

- Attempted puzzles: the number of puzzles that the participants attempted to solve. This comparison confirmed whether the participants in the three groups attempted to solve various puzzles.
- Solved puzzles: the number of puzzles that were solved completely. This comparison compared how many puzzles the participants in the three groups solved completely (i.e., got a top score on a puzzle).
- Times attempted: the number of times participants attempted to solve puzzles. This comparison confirmed whether the participants in the three groups continued attempting to solve puzzles.

- Times solved: the number of times participants solved puzzles completely. This comparison compared how many times the participants in the three groups solved puzzles completely.

To evaluate students' engagement and attitudes toward the learning activities of TGTS, this study compiled an attitudinal questionnaire including three dimensions: system usability, engaging experience, and willingness to participate (Domínguez et al., 2013; Flatla, Gutwin, Nacke, Bateman, & Mandryk, 2011; Guin, Baker, Mechling, & Ruyle, 2012; Li, Grossman, & Fitzmaurice, 2012; Witt, Scheiner, & Robra-Bissantz, 2011). The questionnaire comprised eleven questions based on a five-point Likert scale (Cronbach's $\alpha = 0.944$). Some question examples from the attitudinal questionnaire follow:

- I think that the feedbacks when solving a puzzle can help me solve the puzzles.
- I enjoy solving the puzzles.
- If TGTS adds new activities, I am willing to participate in these activities.

The two previously mentioned content experts from Section 2.2.2 reviewed and revised the questions on the questionnaire to ensure content validity.

2.3. Procedure

The quasi-experiment continued for ten weeks, including a week for the pretest, eight weeks for learning turtle graphics by solving puzzles and a week for the posttest. Four learning activities continued for eight weeks, two weeks for each. The participants engaged in learning activities in computer lessons, which occurred once a week. The computer teacher provided technical support and guided participants enrolled in TGTS; however, he did not teach students how to solve the turtle graphic puzzles or intervene in the learning processes of the participants. To ensure that the time the three treatment groups spent on the learning activities was identical, TGTS limited participants to logging in to TGTS only during computer lessons. The steps were as follows:

1. Pretest

Students took the pretest on algorithmic thinking skills and basic geometric concepts before the treatment.

2. Treatment activities

The three treatment groups were the PBL, PGM, and PGS. The experimental treatment and learning activities for the three groups are presented in Table 2.

Within TGTS, all three groups enrolled in the learning activities of solving puzzles that were designed based on puzzle-based learning. In addition to the PBL, the user interfaces of the PGM and PGS were embedded in the game mechanics mentioned above to promote student engagement. Furthermore, to encourage student reflection, the PGS were required to design puzzles for other students to solve in Activity 2 and Activity 4. Turtle Graphic Puzzles Level 1 in Activity 1 and Turtle Graphic Puzzles Level 2 in Activity 3 each contain nine turtle graphic puzzles that guide students through the basic concepts and solving skills of algorithmic thinking and the operations of command blocks. The turtle graphics used as puzzles in Turtle Graphic Puzzles Level 1 and Turtle Graphic Puzzles Level 2 are as in Fig. 4:

In Turtle Graphic Puzzles Level 1, the commands used for solving puzzles include action commands and iteration commands, and the concepts and skills required to solve puzzles include sequence concepts, iteration concepts, geometric concepts, decomposition, and pattern recognition. In Turtle Graphic Puzzles Level 2, the commands used for solving puzzles include action commands, variable commands, and iteration commands, and the concepts and skills required to solve puzzles include sequence concepts, iteration concepts, geometric concepts, decomposition, pattern recognition, variable operations, reading code, and refinement.

3. Posttest

Table 2
Experimental treatment and learning activities for the three groups.

	PBL	PGM	PGS
Experimental treatment	Puzzle-based game learning	Puzzle-based game learning + Game mechanics	Puzzle-based game learning + Game mechanics + Student-generated questions
Activity 1	Turtle Graphic Puzzles Level 1	Turtle Graphic Puzzles Level 1	Turtle Graphic Puzzles Level 1
Activity 2	Using conditions of level 1 to solve puzzles designed by students in PGS	Using conditions of level 1 to solve puzzles designed by students in PGS	Using conditions of level 1 to design puzzles and solve puzzles designed by students in PGS
Activity 3	Turtle Graphic Puzzles Level 2	Turtle Graphic Puzzles Level 2	Turtle Graphic Puzzles Level 2
Activity 4	Using conditions of level 2 to solve puzzles designed by students in PGS	Using conditions of level 2 to solve puzzles designed by students in PGS	Using conditions of level 2 to design puzzles and solve puzzles designed by students in PGS

Fig. 4. The turtle graphics used as puzzles in Turtle Graphic Puzzles Level 1 and 2.

