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Article

Fibonacci Level Adjustment for Optimizing Player's Performance and Engagement

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Abstract

Players' engagement intensity in computer games is influenced by the level of difficulty the game offers. Traditional game-level plots adopt linear increases that sometimes do not match the users' skill growth, causing boredom and hampering the users' further skill growth. In this study, a nonlinear level adjustment scenario was proposed based on the Fibonacci sequence that provides gradual increases in the early stages of the games but more drastic changes in later phases. Here, the game's difficulty level was automatically decided by a machine learning method. To test the proposed method, comparisons between four level adjustments in computer games: traditional plots, self-selected plots, linear adaptive plots, and the proposed nonlinear adaptive plots were run. The experiment was carried out with 40 testers. The experiment results show that the best player's peak level in the proposed nonlinear adjustment was twice as high as that of linear adjustment. Also, the number of stages required to reach the peak under the proposed scenario was half that of linear games. This high playing performance goes hand in hand with deep playing engagement. The results demonstrate the efficiency of the proposed level adjustment algorithm.

1. Introduction

Computer games have become part of our daily lives in the past decades. It provides entertainment and sometimes educational tools like serious games [1]–[4]. One of the most popular computer games is the maze game. Users attempt to find a path in a labyrinth from a specified starting point to a specified goal while avoiding dangerous enemies and collecting prized items. This study deals with a perfect maze [5], a maze without circular paths and guaranteed to have at least one solution. The maze game is entertaining and may also train the users to increase their cognitive ability for spatial navigation [6]. Previous research indicated that the Growing Tree algorithm could automatically generate a perfect maze with various levels of complexity [7], and the maze' complexity that matches the players' skills is proven to help the learning process in solving problems [8]–[13].

This study proposes a new automatic and adaptive complexity adjustment mechanism called Fibonacci Level Adjustment (FLA). The proposed FLA is a variant of the Dynamic Difficulty Adjustment (DDA) method that provides real-time game scenarios based on the player's abilities or performance [14], [15]. Players' skills are determined using various techniques, including machine learning [16]–[21]. In contrast to previous research, FLA combines two Learning Vector Quantization (LVQ) [22] classifiers to identify players' skills. The players' skills are then utilized to determine the complexity levels of the game automatically.

In a maze game, each player has different motivational and cognitive abilities that influence their ability to face the complexity offered by the game. Therefore, the game engine must generate game complexity that matches the player's current skill based on the cognitive and motivational states of the player. This study uses two pre-trained classifiers from previous research to classify the player's motivational and cognitive states using the player's playing behavior as inputs. The classifier was generated by Syufagi et al. in the Cognitive Skill Game (CSG) [17], [18] and Motivation Behavior Game (MBG) [19]–[21]. In these previous studies, CSG and MBG were used independently for their respective purposes, while in this study they are combined to decide the best current level of the player. Consideration for the utilization of the cognitive and motivational states is due to their positive correlation with playing behavior in the game [23], [24]. Our study significantly differs from these past studies, in that in the previous research, the CSG and MBG were utilized to identify the player's skill but not for deciding the subsequent game's complexity for the player, while the proposed study utilized both of them in deciding the level of the game.

Traditionally the complexity of the game is linearly increased along with the increase of the player's skill. However, the linear increase is not always appropriate for engaging players longer in games [14]. Previous research has also shown that players' achievements have a nonlinear relationship with the level of complexity of the game [25]. When the challenge is easy, the increase should be drastic, while in contrast, a gradual increase is desirable for a more challenging level. Nonlinear adjustment of complexity level proposed in previous research involves drastic increases and decreases to stimulate sensations of tension and entertainment [26]. The complexity levels in the previous research were created automatically through Procedural Content Generation (PCG). The proposed study shares similarity with this previous study in executing automatic level adjustment. However, it differs significantly because the proposed study includes the player's motivational and cognitive characteristics in the level adjustment. This is motivated by the consideration that human factors play important roles in optimizing the player's performance and engagement level.

The level adjustment in the proposed method is based on the Fibonacci sequence. The Fibonacci sequence appears in many natural and social phenomena as well as the human sense of esthetics, humans anatomy [27]–[29], economic science [30]–[32], architecture [33], computing [34]–[36], art [37], [38] and various other fields. The adoption of the Fibonacci sequence in this study is based on the consideration that this sequence is ingrained in human nature and hence provides a comfortable activity tempo for engaging humans in games.

This study compares the proposed FLA with three conventional complexity increment scenarios: traditional, user-defined, and linear adaptive increment. Experimental data are collected from many players and statistical analysis is performed. The results demonstrate the efficiency of the proposed method.

The primary novelties of this paper are as follows: (1) FLA adopts the two mutually supportive factors, cognitive and motivational states, to identify a player's abilities. (2) FLA defines game level based on the player's motivational and cognitive characteristics. (3) FLA adapts the Fibonacci sequence for a nonlinear level arrangement to optimize the player's performance.

The rest of the paper is structured as follows: Section II explains the proposed FLA. Section III presents the result of the conducted experiments and analysis. Section IV presents the conclusion and future work.

2. Fibonacci Level Adjustment (FLA)

The outline of the proposed FLA is given in Figure 1. In this proposed FLA, a player is initially presented with a maze and asked to solve it. The player's behavior in solving the maze is collected as high dimensional input and subsequently given to two LVQ classifiers. The first LVQ is for classifying the motivational state, while the second one is for classifying the cognitive state of the player. The outputs of these classifiers are then utilized to decide the complexity level of the next maze be presented to the player. The maze is generated using a Game Object Generator that guarantees the generation of a perfect maze. Every object in the game, including the maze, will have a growth path arranged according to the Fibonacci sequence. The above process is then repeated ten times. This number of repetitions corresponds to the playing limit of each tester in the experiment.

