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EVENLY MATCHED COMPETITIVE STRATEGIES: DYNAMIC DIFFICULTY ADAPTATION IN A GAME-BASED LEARNING SYSTEM

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Game-based learning is a highly motivational learning approach, with appropriate difficulty level being the key to level of motivation in this type of learning. However, it is not easy to adapt the difficulty of game-based learning for some students. This study proposes two evenly matched competitive strategies to dynamically adapt the difficulty of game-based learning during the game, while matching game progress and maintaining evenly matched game results. The strategies are designed to realize a even opportunity tactic to manipulate perceived performance in game-based learning. This study also proposes three adaptation methods: Adjusting the complexity of learning tasks, uncertain game factors, and virtual characters to realize the strategies. A system was implemented and two preliminary experiments were conducted with a total of 56 participants to validate the strategies and adaptations. The results of the experiments show that adaptations based on strategies can dynamically adjust in order for different students to keep the game evenly matched.

Keywords: Personalized game-based learning system; dynamic difficulty adaptation; adaptive and intelligent educational systems; virtual opponent; even opportunity tactic.

1. Introduction

Game-based learning incorporates learning activity within a game format to motivate students. The game format usually provides goals, rules, fantasy, mystery, challenges, interaction, competition, results and feedback, representation or story, and other entertaining game elements to inspire students to actively engage, to assume a role, and to take a degree of personal responsibility for consequences (Dennis & Kansky, 1984; Garris, Ahlers, & Driskell, 2002; Malone, 1981; Prensky, 2001). Particularly, the game format is aimed at motivating students to learn and attracting students to complete learning tasks. That is, the game format must provide an identifiable cause-effect relationship between students' responses and game results (Hannafin & Peck, 1988).

When students complete or perform a learning task well, the game should be executed to advance the scenario.

Malone (1981) suggested that capabilities of computers can be used to create motivational environments. Game-based learning systems employ the capabilities of computers to enrich game-based learning by providing immediate and adaptive feedback, numerous contents and scenarios, varied graphic representations and animations, different levels of challenge, distance players, virtual opponents, and customized adaptation (Prensky, 2001). Studies show that well-designed game-based learning systems can make students highly motivated and engaged in game-based learning so that they make greater efforts to learn and attain better achievement (Brom, Preuss, & Klement, 2011; Chang et al., 2009; Chen, Chou, Deng, & Chan, 2007; Girard, Ecalle, & Magnant, 2013; Ke, 2008; Miller, Chang, Wang, Beier, & Klisch, 2011; Papastergiou, 2009; Sitzmann, 2011; Yu, Chang, Liu, & Chan, 2002).

Researchers endeavored to investigate the characteristics of motivating learning environments and suggest guidelines for designing game-based learning systems. Malone (1981) analyzed the characteristics of motivational environments and pointed out that key features of these environments are challenging, fantasy, and curiosity. In addition, Malone hypothesized that level of challenge depends on goals with uncertain outcomes. That is, students are neither certain to reach the goal nor certain not reach the goal. Malone also suggested four general ways to make environments challenging for different students or for the same students at different times: Varied difficulty levels, multiple level goals, hidden information, and randomness. The difficulty levels of a game could be determined by the system, chosen by the students, or determined by the opponent's skill to provide students with goals of appropriate difficulty. Csikszentmihaly (1975) also proposed a flow theory and suggested that challenges of tasks and person's skill should be matched to prevent the person from being anxious or bored.

However, it is not easy to design game-based learning systems to provide goals with appropriate levels for students with different ability levels. The difficulty of game-based learning could be determined by complexity of learning tasks, rules, goals, opponent's competence, student's skill, and luck element. In general, systems provide different modes or stages with different difficulties by changing the complexity of learning tasks, scaffoldings, rules, and goals. For instance, the goal of novice mode and first stage is to solve three essential problems with hints and without any time limit. The goal of intermediate mode and second stage is to solve the same problems without hints and within 10 minutes. These systems might allow students to choose modes or to be challenged stage by stage. However, students are easily aware of such explicit difficulty adaptation and, furthermore, "*less-able students can hardly have the same opportunity for performing well and owning the sense of achievements as more-able students*" (Cheng, Wu, Liao, & Chan, 2009). Thus, Cheng and his colleagues proposed an equal opportunity tactic to assign each student an opponent with similar ability in competitive educational games for moderating the difference in the opportunity for performing well between more-able and less-able students (Cheng et al., 2009). The evaluation results show that the equal opportunity tactic successfully made less-able students have a similar perceived performance and predicted performance as more-able students. Nevertheless, it might be unable to find an opponent with similar ability. Chou and his colleagues designed a game-based learning system with virtual characters. The system adapts difficulty by changing different roles (opponent, collaborator) and competence (novice, intermediate, or expert) of virtual characters (Chou, Chan, & Lin, 2002). However, these above difficulty adaptation mechanisms are usually applied before the start of a game and are not real-time applied during the game. Some researchers developed real-time adaptation mechanisms in computer entertainment games (Dormans & Bakkes, 2011; Liu, Agrawal, Sarkar, & Chen, 2009; Lopes & Bidarra, 2011; Spronck, Ponsen, Sprinkhuizen-Kuyper, & Postma, 2006; Yannakakis & Hallam, 2007, 2009). Although these real-time adaptation mechanisms can also be applied in game-based learning system, these mechanisms mainly focus on entertainment and game progress and are not concerned with learning and game results. This study proposes evenly matched competitive strategies to realize the even opportunity tactic by dynamically adapting difficulty of game-based learning to different students during the game to make the game evenly matched in progress and results.