After the four learning activities of solving puzzles were concluded, the students took the posttest on algorithmic thinking skills and completed TGTS feedback questionnaires.

3. Analyses and results

To examine whether there were significant differences among the three treatment groups in algorithmic thinking skills, puzzle-solving performance, and attitudes toward learning activities, this study performed an analysis of covariance (ANCOVA) on the posttest scores, a multivariate analysis of variance (MANOVA) on the collected numbers of various types of puzzle-solving performances, and a multivariate analysis of variance (MANOVA) on the scores of the three dimensions of the students' attitudes toward learning activities.

3.1. Algorithmic thinking skills

Table 3 reports on the means and standard deviations of the posttest scores for the three treatment groups.

Tests of the homogeneity of the regression coefficient indicate that the interaction $F = 1.941$ between the independent variables and covariance was .146 ($p > .05$). This confirms the hypothesis of the homogeneity of the regression coefficient.

Table 4 presents the results of the ANCOVA on the posttest. The independent variable was whether game mechanics or the student-generated questions strategy was used during the process of learning activities, and the dependent variable was the student's posttest score on algorithmic thinking skills.

The post ANCOVA and pairwise comparisons reveal that the PGM and PGS groups both scored significantly higher than the PBL [PGM ($p = .000$), PGS ($p = .000$)], and the PGS scored significantly higher than the PGM ($p = .033$). This result indicates that the performance of the PGS in algorithmic thinking skills was the highest of the three groups and the performance of the PGM in algorithmic thinking skills was significantly better than the PBL.

3.2. Comparison of puzzle-solving performances

Table 5 presents the summary of the MANOVA results for the puzzle-solving performances. The independent variable was whether game mechanics or the student-generated questions strategy was used during the process of learning activities, and the dependent variables were the numbers of various types of puzzle-solving performances.

The results indicated significant differences among the three treatment groups in all four puzzle-solving performances. The *post hoc* comparisons reveal the following:

Table 3
Summary of means (*M*) and standard deviations (*SD*) for the posttest.

	n	*M*	*SD*
PBL	82	27.21	12.222
PGM	79	37.57	12.625
PGS	81	40.25	11.879
Total	242	34.95	13.443

n, the number of participants.

Table 4
Summary of the ANCOVA results on the posttest with the pretest as the covariate.

	SS	*df*	*MS*	*F*	*p*
Contrast	9282.741	2	4641.370	54.817	.000***
Error	20151.651	238	84.671		

***$p < .001$ level; *df*, degrees of freedom; *SS*, sum of squares; *MS*, mean squares.

Table 5
Summary of the MANOVA results for puzzle-solving performances.

	Group	*M*	*SD*	*F*	*p*	Post Hoc
Attempted puzzles	PBL(n = 82)	31.476	0.910	28.332	.000***	PGM > PGS > PBL
	PGM(n = 79)	41.253	0.927			
	PGS(n = 81)	36.296	0.915			
Solved puzzles	PBL(n = 82)	22.756	0.746	22.324	.000***	PGM > PGS > PBL
	PGM(n = 79)	29.835	0.760			
	PGS(n = 81)	26.852	0.751			
Times attempted	PBL(n = 82)	142.171	9.829	26.160	.000***	PGM > PGS > PBL
	PGM(n = 79)	243.646	10.014			
	PGS(n = 81)	190.407	9.889			
Times solved	PBL(n = 82)	25.000	4.579	20.292	.000***	PGM > PGS > PBL
	PGM(n = 79)	66.620	4.665			
	PGS(n = 81)	44.173	4.607			

***$p < .001$ level.

- For the number of puzzles attempted performances, the PGM and PGS groups were both significantly higher than the PBL [PGM ($p = .000$), PGS ($p = .001$)] with the PGM higher than the PGS ($p = .001$).
- For the number of puzzles solved completely, the PGM and PGS groups were both significantly higher than the PBL [PGM ($p = .000$), PGS ($p = .001$)] with the PGM higher than the PGS ($p = .022$).
- For the number of times participants attempted to solve puzzles, the PGM and PGS groups were both significantly higher than the PBL [PGM ($p = .000$), PGS ($p = .000$)] with the PGM higher than the PGS ($p = .004$);
- For the number of times participants solved puzzles completely, the PGM and PGS groups were both significantly higher than the PBL [PGM ($p = .000$), PGS ($p = .000$)] with the PGM higher than the PGS ($p = .018$).