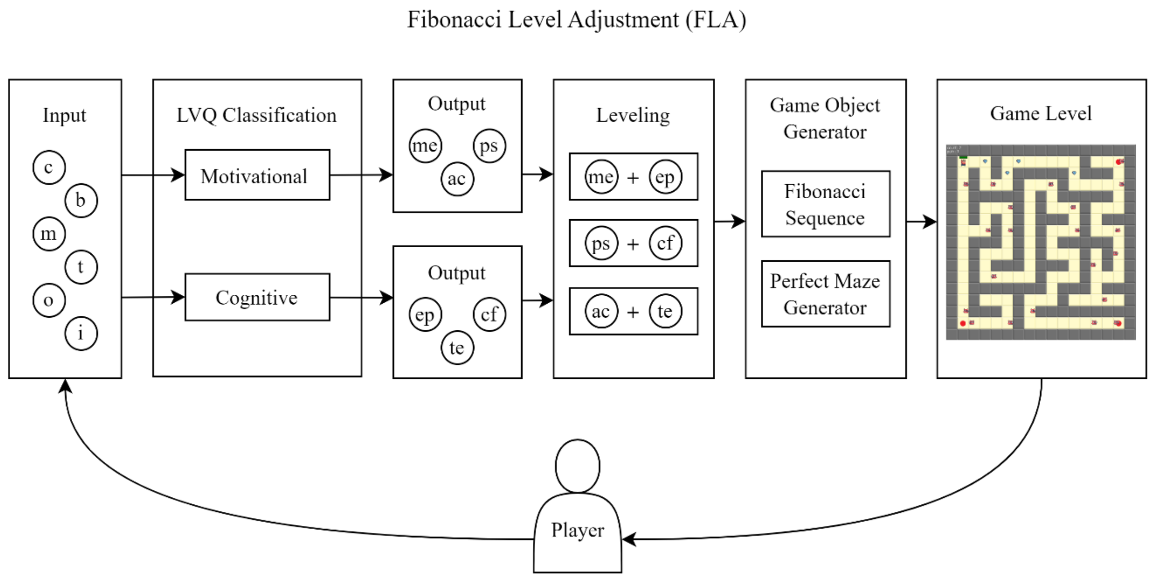

Figure 1. Proposed FLA.

This study adopted the reference vectors collected in the previous study [17], [19] for the classifications of the two LVQs. In previous studies, the data sets for training the prototype vectors were collected from math learning games. Previous studies indicated that the two classifiers succeeded in determining the characteristics of the players in completing a game. The similarity of the previous case studies makes all the features used in the previous game relevant to this study. In the previous study, six parameters were collected from the player's behavior and four new features were calculated to enhance the relevancy of the input vectors. The parameters and their meaning are shown in Table 1. The four new features are *e:* the value of the player's ability or self-efficacy, *tr*: the user's effort, *q:* that denotes a more comprehensive effort of the user that includes behavioral uncertainty, and *st:* the value of the player's step. Seven of these ten features are input vectors for motivational classification and six for cognitive classification. The input vectors for classifying the player's motivation are *t*, *b*, *e*, *st*, *tr*, *q*, and *i*, while for cognitive classification are *e*, *c*, *m*, *q*, and *tr*.

While playing a level, six parameters for motivation and cognitive classification are collected and subsequently used as input to the two LVQs. As in the standard LVQ, the classification is carried out by calculating the smallest Euclidean distance between the input vector with the reference vectors of the LVQ [22]. The output of this classification process produces motivational and cognitive states of the player that are respectively characterized by each of the three factors shown in Table 2. Referring to previous research [19]–[21] related to the classification of motivation, there are three factors in the MBG classification: *me*, *ps*, and *ac*. In the cognitive classification or CSG referring to previous studies [17], [18], players will be characterized by three factors: *ep*, *cf*, and *te*. Each motivational and cognitive classification factor has three possible outcome classes: high, intermediate, and low.

Table 1. Features of motivational and cognitive classification

Feature	Description	
c	Number of uncertainty (cancel)/ escape	
b	Number of correct answers/ number of victories in the game	
m	Number of wrong turns/lost	
t	The time to finish the current level	
o	Number of missed points	
i	Number of information-seeking activities	
e	e = 0.5 (b) + 0.3 (m) + 0.2 (c)	(1)
tr	tr = (b + m) / 2	(2)
q	q = (b + m + c) / 3	(3)
st	st = (o + i + q + tr) / 4	(4)

Table 2. Classes of motivational and cognitive classification

Factor	Description
me	Mental effort level for motivational classification
ps	Persistence level for motivational classification
ac	Active choice level for motivational classification
ep	Expertise level for cognitive classification
cf	Carefulness level for cognitive classification
te	Trial and error level for cognitive classification

Determining the maze complexity level is done by combining the outputs of the two LVQs. The motivational and cognitive factors produced by the two LVQs determine the values of the maze's elements at the subsequent level. Here, maze elements such as player characters (*pc*), enemies (*en*), environment (*ev*), and additional other (*oh*) elements are adjusted after the completion of each level. Elements in the game are divided into four categories according to the Game Design Document [39], as shown in Table 3. All these elements will be generated automatically at the start of each level while their interaction between elements is shown in Table 4.

Table 3. Game Element

Name	Category	Description	Action
King	Player Character	A character that the player can control. King must collect Diamonds guarded by Pigs and find a path to the target point.	Run to the right, run to the left, run upstairs, run downstairs
Pig	Enemy	Characters that can attack King while collecting diamonds and searching the path.	Run to the right, run to the left
Wall	Environment	Objects that will block King's path.	No action
Floor	Environment	Objects that the King can traverse.	No action
Diamond	Other objects	Objects collected by King to get points.	No action
Target	Other objects	Objects to pass the level further and earn points.	No action

Table 4. Interaction rules

Element	Element	Action
King	Pig	When the King is less than three pixels away from the Pig, the Pig will head toward the King and attack him, reducing his power.
King	Wall	When the King touches the Wall, the King cannot move through it.
King	Floor	When on the floor, the King can move right, left, up, and down.
King	Diamond	When King touches the Diamond, the Diamond will disappear, and points will increase.
King	Target	When the King touches the Target, the current level ends, and the King will be moved to the next level.