2. Perceived Performance and Even Opportunity Tactic

Cheng and his colleagues argued the difference between actual performance and perceived performance (Cheng et al., 2009). Actual performance indicates students' ability in learning tasks. Perceived performances in game-based learning denote the game results, such as win or lose, score, ranking, etc. Perceived performance could be influenced by actual performance, rules, opponents, luck, and other game factors. Most learning activities, including game-based learning activities, are designed to link perceived performance and actual performance, thus less-able students have less of a chance to own the sense of achievement than more-able students. Studies show that students' past academic performance and experience influence their perceived self-efficacy, and their perceived self-efficacy will positively influence their future performance, motivation, and self-regulation (Bandura, 1993; Schunk, 1985; Zimmerman, 2000). However, less-able students have less opportunity to increase their performance to enhance their perceived self-efficacy. Cheng and his colleagues proposed an even opportunity tactic to break the link between perceived performance and actual performance for reducing the difference in perceived performance between more-able and less-able students by assigning each student an opponent with similar ability (Cheng et al., 2009). The results show that even opportunity tactic enabled less-able students to have similar perceived performance and build similar confidence in the game as more-able students. Therefore, perceived performance could be manipulated and used to make students confident in accomplishing their learning goals and promote students to engage and make greater efforts in the following game-based learning. This study proposes evenly matched competitive strategies as possible methods to manipulate perceived performance in game-based learning.

3. Evenly Matched Competitive Strategies

Games have different game formats and game objectives. For example, some games ask players to finish assigned tasks with limited time or resources without opponents. Competitive games ask players to compete against other players or virtual opponents. This study mainly proposes evenly matched competitive strategies to dynamically adapt the difficulty of competitive educational games. The evenly matched competitive strategies include two strategies:

(1) Strategy of keeping evenly matched game progress: Evenly matched game progress indicates that there is no significant difference in player performance between players during the game. If a player was far ahead of the other player during the game, the leading player might feel bored and the other player might feel anxious or depressed. The strategy is to keep the game result uncertain until the last moment. Each player has the opportunity to win, but is unsure whether he/she will win or not. The evenly matched game progress and uncertain result may make students feel challenged and excited.

(2) Strategy of maintaining evenly matched game results: Even players are matched and it is possible that a player always defeats the other player. The always-losing player might feel depressed. The strategy is to maintain game results within an appropriate range; that is, allowing each player to win in some rounds in order to attain a sense of achievement, and to lose in some rounds to make the player feel challenged and willing to engage in the next round in order to defeat the opponent. Evenly matched game results might depend on the individual personality of the student. Some students are self-confident or adventurous and losses may encourage them to make greater efforts. On the other hand, some students are less self-confident and need more wins to encourage them. Thus, evenly matched game results could be planned as a range and might be adjusted according to a student's individual personality.

While difficulty adaptation is required according to the strategies, there are many possible methods such as adjusting complexity of learning tasks, goals, or even rules. This study proposes three adapting methods to realize the strategies:

(1) Adjusting the complexity of learning tasks: A player might be far behind in the game because of less-ability. The method is to adjust the complexity of learning tasks to fit the student ability. In some games, players might be assigned to finish different learning tasks with different complexity. If players are asked to finish the same learning tasks in a game, less-able players might have supports such as tools, hints, or teammates, to reduce the complexity. However, for a game-based learning system, the system should gradually increase the complexity of learning tasks or change the learning tasks to lead students to learn.

(2) Adjusting uncertain game factors: Many games have uncertain factors to make the game fun, such as dice and cards. Pairing opponents in competitive games could also be an uncertain factor. In game-based learning, the next learning task could be uncertain before the student finishes the current learning task. In general, uncertain factors in games are determined by drawing lots, randomness, or a hidden sequence.

The method is to adjust uncertain game factors to favor the player, which is far behind, to allow the player to catch up or even to win.

(3) Adjusting virtual characters: Many games have virtual characters (non-player characters) be opponents, collaborators (teammates), or assistants to the players. These virtual characters can be adjusted to adapt the difficulty of the game. For example, the competence of virtual opponents can be adjusted to reduce the distance between players. If a student is far ahead of the virtual opponent, the method increases the virtual opponent's competence so that the opponent can perform better to catch up with the student. Contrarily, the method decreases the virtual opponent's competence to allow the student to catch up. Similarly, the virtual collaborators and assistants could be adjusted to provide less supports for able players and more supports for less-able players.

When a system determines to adapt difficulty based on the evenly matched competitive strategies, it may apply one adaptation method or simultaneously apply several adapting methods. Whether the adapting methods are applicable depends on the game format and rules. However, the adaptations might lead to unfairness and should be hidden and unperceived by players. Otherwise, players may feel cheated and refuse to play again or make an effort in their existing game. In addition, the adaptations might lead to inconsistency between game results and the actual performance of students; thus, the game results should not be used to evaluate the actual student performance.