These results confirmed that in all four performance dimensions, the PGM performed the best among the three groups and the PGS performed better than the PBL.

3.3. Comparison of attitudes toward learning activities

Table 6 presents the summary of the MANOVA results for attitudes toward learning activities. The independent variable was whether game mechanics or the student-generated questions strategy was used during the process of learning activities, and the dependent variables were the scores on the three dimensions of the students' attitudes toward learning activities.

The results of the MANOVA indicated that there was no significant difference among the three treatment groups in system usability; however, there were significant differences among the three treatment groups in engaging experiences and willingness to participate. The *post hoc* comparisons of engaging experiences indicated that the PGS scored significantly higher than the PBL ($p = .001$) and PGM groups ($p = .004$), indicating that participants in the PGS had more engaging experiences than members of the

Table 6
Summary of the MANOVA results for attitudes toward learning activities.

	Group	*M*	*SD*	*F*	*p*	Post Hoc
System usability	PBL(n = 82)	10.61	3.177	2.374	.095	
	PGM(n = 79)	11.15	2.842			
	PGS(n = 81)	11.62	2.827			
Engaging experiences	PBL(n = 82)	21.78	5.843	7.715	.001**	PGS > PBL, PGM
	PGM(n = 79)	22.37	4.933			
	PGS(n = 81)	24.73	4.269			
Willingness to participate	PBL(n = 82)	7.45	2.410	6.175	.002**	PGS > PBL
	PGM(n = 79)	8.03	2.088			
	PGS(n = 81)	8.63	1.887			

**$p < .01$ level.

PBL and PGM groups in the learning activities of TGTS. The *post hoc* comparisons of willingness to participate indicate that the PGS was significantly higher than the PBL ($p = .002$), indicating that participants in the PGS were more willing to participate in the learning activities of TGTS than members of the PBL.

4. Discussion

To identify the performance differences among the three settings – puzzle-based learning without game mechanics (PBL), with game mechanics (PGM) only, and with game mechanics plus the student-generated questions strategy (PGS) – this study analyzed and compared the activities when solving puzzles and the attitudes toward learning activities.

The results of the ANCOVA of algorithmic thinking skills indicated that the performances of the members of the PGM and PGS, who participated in the learning activities of TGTS based on puzzle-based game learning with game mechanics, were both better than the members of the PBL, who participated in the learning activities of TGTS based on puzzle-based game learning without game mechanics. Furthermore, the performance of the members of the PGS, who participated in the learning activities of TGTS by further applying the student-generated questions strategy, was significantly better than the performance of the members of the PGM in algorithmic thinking skills. To further confirm this result, this study reviewed the pseudocodes that students replied to the free-response questions of the posttest to compare the performance differences among the three settings. Pseudocodes assessment indicated that the majority of the participants were familiar with commands operation and sequence concepts, although there were huge differences among participants in familiarity with iteration concepts, decomposition, pattern recognition, and variable operations. Overall, pseudocodes produced by the members of the PGM and PGS groups, particularly for the PGS, were better than those produced by the members of the PBL in accuracy and integrality. This result indicated that the members of the PGM and PGS groups were more familiar with the concepts, algorithms and skills of solving puzzles and more adept at applying those skills to solve various problems than the members of the PBL. Because the results indicated that the PGM and PGS groups were better than the PBL in all four puzzle-solving performances, the results of the ANCOVA of algorithmic thinking skills and the review of the pseudocodes were both reasonable. Using game mechanics, this study encouraged members of the PGM and PGS groups not only to try and solve a puzzle more times but also to try and solve more puzzles. Practice has been regarded as one of the major fundamentals in learning process (Dick, Carey, & Carey, 2005; Yu & Chen, 2014). In addition, Futschek (2006) suggested that engaging students in solving various problems is a fundamental and practical strategy for promoting algorithmic thinking skills. Practicing and experiencing puzzle-solving more times and more puzzles helped the members of the PGM and PGS groups mastering the concepts and skills of algorithmic thinking. Furthermore, previous studies indicated that using the student-generated questions strategy might help students enhance comprehension, promote diverse and flexible thinking, and increase problem-solving abilities (Abramovich & Cho, 2006; Barlow & Cates, 2006; Dori & Herscovitz, 1999; English, 1997). Therefore, members of the PGS group further enhanced the comprehension and application of algorithmic thinking skills. These results can confirm that applying game mechanics to online puzzle-based game learning systems can promote algorithmic thinking skills, and the additional student-generated questions strategy can further promote algorithmic thinking skills.