Table 5. Combination of expertise and mental effort classification for level determination

Input		Output			
ep	*me*	*pc*	*en*	*ev*	*oh*
High	High	+2	+2	+2	-2
High	Intermediate	+1	+1	+1	-1
High	Low	0	0	0	0
Intermediate	High	+1	+1	+1	-1
Intermediate	Intermediate	0	0	0	0
Intermediate	Low	-1	-1	-1	+1
Low	High	0	0	0	0
Low	Intermediate	-1	-1	-1	+1
Low	Low	-2	-2	-2	+2

The classification results of the level of expertise (*ep*) and mental effort (*me*) will affect the number of Pigs, Walls, Floors, Diamonds, and the movement speed of the King, as shown in Table 5. The carefulness (*cf*) and persistence (*ps*) level classification result will affect Pig's punch power and King's life regeneration ability as shown in Table 6. While the results of trial and error (*te*) and active choice (*ac*) classification will affect the additional number of King's lives and the speed of Pig's movement as shown in Table 7. Each element in the game has an impact on the difficulty level of the game.

Table 6. Combination of carefulness and persistence classification for level determination

Input		Output	
cf	*ps*	*pc*	*en*
High	High	+2	+2
High	Intermediate	+1	+1
High	Low	0	0
Intermediate	High	+1	+1
Intermediate	Intermediate	0	0
Intermediate	Low	-1	-1
Low	High	0	0
Low	Intermediate	-1	-1
Low	Low	-2	-2

Table 7. Combination of trial and error and active choice classification for level determination

Input		Output	
te	*ac*	*pc*	*en*
High	High	+2	+2
High	Intermediate	+1	+1
High	Low	0	0
Intermediate	High	+1	+1
Intermediate	Intermediate	0	0
Intermediate	Low	-1	-1
Low	High	0	0
Low	Intermediate	-1	-1
Low	Low	-2	-2

The proposed FLA adopts the Fibonacci sequence for the complexity-level of the game. Mathematician Leonardo Pisano Fibonacci proposed the Fibonacci sequence in his book Liber Abaci. The *n*-th Fibonacci number, F_n formulated as follows.

$$F_n = F_{n-1} + F_{n-2} \tag{5}$$

Where:

$$F_1 = F_2 = 1$$

More generally, it can be reformulated as Binet's formula as follows.

$$F_n = \frac{1}{\sqrt{5}}\left\{\left(\frac{1+\sqrt{5}}{2}\right)^n - \left(\frac{1-\sqrt{5}}{2}\right)^n\right\} \tag{6}$$

The graph of the Fibonacci sequence is shown in Figure 2, the x-axis is the Fibonacci number which is the level reached by the player based on the classification results. And the y-axis is the 10-stage limit of playing in one experiment. It is obvious from Figure 2 that in the initial phase of the game, the increment is for the early terms but gains speed in the later terms. This phase change is beneficial in engaging the players longer and thus increasing their achievement level. Here, a novice player is given a gradual chance to increase their proficiency, while an expert player is given a chance to skip many levels and thus always face a challenging game.

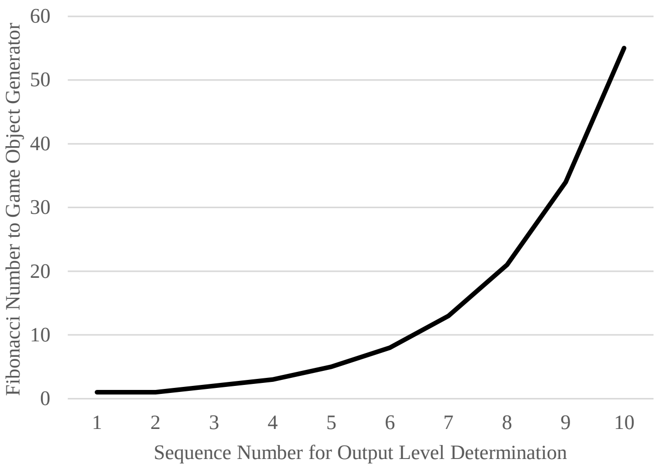

Figure 2. Fibonacci sequence.

For example, as in the first row of Table 5, when a player has completed one level and is classified as having high expertise and high mental effort, the number of enemies will increase by two. The increase in the level will be converted into a value according to the adjustment scenario being used. In FLA, for example when the current grid maze level (*ev*) is 13, then for the next level the player will be given a grid maze level of 35. The original Fibonacci number generated is 34, but it must be raised to an odd number for the technicality of creating the grid maze. The same thing is also done to increase the number of Pigs (*en*). But for King's (*pc*) moving speed, the Fibonacci number will be multiplied by 0.05 to match the speed scale in the game. An illustration of game-level growth using nonlinear arrangement is shown in Figure 3. The pseudocode of Algorithm 1 provides an overview of the proposed method.

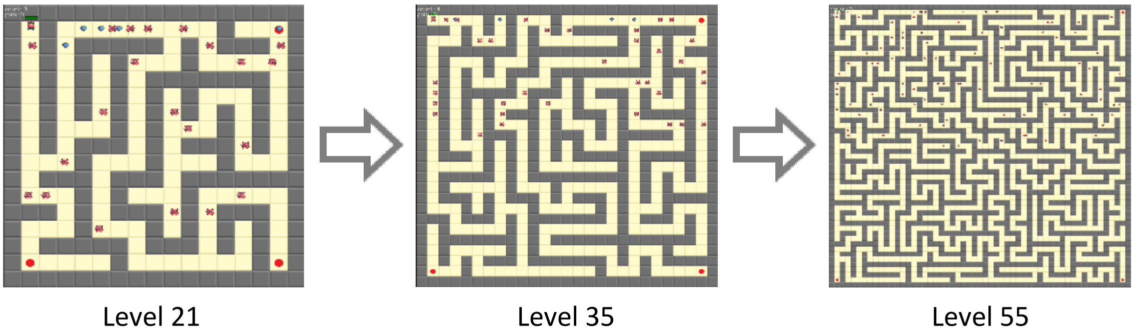

Figure 3. Nonlinear game-level growth.