4. ArithmeticWinner: An Implementation of Evenly Matched Competitive Strategies

4.1. *Game rules of ArithmeticWinner*

A game-based learning system, named ArithmeticWinner (Chou, Lu, & Chen, 2012), was implemented to validate the evenly matched competitive strategies and adaptations. ArithmeticWinner adopts the game format of WEST (Burton & Brown, 1979), which incorporates a racing game with drill and practice of arithmetic procedures of four fundamental operations. Mathematical proficiency consists of conceptual understanding, procedural fluency, strategic competence, adaptive reasoning, and productive disposition (Kilpatrick, Swafford, & Findell, 2001). Procedural fluency is defined as, "knowledge of procedures, knowledge of when and how to use them flexibly, accurately, efficiently, and appropriately, and skill in performing them flexibly, accurately, and efficiently." Good conceptual understanding of numbers supports the development of fluency in arithmetic operations and practice improves fluency. ArithmeticWinner aims to facilitate procedure fluency of students who have learned arithmetic operation procedures and own good conceptual understanding of numbers. In ArithmeticWinner, two players compete to first reach the goal by moving via turns (Figure 1). A player is a virtual opponent and the other player is a student. In a player's turn, the player will get three numbers and need to choose two operations from "+", "-", "×", and "/" to compose an arithmetic expression, such as "1+2×3". Each number should be used exactly once in the expression. An

Figure 1. Screenshot of ArithmeticWinner.

operator can be used twice in the expression, such as “1+2+3”. Thus, there are 96 (3×2×1×4×4) possible expressions. The calculation result of the expression determines the move of the player. If the result was six, the player will move forward six steps. There are three special rules to affect the player’s move. First, when a player moves to a castle, the player will jump to the next castle once. Second, when a player moves to the beginning of a shortcut, the player will jump to the end of the shortcut. There are three shortcuts, which are from 6 to 15, from 23 to 36, and from 47 to 55. Third, when a player moves to the location of the other player, the other player will be “bumped” and moved backward ten steps. These special rules make the game more fun and variable, therefore it might not be best to attain maximum calculation results of three numbers. For instance, a student is at location eight and gets three numbers: 1, 2, and 3, an arithmetic expression of “1+2×3” can obtain the maximum calculation result and cause the student to move forward seven steps to reach location 15. However, the arithmetic expression of “3+1-2” can make the student move forward two steps to reach location ten and jump to location 20 according to the castle special rule. Therefore, students need to explore and compare possible combinations of numbers and operators to attain the best move. The game design aims to provide various practice situations to facilitate student arithmetic procedure fluency in performing procedures flexibly, accurately, and efficiently.

4.2. *Implementation of the virtual opponent*

The main purpose of the virtual opponent is to simulate how the virtual opponent composes an expression in its turn. When a player gets three numbers, there are 96 possible expressions. The system calculates the results of all possible expressions and the corresponding location after moving. After calculations, all expressions are sorted by location from minimum to maximum. The expression with the maximum location is the best move in this turn. The system chooses an appropriate expression from all possible expressions according to the virtual opponent's competence level to simulate the opponent's expression (Chou et al., 2002). The virtual opponent composition is determined by an opponent competence level, which is assigned in advanced and may be adaptively modified during the game. The level is a decimal, which ranges between zero (novice) and one (expert). For instance, if the opponent competence level is one, the component chooses the 96th (96 × 1) expression in the sorted expressions as the opponent's expression; that is, the expression with maximum location. If the opponent's competence level is 0.5, the component chooses the 48th (96 × 0.5) expression as the opponent's expression.

4.3. *Dynamic difficulty adaptations*

Figure 2 illustrates the process of dynamic difficulty adaptations in the ArithmeticWinner. The system checks whether the result strategy is activated. If the result strategy was activated, the system may only adjust the generated numbers or adjust both the generated numbers and the opponent. Otherwise, the system checks whether the progress strategy is activated. If the progress strategy was activated, the system either adjusts the generated numbers or adjusts the opponent. The detailed heuristic rules of adaptations are described as follows.

ArithmeticWinner adopts some heuristic rules to implement evenly matched competitive strategies and dynamic difficulty adaptations. ArithmeticWinner adopts two dynamic difficulty adaptations to realize evenly matched competitive strategies: Adjusting virtual opponent competence and uncertain game factors (three numbers

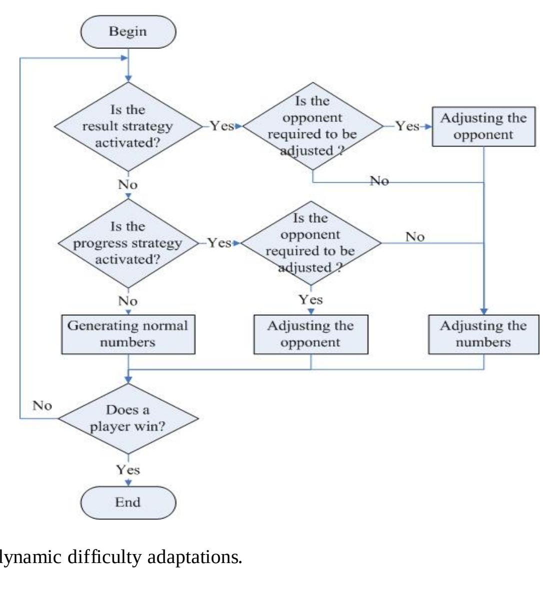

Figure 2. Process of dynamic difficulty adaptations.