Comparing the number of puzzles solved and the number of times puzzles were solved completely among the three groups [PBL (22.756, 25.000); PGM (29.835, 66.620); PGS (26.852, 44.173)], this study found that the participants in the PGM (29.835, 66.620) and PGS (26.852, 44.173) groups attempted repeatedly to solve puzzles they had solved completely before. The participants in the PBL group (22.756, 25.000), while, tried fewer times to solve again a puzzle that they had previously solved. In addition, comparing the number of puzzles attempted (PBL, 31.476; PGM, 41.253; PGS, 36.296) and the number of times puzzles were attempted among the three groups (PBL, 142.171; PGM, 243.646; PGS, 190.407), this study found that the participants in the PGM and PGS groups attempted to solve not only more puzzles but also more times than the participants in the PBL. This result indicated that the members of the PGM and PGS groups were more energetic than the members of the PBL in attempting to solve various puzzles and in making more attempts to solve puzzles. Calculating a ratio by the number of attempts to solve puzzles (243.646 times) over the time of using the learning system (266.2 min) for the PGM, the participants in the PGM attempted to solve puzzles nearly once per minute (0.915 times/minutes). This result indicates that the participants in the PGM group have acted quickly and energetically to think about the algorithm of solving a puzzle, drag the command blocks to complete the algorithm, and run the algorithm to test whether the puzzle could be solved in a short time. This analysis indicates that using game mechanics in an online puzzle-based game learning system can encourage students to solve puzzles repeatedly and energetically, in accordance with previous studies that indicated using game mechanics could promote desired behaviors (Elverdam & Aarseth, 2007; Hamari et al., 2014; Lee & Hammer, 2011; Muntean, 2011; Robson, Plangger, Kietzmann, McCarthy, & Pitt, 2015). By enhancing puzzle-solving performances, the use of game mechanics can engage students in experiencing various puzzles and in mastering methods of solving puzzles and the concepts of algorithmic thinking; thus, using game mechanics can encourage students to learn algorithmic thinking skills. However, observing the puzzles that students repeatedly solved, this study found that because the students were free to select puzzles in an activity, the students tended to select easy puzzles to solve quickly to accumulate “magic points” quickly and upgrade their wizard levels. This behavior of “bumping up points” is expected to encourage students to learn and master the concepts and puzzle-solving skills of algorithmic thinking; however, if students only select easy puzzles to solve repeatedly, the effect of helping them master the difficult and complex concepts and puzzle-solving skills of algorithmic thinking will be reduced. This issue must be addressed in future studies.

Although the performance of the members of the PGS group was better than the members of the PGM in algorithmic thinking skills, the results of the MANOVA indicated that in all four puzzle-solving performances, the PGM group scored higher than the PGS. The observations revealed that because the PGS, using the student-generated questions strategy, was required to spend some time designing puzzles in Activity 2 and Activity 4, the number of attempted puzzles and solved puzzles and the numbers of times attempted and times solved were reduced during the period of these two activities. However, when students designed turtle graphics freely, they not only reflected on the concepts, algorithms and skills of solving puzzles but also tried to apply these concepts, algorithms and skills to composing, restructuring or constructing new puzzles for their peers to solve. By involving students in thinking about generating turtle graphics actively and creatively, the student-generated questions strategy further encouraged students to learn algorithmic thinking skills. In this manner, students not only reflected on what they had learned but also learned to employ the concepts, algorithms, and problem-solving skills of algorithmic thinking in a creative manner.

In addition to assessing algorithmic thinking skills and comparing puzzle-solving performances, this study also compared attitudes toward learning activities. The results of comparing attitudes toward system usability indicated no significant differences among the three treatment groups. This result indicates that applying game mechanics or game mechanics plus the student-generated questions strategy in online puzzle-based learning systems has no effect on system usability.