Algorithm 1: FLA

INIT: *c*, *b*, *m*, *t*, *o*, *i*, grid size, *pc*, *en*, *oh*.
FOR 10 iterations
    CALL function PerfectMazeGenerator with input grid size, *pc*, *en*, *oh*.
    A game level starts.
        GET: *c*, *b*, *m*, *t*, *o*, *i*.
    A game level ends.
    CALL function Classifier with input *c*, *b*, *m*, *t*, *o*, *i*
    SET: grid size, *pc*, *en*, *oh* based on the classification results and the Fibonacci level.
ENDFOR

Here, a growing tree algorithm [7] is applied to automate the fast and efficient generation of perfect mazes. The complexity of the maze is determined based on the number of grids, which are equal in length and width to produce an equilateral square shape. The Grid which represents the size of this maze is also the game level which will be analyzed later. Other elements such as *pc*, *en*, and *oh* are similarly decided based on the user's motivational and cognitive classifications. The procedure for generating a perfect maze is shown in pseudocode Algorithm 2.

Algorithm 2: PerfectMazeGenerator

INPUT: grid size, *pc*, *en*, and *oh*.
Create a new maze area.
SET: distribution probability.
REPEAT
    Select one cell in the grid randomly and make it the visited cell.
    Randomly determine one next direction from the visited cell (north/south/east/west).
    IF the next cell has not been visited THEN.
        Mark this cell as visited.
        Place *en* and *oh* in this cell randomly depending on the placement distribution probability.
    ENDIF
UNTIL all cells are visited.
Place *pc* in the cell(1,1).

3. Experiment and result analysis

Game scenario testing was carried out on 40 testers. The testers' age range was between 14-25 years. This age range was chosen due to the assumption that players in this range are to some extent familiar with this game. In addition, the testers can understand the content of the given questionnaires and can complete them. The testing phase was conducted at campuses and schools. Each tester plays all three game scenarios in a random order. The three scenarios are, 1) a traditional scenario with linear level plots and level determination of points collected, 2) a user-defined scenario with the player's own chosen level, 3) a linear level plot arrangement (LLA) with automatic level adjustment, and 4) the proposed FLA.

Testing in each scenario was limited to 10 stages. At each stage, the player has one level to play. The initial level in the traditional scenario starts from level zero, LLA and FLA start from level 13, and the user-defined scenario was chosen by the player. In LLA and FLA the initial level does not start from the lowest level because it relates to the scenario's objective to provide a level that matches the player's skills. LLA and FLA make it possible to give an initial level drop if the player's ability was lower than the initial level. The level was limited to 117, as beyond that level the detail of the path may not be visible to the players.

Moreover, after completing 10 stages in each scenario, a player was given a questionnaire. This questionnaire was adapted from previous research [40], [41] that contains 31 items. The User Engagement Scale (UES) questionnaire was used to measure player engagement in each scenario. There are six factors in UES, namely Perceived Usability (PU), Aesthetics (AE), Novelty (NO), Felt Involvement (FI), Focused Attention (FA), and Endurability (EN). Questions on each parameter were measured using a 7-point Likert scale.

Comparative analysis of these four scenarios was carried out by comparing the player activity log data when completing a level. This player activity data log includes the completed levels, the time for completing the respective level, and the player's motivational and cognitive classification result. Performance measurement was carried out by analyzing the achievement of the player's level. The One-Way ANOVA test was used to measure the difference in the results of each test in the four scenarios. In addition, further analysis was also carried out regarding how the behavior of players reached the maximum level of their abilities.

Two analyses from questionnaire data were carried out to measure player engagement using the UES method. First, a reliability test was executed to determine each factor's consistency. Next, a comparative analysis of the respective results of the three scenario questionnaires based on six factors was performed. This analysis was intended to investigate the relationship between players' level achievement and engagement.

To find out the importance of combining motivational and cognitive classifications, three-game scenarios, games with motivational classification, games with cognitive classification, and games with the combination of the two, were compared. The three-game scenarios were tested directly on ten players. The test parameter used was the level increase in each classification class. The test results were analyzed using a t-test to compare the pairwise schemes. The results of the comparative analysis test in Figure 4 showed that the combination of the two classification methods produced better results than one independent classification for increasing the level of players. With a 60% increase in player level, an insignificant increase of 33%, and a significant increase of 27%.

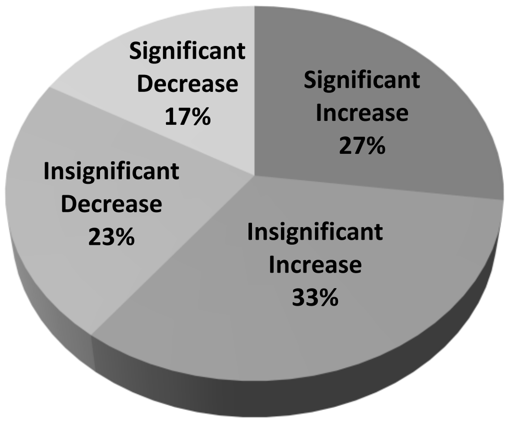

Figure 4. Classification method combination.

Naturally, each player produced a different growth compared to others. Figure 5 shows the level development of the best player under FLA, regarding the final level achieved. The graph showed some drastic increases due to the nonlinear arrangement implementation. Meanwhile, on the traditional scenario, user-defined scenario, and LLA charts, both had the same increment because players tended to choose easy levels and increased them gradually.

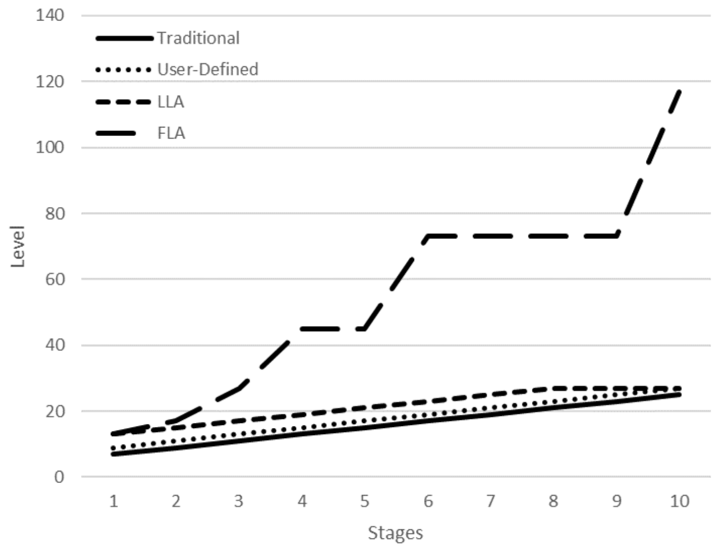

Figure 5. Graph of level growth on the best player.