Table 1. Heuristic rules of generating numbers.

Rule ID	Adjustment	Constraints
GN#1	No	All calculation results are less than 20.
GN#2	Favorable	All calculation results are less than 30.
GN#3	Against	All calculation results are less than 15.
GN#4	Against	All moves cannot reach the goal.

generated for the player in each turn). If a student is far ahead of the virtual opponent, the system increases the virtual opponent competence level so that the opponent can perform better to catch up with the student. In contrast, the system decreases the virtual opponent competence level to allow the student to catch up. There are four heuristic rules of generating numbers (Table 1). In the regular case, ArithmeticWinner randomly generates three numbers, which are from 1 to 4, and the maximum move of the three numbers does not exceed a move threshold such as 20 moves (GN#1). In the adaptation case of favoring a player, the move threshold is increased, such as 30, so that the player may get the numbers to move further to catch up or even to win (GN#2). In the adaptation case of against a player, the move threshold is decreased, such as 15 (GN#3). If a player is close to the goal and the system prevents the player from winning this round according to the strategy of maintaining evenly matched game results, the system will not provide the numbers that can reach the goal (GN#4).

There are nine heuristic rules of difficulty dynamic adaptations (Table 2). To realize the strategy of maintaining evenly matched game progress, ArithmeticWinner defines obvious distance as 10 moves and far distance as 15 moves. If the distance between the virtual opponent and the student is less than the obvious distance, the system does not make any adaptation. When the virtual opponent is in turn to move and the distance is

Table 2. Heuristic rules of difficulty dynamic adaptations.

Rule ID	Player	Strategy	Condition	Action
DA#1	Opponent	Progress	LO <= 40, 15> (LS – LO) > 10	Increase PO (+0.1)
DA#2	Opponent	Progress	LO<= 40, 15 > (LO – LS) > 10	Decrease PO (-0.2)
DA#3	Student	Progress	LS <= 40, (LS – LO) > 15	Activate NG#3
DA#4	Student	Progress	LS <= 40, (LO – LS) > 15	Activate NG#2
DA#5	Opponent	Progress	LO <= 40, (LS – LO) > 15	Activate NG#2
DA#6	Opponent	Progress	LO <= 40, (LO – LS) > 15	Activate NG#3
DA#7	Student	Result	LS > 40, student needs to lose in this round	Activate NG#4
DA#8	Opponent	Result	LO > 40, student needs to win in this round	Decrease PO (-0.2), Activate NG#4
DA#9	Opponent	Result	LO > 40, student needs to lose in this round	Increase PO (+0.1), Activate NG#2

LO: Location of the opponent; LS: Location of the student; PO: Proficiency level of the opponent between the obvious distance and the far distance, the strategy is activated to adapt virtual opponent competence. If the opponent is behind the student and the virtual opponent is not an expert (the competence level is less than 1), the system increases the competence level of the virtual opponent by adding 0.1 (DA#1). If the opponent is ahead of the student, the system decreases the competence level of the virtual opponent by subtracting 0.2 (DA#2). If the distance is larger than the far distance, the strategy is activated to adapt generated numbers (DA#3~DA#6). The leading player will get the numbers with less move threshold and the behind player will get the numbers with larger move threshold.

To realize the strategy of maintaining evenly matched game results, appropriate game results are planned in advance and assigned in ArithmeticWinner. The planned game results can be a specific result; for instance the students win 8 rounds among 10 rounds. The game results can also be planned as a range; for instance the students win at least 6 rounds among 10 rounds. When the location of a player is larger than 40 (the goal location is 70), the strategy of maintaining evenly matched game results is activated to check the planned game results. If the player needs to lose in this round to fit to the planned game results, the player will not get the numbers that can reach the goal (DA#7). If the player is the student, the system also increases the competence level of the virtual opponent by adding 0.1 (DA#8). If the player is the virtual opponent, the system decreases the competence level of the virtual opponent by subtracting 0.2 (DA#9).

5. Preliminary Experiments

Two preliminary experiments were conducted to investigate whether the evenly matched competitive strategies and dynamic difficulty adaptations would work or not.

5.1. *Experiment I*

In experiment I, participants were 27 fifth-grade elementary students (age 11 or 12), including 13 male and 14 female students. The experiment was conducted in a computer laboratory. Each student was allotted a computer to play ArithmeticWinner. First, students were instructed in how to play ArithmeticWinner. Then students were randomly assigned to two groups: control group and experimental group. Students in the control group played ArithmeticWinner six rounds without the adaptations mechanisms based on evenly matched competitive strategies. Students in the experimental group played ArithmeticWinner six rounds with the adaptations mechanisms based on evenly matched competitive strategies. Game results in the experimental group were planned as four wins and two losses. The competence of virtual opponent was initially set as 0.9 both in the control group and the experimental group. Detailed dynamic difficulty adaptation data for each student in the experimental group and students' game results in both groups were recorded in the server during the game.