The results of comparing attitudes toward engagement experiences and willingness to participate among the three treatment groups indicated that the PGS group scored significantly higher than the PBL and PGM in engagement experiences and scored significantly higher than the PBL in willingness to participate. As some studies have noted, in addition to fostering comprehension, the student-generated questions strategy also helps students become more involved in learning activities, and positive attitudes toward learning are important (Chin & Brown, 2002; Keil, 1965; Perez, 1985; Yu, 2009). Similarly, this result indicates that the student-generated questions strategy plus game mechanics can encourage students to engage in learning activities and enhance their willingness to participate in an online puzzle-based learning system. Therefore, a student-generated questions strategy plus game mechanics is beneficial in promoting not only the performance of algorithmic thinking but also positive attitudes toward engaging experiences and willingness to participate.

However, the results of comparing attitudes toward engagement experiences and willingness to participate indicated no difference between the PBL and PGM groups. These results indicate that although applying game mechanics may promote students' puzzle-solving performance it did not enhance attitudes toward engagement experiences and willingness to participate in an online puzzle-based game learning system. The situation in this study is that both the PBL and PGM used a puzzle-based game learning system with game characteristics as a fundamental strategy. Malone (1980) indicated that educational games could improve students' motivation and engagement by embedding essential game characteristics such as challenge, fantasy and curiosity. Moreover, some studies reported that although using game mechanics indeed promotes the desired behaviors, some effects that arose from using game mechanics, such as increasing competition, must nevertheless be considered (Hakulinen, Auvinen, & Korhonen, 2013; Hamari et al., 2014; Hanus & Fox, 2015; Huotari & Hamari, 2012). The issue on how to use game mechanics to not only promote behaviors but also enhance attitudes toward an online game-based learning system must be further investigated in the future.

Although this study produced positive findings regarding the use of game mechanics and the use of a student-generated questions strategy in an online puzzle-based game learning system, a limitation of this study is that the experiment was conducted over a short period. Many studies have noted that using game mechanics may not be effective over a long run (Farzan et al., 2008; Hamari, 2013; Hamari et al., 2014). Whether using game mechanics or the student-generated questions strategy has significant effects on an online puzzle-based game learning system for a longer experimental period remains to be addressed in the future.

5. Conclusions

This study investigated whether using game mechanics and a student-generated questions strategy in an online puzzle-based game learning system can promote algorithmic thinking skills. For that, an online puzzle-based game learning system, TGTS, which can integrate game mechanics and embed a student-generated questions strategy beyond using puzzle-based game learning as its basic strategy, was developed. The results of assessing algorithmic thinking skills indicated that the PGM group, using puzzle-based game learning with game mechanics only, and the PGS group, using puzzle-based game learning with game mechanics plus the student-generated questions strategy, both of which participated in the learning activities with game mechanics, were more effective than the PBL group, which participated in the learning activities without game mechanics. Furthermore, the PGS group was significantly more effective than the PGM. The results of comparing puzzle-solving performances indicate that using game mechanics in an online puzzle-based game learning system can enhance all four types of performances: the number of puzzles attempted, the number of puzzles solved, the number of times students attempted to solve puzzles and the number of times students solved puzzles completely. Thus, using game mechanics in an online puzzle-based game learning system can positively influence the behaviors of students participating in learning activities. The results of comparing attitudes toward learning activities indicate that using game mechanics plus a student-generated questions strategy in an online puzzle-based game learning system can enhance engagement experiences and willingness to participate. In conclusion, the results revealed that in an online puzzle-based game learning system, using game mechanics can enhance algorithmic thinking skills and performance in solving puzzles. Furthermore, although in terms of puzzle-solving performance, using game mechanics plus a student-generated questions strategy is less effective than using only game mechanics, the former may nevertheless enhance algorithmic thinking skills more than the latter. Additionally, using game mechanics plus a student-generated questions strategy can enhance students' engagement experiences and willingness to participate in the learning activities of an online puzzle-based game learning system.

The results of this study can be a reference for developing online puzzle-based game learning systems to promote algorithmic thinking skills. Although some issues, such as selecting easy puzzles to gain more points and learning for a short period of time, must be addressed in further studies, the positive effects of using game mechanics and a student-generated questions strategy can be used as a reference in developing an online game learning system or designing learning activities to help students learn algorithmic thinking skills more effectively.

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