The growth of the worst player under FLA is shown in Figure 6. It could be observed that this player was stuck at the same level at several stages before finally dropping and then rising again. This shows that the proposed method can maintain the stability of player engagement. The lowest level was offered to the player since it was appropriate given the player's skill level. Consequently, giving the worst player a higher level will also result in high stress. The level achievements at the last stage under FLA and LLA were similar, while under the user-defined scenarios, the level achieved was higher than FLA and LLA.

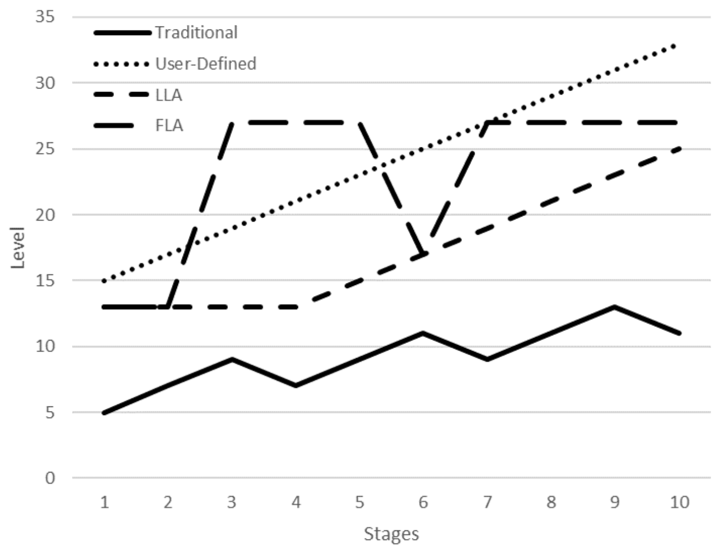

Figure 6. Graph of level growth on the worst player.

Figure 7 shows the average level growth among all the players. It could be observed that the level under FLA had a drastic increase followed by a slight decrease and re-increase after stage 6. LLA and user-defined scenarios had similar level growth, with a constant gradient. It could be observed that LLA generates a lower level compared to the user-defined scenario while the level was increasing. This fact indicates that the LLA underestimates the player's ability.

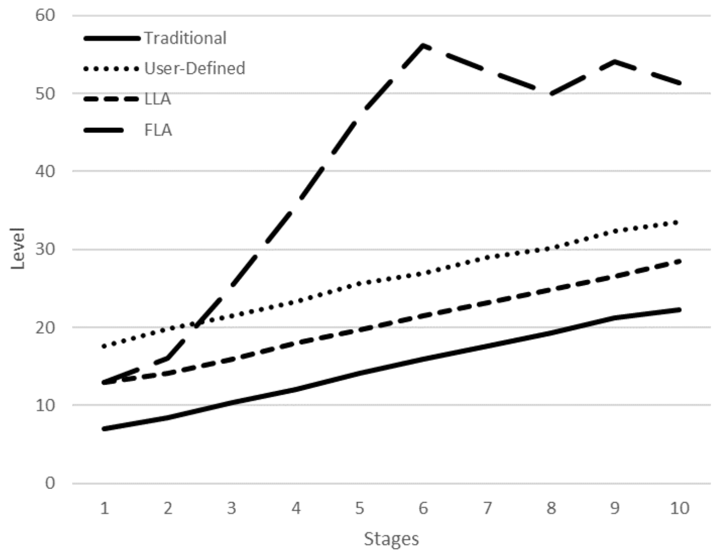

Figure 7. Graph of average level growth.

3.1 Player Performance Analysis

In the first analysis, a comparison was made from the log data of each scenario. The analysis of the log data was intended to reveal the scenario that optimizes the users' performance. The level achievement data for each scenario have skewed distribution. In this distribution, several outliers were found. Hence, Inter Quantile Range (IQR) was used to deal with outliers, with the capping results shown in Figure 8. Before carrying out the ANOVA test, testing on equality variance using Levene showed that the data had unequal variances, so the test used was One-Way Welch ANOVA.