Table 3 lists students' game results from experiment I. The game results of students in the control group were different. Participants in experiment I were fifth-grade students, which were supposed to master four fundamental operations of arithmetic. Most (85%)

Table 3. Game results from different groups in the experiment I.

Groups	6W0L	5W1L	4W2L	3W3L	2W4L	1W5L	0W6L
Control	1	5	5	1	0	1	0
Experimental	0	0	14	0	0	0	0

Note: W indicates Win; L indicates Loss

students from the control group won at least four rounds, but one student lost five rounds and did not perform similarly to the others. By contrast, the game results of all students in the experimental group aligned with the previous plan and students received similar perceived performance. Comparing the distance of players after each move during the game, the distance (M = 12.5, SD = 8.7) from the control group is statistically larger than the distance (M = 9.1, SD = 6.1) from the experimental group [t(2039) = 11.279, p < 0.001]. Comparing the final distance of players when a player won, the distance (M = 20.2, SD = 11.4) from the control group is statistically larger than the distance (M = 13.2, SD = 7.7) from the experimental group [t(134) = 4.528, p < 0.001]. The results reveal that the dynamic difficulty adaptations with evenly matched competitive strategies produce well-matched game progress and results.

Dynamic adaptations in ArithmeticWinner during the game in the experimental groups were recorded. The statistics of adapting frequency in experiment I are shown in Figure 3 and are based on whether it was activated by evenly matched game progress strategy or game result strategy. The frequency activated by evenly matched game progress strategy was observably more than the frequency by game result strategy in four

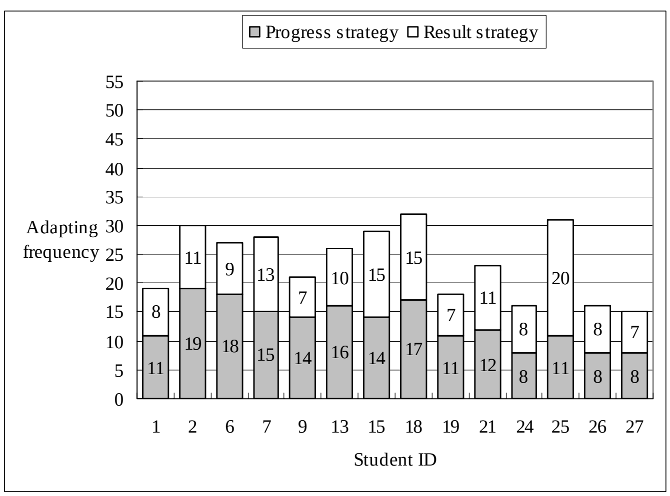

Figure 3. Statistics of adapting strategy in experiment I.

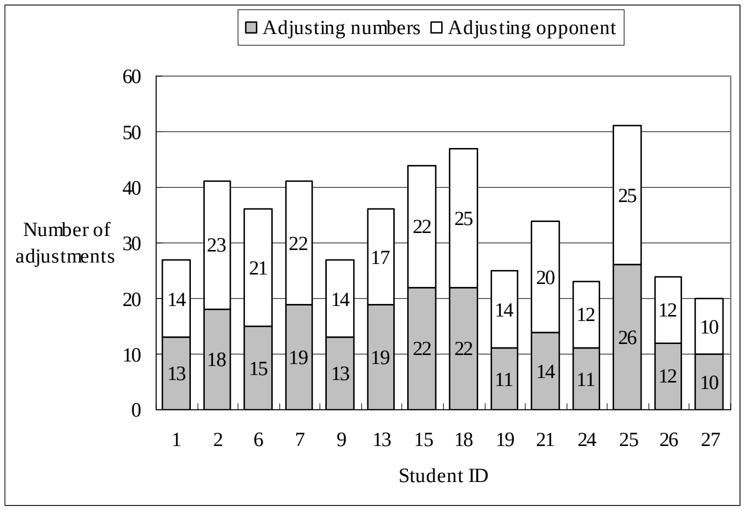

Figure 4. Statistics for adapting methods in the experiment I.

students (# 2, #6, #9, and #13). Three students (#2, #6, and #13) performed poorly and fell behind the opponent, while one student (#9) had good performance and was ahead of the opponent. One student (#25) activated more frequencies of game result strategy than that of game progress strategy. The student performed poorly and the adapting strategies of progress were frequently activated in the front part of the game, but the student still did not catch up to the opponent. Thus, the adapting strategies of result were frequently activated in the latter part of the game to produce the planned game results. The frequencies of two strategies were similar in other students.

When an adapting strategy was activated, ArithmeticWinner might adjust numbers, adjust the virtual opponents' competence, or adjust both numbers and the opponent. Thus, the number of adjustments is larger than adapting frequency. Figure 4 lists the statistics of adjustments in experiment I according to two adapting methods. Three students (#2, #6 and #21) received more adjustments in the opponent than adjustments in numbers. Others received similar quantity of adjustments in the opponent and in numbers.