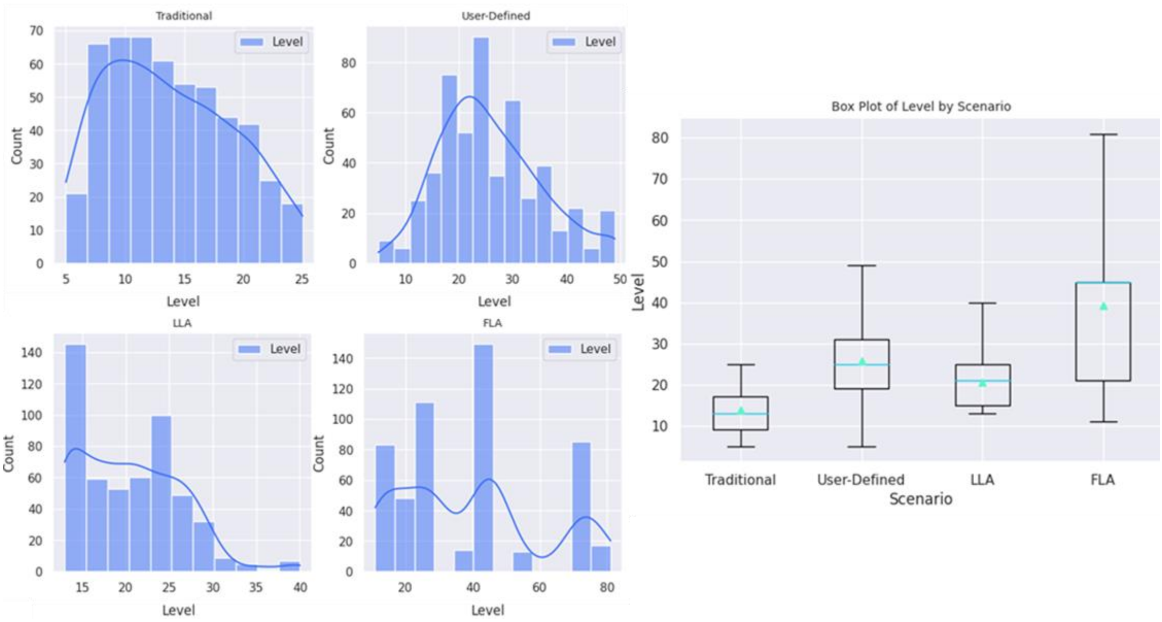

Figure 8. Distribution after capping.

The results from the ANOVA test show significant differences between the four scenarios. The p-value of the ANOVA test on the player-level achievement shows the result of Pr(>F) 5.062e-171, showing the effect of the leveling scenario on the player's level achievement. Therefore, the analysis was followed with a post hoc Games-Howell test. The results of the

Games-Howell test also show a significant difference between the four scenarios, with each p-value lower than 0.05. Furthermore, the comparison of levels achievements in each scenario was visualized in a diagram in Figure 9. Here, the black dots are the means and a line that shows the 95% confidence interval for each scenario.

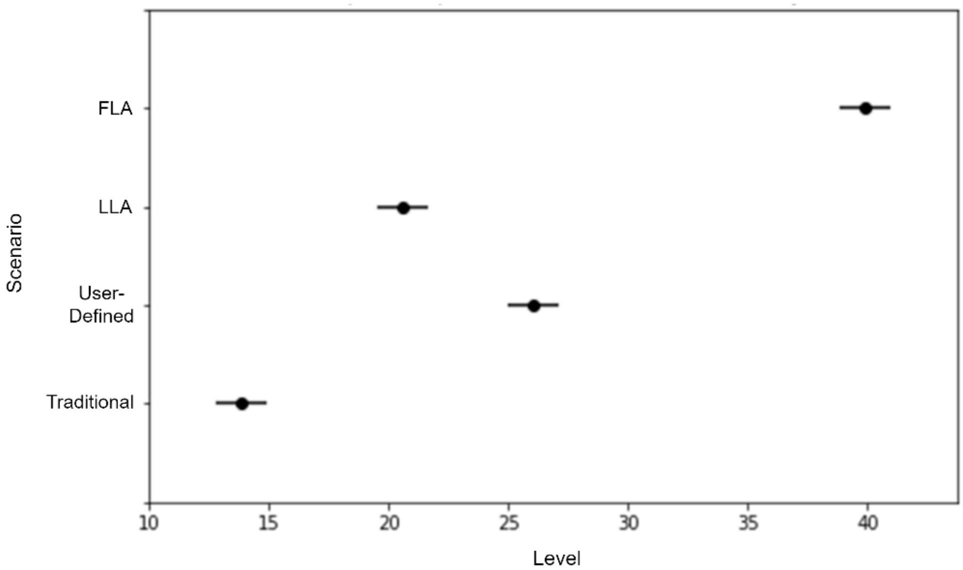

Figure 9. Comparison of levels achievements of each scenario.

The level-achievement shows that the FLA has a significant impact compared to the traditional, user-defined, and LLA scenarios. This was due to the classifications of the user's condition and the Fibonacci sequences-based adjustment that provides a more objective level.

The runner-up in the experiments was the user-defined scenario where the users subjectively selected their level. Here, some players try high levels first to gauge their abilities. However, some players choose to start from a low level to finish the game easily and quickly. When compared to FLA, no players chose the same level as their maximum point under FLA, indicating that their subjectivities are not necessarily appropriate. Meanwhile, compared to LLA, several players overestimated themselves by choosing levels much higher than the peak point they reached in LLA. Naturally, the player's peak point in the user-defined scenario can be better than LLA, but not better than the achievement under FLA. This was in line with the conclusions in previous research [14] which states that players tend not to be able to assess their abilities objectively.

In the LLA scenario, the level flow linear growth was applied, as in the traditional scenario, except that in LLA the player's motivational and cognitive classifications were executed. The p-value of the two scenarios indicates that their difference was insignificant. Level growth in these two scenarios was almost the same for every player because of the linear arrangement of levels. The level given tends to be lower than the player's skill, so there was almost no level drop. However, the level achievement in both scenarios still cannot describe the suitability of the level with the player's skills because players cannot reach the highest level that can be achieved in FLA or the one that was self-selected in the user-defined scenario.

Further analysis was performed on the log data of FLA and LLA scenarios that adopt classification to determine level growth. In this comparison, several evaluation items were considered: the highest level achieved, the number of stages required to reach the peak, and the standard deviation of the level passed after reaching the peak point, were considered. The average peak achievement level in the LLA scenario was 29. To reach this peak, on average the players needed 10 stages with a standard deviation of 0.22, as most players reached their peak in the last stage. With a total maximum level that could be played in one trial was 10, it could be said that peak achievement occurred at the end of the stages. This also indicated that further growth was still possible as the chart was still increasing. However, due to the limit on the number of games that had been determined, the player had run out of time even though the peak point had yet to be maximized. Reaching the peak in the last stage makes the standard deviation zero.

In FLA the average player reached a peak at the level of 74. The number of stages required by the players to reach the average level was 6 out of the maximum of 10 stages. According to earlier research, the player's achievements will significantly rise at the beginning of the game when the challenge was easy [25]. In line with that statement, FLA helps players reach a level that suits their abilities more quickly. So that players don't feel bored because the levels are too easy. The achievement of the peak point with fewer stages demonstrated the effect of the adoption of nonlinear level adjustment. Applying Fibonacci sequence could provide a high jump to cause acceleration for some players to be able to reach the peak point with fewer stages. However, there were some differences in the characteristics of players after reaching the peak. Some players could maintain the peak point until the end of the game. And several other players were not able to maintain their achievements. Players' level drops also vary; some players dropped right away after reaching peak levels, while others stayed at peak levels for some time.

The standard deviation calculation was carried out to determine the players' characteristics after reaching the peak point under FLA. Combining the use of nonlinear level plots with level growth control based on cognitive and motivational classification led to the existence of this deviation. A nonlinear flow would try to provide a faster level jump and controlled level growth with a classification that kept the level suitable to the abilities of the player. Keeping the level according to the player's abilities allows for a decrease in the level after the peak point. This decrease in level indicates that FLA keeps the low-stress level by occasionally decreasing the game's complexity. This was relevant to claims in the earlier study [26] that stress at high game levels and relaxation at low game levels should be combined to create engagement. The average standard deviation of the level from the peak to the end of the stage was 11 levels. Hence, if the deviation reduced the peak point, the new peak point that could be achieved by the player was at level 63. The analysis results from reaching the peak point in FLA showed a much higher value than LLA. Even though the deviations have reduced the peak point value for FLA, the value was still twice as large as LLA.

The head-to-head comparison between LLA and FLA on player achievements was shown in Table 8. The difference between the average peak points reached by players in FLA and LLA was 45 levels. This result was obtained when the average of the peak achievement in FLA was not reduced by deviation. At the same time, the difference that was shown when the deviation reduced the peak in FLA was 36 levels. The number of stages also taken to reach the peak showed that FLA was superior. In LLA the average peak point was reached at stage 10, while in FLA, the average could be achieved at stage 6. So that the resulting stage difference was a total of 4 stages. The value of the difference showed that the number of stages to the peak point in FLA was almost twice as fast as in LLA.

Table 8. Achievement comparison between LLA and FLA

	LLA	FLA	Diff.
Peak Achievement Level	28.70	73.90	45.20
Standard Deviation	0.22	10.47	10.24
Stages to Peak Achievement Level	9.60	6.45	3.15

Under FLA, seven players could reach the maximum level of 117. Considering the standard deviation, there are two players whose peaks are 117. While in LLA, the peak that could be achieved was level 47. Players who reach level 117 in FLA could only reach levels 23 and 27 in LLA. Meanwhile, players who reached the highest level in LLA, level 47, could reach level 55 in FLA. This again showed that the linear level flow was limiting the growth of players who should be able to advance faster. These results indicate that linear adjustment constraints the players to reach their maximum abilities in the game. At the same time, it shows that FLA enables the players to maximize their performance by providing levels that better match their ability. Adjusting the maze's complexity to the players' abilities also advances the study of maze games. Therefore, the spatial learning process in the maze game can also be maximized.

3.2 Player Engagement Analysis

The results of the UES questionnaire data from 40 testers were analyzed to determine the impact of each scenario on player engagement. The analysis was carried out by analyzing the impact of each scenario on each of the UES factors. The results of the first test for the UES questionnaire data are shown in Table 9. The first test carried out was the calculation of reliability using Cronbach's alpha. This test was carried out on the four scenarios on each factor. Cronbach alpha value was acceptable when it was > 0.7.

Table 9. Reliability test

Factor	Traditional	User-Defined	LLA	FLA
FA	0.789	0.859	0.873	0.887
PU	0.955	0.961	0.933	0.927
EN	0.949	0.962	0.946	0.965
NO	-45.158	-3.462	0	-38.974
FI	inf	0.840	-1.923	-6.382
AE	0.745	0.752	0.898	0.828

The analysis was followed by a discussion of the Cronbach alpha test result for each scenario. In traditional, LLA, and FLA, all factors were stated to be consistent except for the NO and FI factors. This was because there were many equal values at each point in both factors. The homogeneity test results showed that the data in both factors were homogeneous. Slightly different in the user-defined scenario, the inconsistency occurred only in the NO factor. This was also because the data had a high homogeneity. The homogeneity of the data on the NO and FI factors might be due to a fewer number of questions than the other factors, which were only three questions.

The visualization of the UES questionnaire assessment was presented in the form of a diverging stacked bar chart. There were three negative options, one neutral option, and three positive options. Data visualization in Figure 10 showed the results of the assessment of each scenario based on six factors. The traditional scenario was represented by yellow bars, blue bars for the user-defined scenario, red bars for LLA, and green bars for FLA. From these data, a comparative analysis of the assessments of the four scenarios could be carried out.

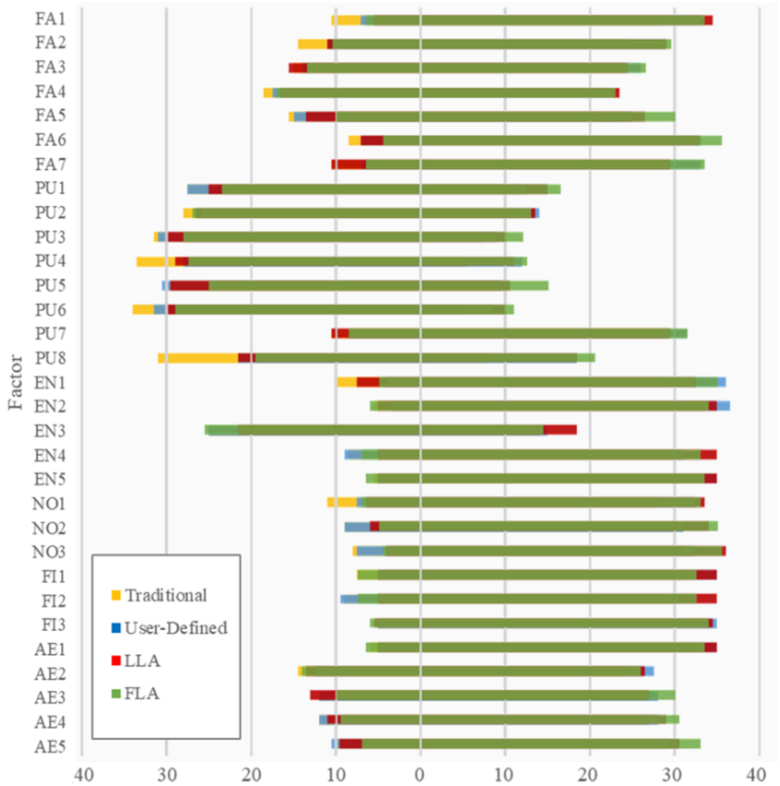

Figure 10. UES diverging stacked bar chart Traditional, User-Defined, LLA, and FLA.