An adjustment, no matter in numbers or in the virtual opponent, may favor the student or work against the student (favor the opponent). Figure 5 shows the statistics of adjustments in experiment I according to adjusted direction. The number of adjustments favoring the student was more than that of favoring the opponent on most (86%) students because these students were behind the opponent most of the time. Contrarily, ArithmeticWinner made more adjustments favoring the opponent in two students (#9 and #27). These two students performed well and were ahead of the opponent.

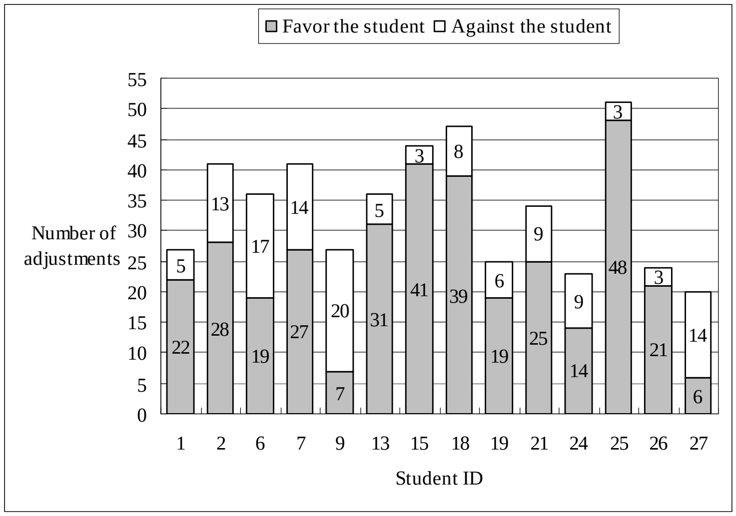

Figure 5. Statistics of direction of adjustments in experiment I.

5.2. *Experiment II*

In experiment I, most students from the control group did not obviously have different game results as students from the experimental group. Different from experiment I, experiment II aims to evaluate whether the evenly matched competitive strategies and dynamic difficulty adaptations also work in situations that require a great quantity of adaptations. The procedure for experiment II was the same as that of experiment I. In experiment II, participants were 29 fourth-grade (ages 10 or 11) elementary students, including 15 male and 14 female students. These students were supposed to have medium proficiency in four fundamental operations of arithmetic and were less-able than students in experiment I. The competence of virtual opponent was initially set as 1.0 (master), a more competent opponent than that in experiment I, both within the control group and experimental group. Therefore, it is difficult for students from the control group to win the game. By contrast, the planned game results in the experimental group were five wins and one loss, thus the system was supposed to have more adaptations in experiment II.

Table 4 lists the game results of experiment II. The results, in accordance with our supposition, show that most (86%) students in the control group lost at least five rounds and six students even lost all six rounds. By contrast, the game results from the experimental group were in accordance to the previous plan. In sum, the results indicate that the evenly matched competitive strategies and dynamic difficulty adaptations can make students' game results occur as in the previous plan and even the planned game results are extremely assigned. Comparing the distance of players after each move during the game, the distance (M = 13.7, SD = 10.1) from the control group is statistically larger than the distance (M = 10.2, SD = 7.1) from the experimental group [t(1928) = 9.764,

Table 4. Game results of different groups in experiment II.

Groups	6W0L	5W1L	4W2L	3W3L	2W4L	1W5L	0W6L
Control	0	0	0	1	1	6	6
Experimental	0	15	0	0	0	0	0

Note: W indicates Win; L indicates Loss

$p < 0.001$]. Comparing the final distance of players when a player won, the distance ($M = 22.1$, $SD = 13.3$) from the control group is statistically larger than the distance ($M = 12.5$, $SD = 7.4$) from the experimental group [$t(128) = 5.781$, $p < 0.001$]. The results reveal that the dynamic difficulty adaptations with evenly matched competitive strategies produce well-matched game progress and results even in an extreme situation.

Similarly, the statistics of adapting strategies in the experimental group in experiment II are listed in Figure 6. Regardless of the adapting strategy, the adapting frequencies ($M = 23.6$, $SD = 6.1$) in experiment I were significantly smaller than the frequencies ($M = 29$, $SD = 7.5$) in experiment II [$t(27) = -2.096$, $p < 0.05$]. The results, in accordance with our supposition, reveal that the system needed more adaptations to produce a well-matched game in experiment II. Compared to experiment I, most students (12 – 15ths, i.e. 80%) in experiment II obviously activated more frequencies of game result strategy than that of game progress strategy. The phenomenon could be explained by comparing the game results of the control group and the experimental group. Most students in the

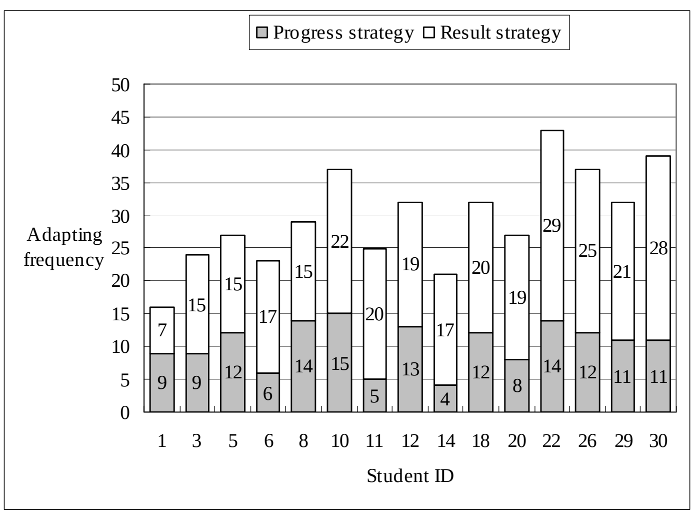

Figure 6. Statistics of adapting strategy in experiment II.

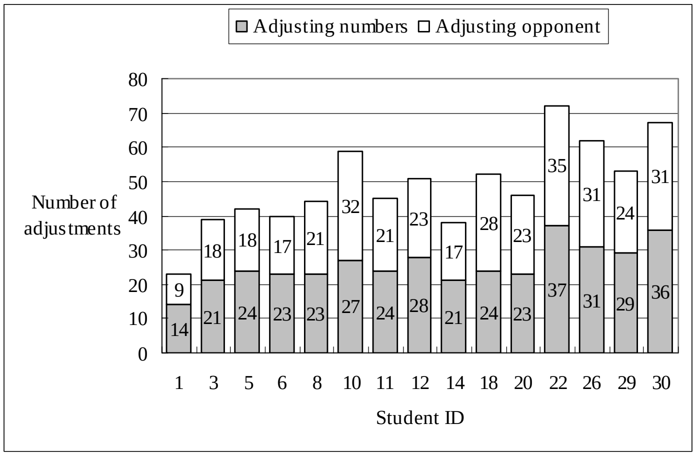

Figure 7. Statistics of adapting methods in experiment II.

control group lost five rounds because they were not proficient in four fundamental operations of arithmetic and the opponent was a master. However, the planned game results of the experimental group were five wins and one loss, so ArithmeticWinner required more adaptations to make students in the experimental group fit the planned game results.

Figure 7 lists the statistics of adjustments in experiment II. In general, students received similar quantity of adjustments in the opponent and in numbers. The phenomenon was consistent with experiment I. Figure 8 lists the statistics of adjustments

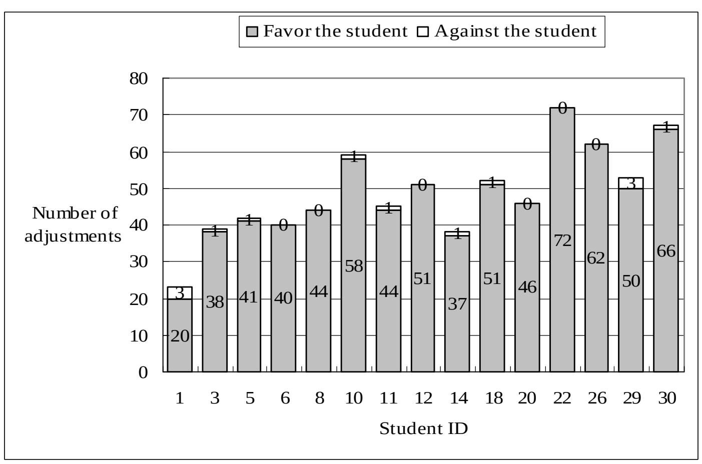

Figure 8. Statistics of direction of adjustments in experiment II.

in experiment II, according to adjusted direction. The statistics, in accordance with our supposition, reveal that adjustments were almost favoring the student in all students. Six students did not receive any adjustments, which were against them. The phenomenon could also be due to the gap between students' actual proficiencies and planned game results.

In experiment II, each student's proficiency level was estimated by ArithmeticWinner according to the student's expressions during the game. When the student composes an expression in a turn, the system generates all possible 96 expressions and locates the student's expression from the sorting moves of all expressions from minimum moves to maximum moves. If the student's expression is located at the 96th expression, the student's proficiency level in this turn is estimated as 1 (96 / 96). If the student's expression is located at the 24th expression, the student's proficiency level in this turn is estimated as 0.25 (24 / 96). Student's proficiency level is calculated by averaging the estimated proficiency levels in all turns. The proficiency level estimated by the system in this study is only used for analyzing the relationship between the student's proficiency level and the frequency of dynamic adaptation. However, the estimated student's proficiency level could be used as a factor to determine whether to adapt difficulty or not and how to adapt.

In addition, a value of favorable bias for each student was calculated to represent whether the system favored the student or the opponent and the favor amount. The value was calculated by subtracting the number of adjustments that favor the opponent, from the number of adjustments that favor the student. A positive value means that the system favored the student and a negative value indicates that the system favored the opponent. Figure 9 illustrates the distribution of students' proficiency level and favorable bias in

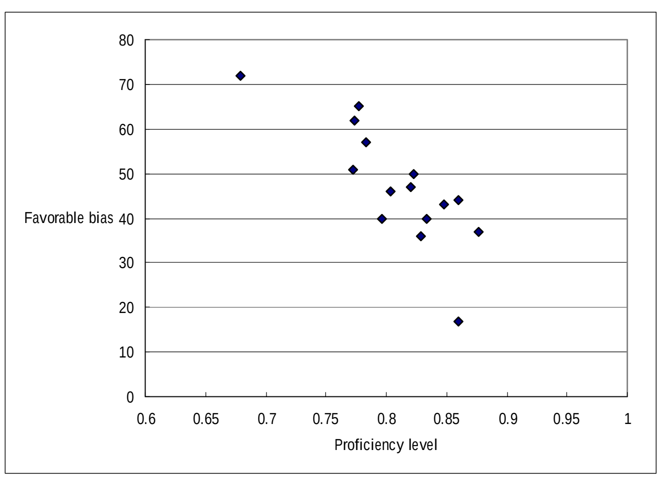

Figure 9. Distribution of students' proficiency level and favorable bias in experiment II.

experiment II. An analysis of Pearson's correlation shows that student's proficiency level was statistically negatively correlated with his/her favorable bias (coefficient = -0.81, $p < 0.001$). The results indicate that less proficient students attained more favoring adjustments. It also supports that the dynamic difficulty adaptations based on the evenly matched competitive strategies can dynamically adapt difficulty according to the student proficiency level even though the adaptations do not take the student proficiency level into account. However, it would help the adaptations to be more powerful and sensitive if the student proficiency level was taken into account.

In sum, the results of experiment I and experiment II reveal that the proposed evenly matched competitive strategies can adapt to different students' proficiency levels and planned game results through personalized dynamic adaptations during the game.

6. Conclusion and Discussion

This study proposed two evenly matched competitive strategies to dynamically adapt the difficulty of game-based learning during the game: Keeping evenly matched game progress and maintaining evenly matched game results. The strategies are designed to realize even opportunity tactic to manipulate perceived performance in game-based learning. This study also proposes three adapting methods to realize the strategies by adjusting the complexity of the learning tasks, uncertain game factors, and virtual characters. A game-based learning system, ArithmeticWinner, was implemented and two preliminary experiments were conducted to validate the strategies. The results of preliminary experiments reveal that dynamic difficulty adaptations, based on evenly matched competitive strategies, can adapt to different students and planned results through personalized dynamic adaptations during the game to realize even opportunity tactic.

The preliminary experiments aim to evaluate the feasibility of evenly matched competitive strategies and dynamic difficulty adaptations to keep well-matched game progress and results for manipulating perceived performance. The preliminary experiments have limitations in small participants, short-term evaluation, and mere measure of game results. Further long-term experiments with more participants are required to investigate the impact on student motivation, perceived performance, self-efficacy, and procedural fluency. In addition, the feasibility of applying the strategies and adaptations for other game formats and domains require further investigations. For example, Joyce system is a domain-independent competitive game-based learning system used to engage students in drill and practice (Yu et al., 2002). Joyce system enables students to get two numbers by correctly answering questions before composing an arithmetic operation of the two numbers to move forward. The strategies and adaptations proposed in this study might be applied to Joyce system for practicing procedures of different domains.

The dynamic difficulty adaptations unlink perceived performance and actual performance or effort. A study of game-based learning found that some students felt bored and became mischievous because they found the major cause of their wins or losses was luck rather than their efforts or abilities (Cheng, Deng, Chang, & Chan, 2007). Therefore, the dynamic difficulty adaptations should be hidden; otherwise students might not engage or make any effort in game-based learning. The dynamic difficulty adaptations might be regarded as unfairness or even cheating in competition. However, games often involving a luck factor and dynamic difficulty adaptations aim to make different students motivated in game-based learning.

ArithmeticWinner is an implementation for validating the dynamic difficulty adaptations based on evenly matched competitive strategies. The evenly matched competitive strategies can be implemented via different approaches. First, ArithmeticWinner employs heuristic adapting rules to implement the strategies and adaptations. These heuristic rules would be different for different games. In addition, the real-time adaptation mechanisms in computer entertainment games (Spronck et al., 2006; Yannakakis & Hallam, 2007, 2009) can be used to realize the dynamic difficulty adaptations based on evenly matched competitive strategies. Second, this study planned exact game results in the experiments to validate the evenly matched competitive strategies. The evenly matched game results can be planned as a range for more variations. Furthermore, individual differences might exist in the feeling of the well-matched progress and game results, thus appropriate evenly matched game results should depend on individual personality. For example, the result of a study revealed that students have different preferences of the opponent ability (Chou et al., 2002). Some students preferred the expert opponent to feel challenged, some preferred the opponent with similar ability, and some preferred the less-able opponent so that they could defeat the opponent to attain a sense of achievement. Third, adapting methods could be changed according to the game format. If a game has no uncertain factors, such as chess, the adapting method can focus on adjustment of the virtual opponent. If a game has uncertain game factors but has no opponent, it can focus on adjusting uncertain game factors. Evenly matched competitive strategies might also work through only one adapting method. It might also be possible to have other adapting methods to realize evenly matched competitive strategies, such as adjusting supports or goals. It would also be feasible to combine different kinds of adjustments or adaptively select adapting method. Fourth, ArithmeticWinner does not adjust the complexity of learning tasks. In a game-based learning system, it would be better to adjust the complexity of learning tasks to fit the student proficiency level. Furthermore, the system should lead students to learn and to be more proficient in the learning tasks by gradually increasing the complexity of learning tasks. The uncertain game factors and virtual characters can be adjusted in coordination to make the difficulty invariable when the complexity of learning tasks increases.

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