The FA factor related to player focus and concentration showed that LLA was superior to two questionnaire items while the other five points were superior to FLA. However, the difference between the four scenarios was insignificant when tested using ANOVA. Significant differences occurred only in one questionnaire item. The advantage of FLA could be seen on the positive sidebar because all seven questionnaire items on the FA were positive questions in Figure 10. The FLA has the highest average value compared to other scenarios in terms of the level of focus involved when playing, according to the box plot in Figure 11. Therefore, the analysis indicates that FLA triggers deeper focus and concentration levels for the players. This was due to adopting the player's motivational and cognitive classifications that further yield significant levels-leap by the Fibonacci sequence. This statement was following previous research [42], which states that using the DDA method can increase player focus by providing a higher level.

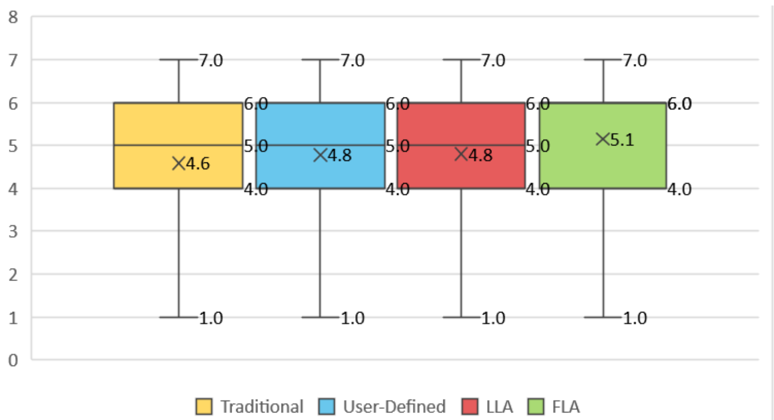

Figure 11. Focused Attention (FA) factor box plot.

The PU factor was related to the player's response based on his/her cognitive ability. This factor contained eight negative questionnaire items. On this factor, the user-defined scenario was superior in level suitability to the player's cognitive ability based on Figure 10. This was because the user-defined scenario was at a self-chosen level. So that players could choose a level that does not mentally tire them. This factor also shows that LLA presented a lower level of player ability. FLA, though, was a little more stressful and demanding for certain players. The previous statements are also aligned with the values obtained in Figure 12. The lowest stress level was shared by traditional with an average value of 3.0 followed by user-defined scenario and LLA. Extremely low-stress levels in traditional scenarios can indicate boredom due to low levels [42]. While the user-defined scenario and LLA provide the right level of stress. Meanwhile, the average stress level in FLA was rather high at 3.6, which is due to the higher level of difficulty.

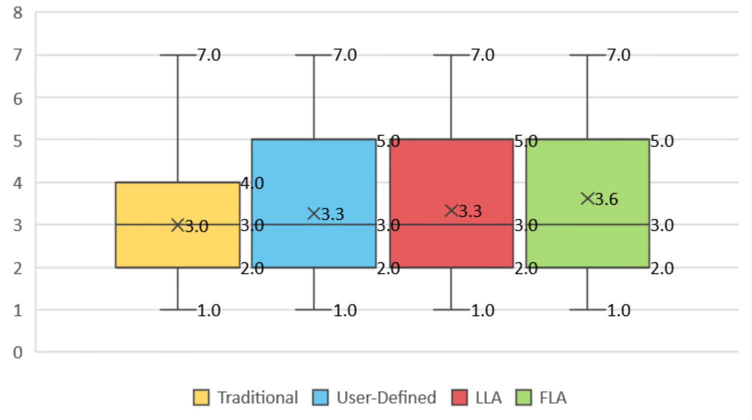

Figure 12. Perceived Usability (PU) factor box plot.

The EN factor included a five-point question regarding player satisfaction. In this factor, the user-defined scenario outperformed the three questionnaire items based on Figure 10. The advantage of the user-defined scenario showed that players felt that they had completed all levels well in a user-defined scenario whose levels were chosen independently. The EN factor also shows that FLA was the scenario that presented the level that best suited the expectations of the player. It demonstrates LLA and FLA scenarios as well as provides a beneficial game experience, making it worthy of recommendations. This explains that LLA and FLA's average values were higher in Figure 13.

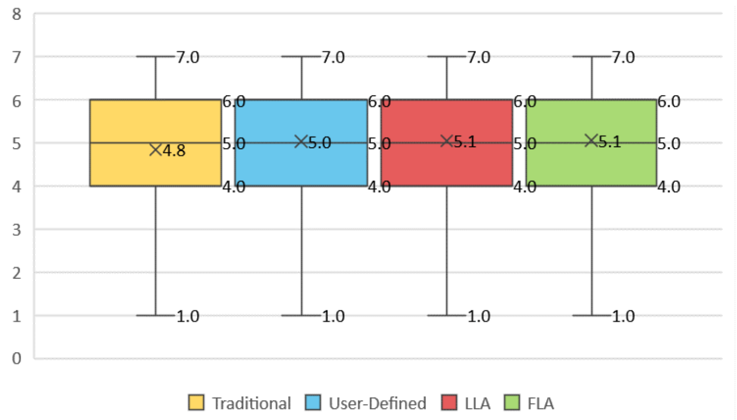

Figure 13. Endurability (EN) factor box plot.

Based on earlier experiments, the NO factor has a low-reliability value. This makes the arguments derived from these factors less valid. The NO factor was related to the players' curiosity. From this factor, LLA and FLA tend to be more curious than other scenarios. The FLA scenario piques the players' curiosity the most, as seen by the mean value and distribution of answers for the FLA from the box plot in Figure 14.

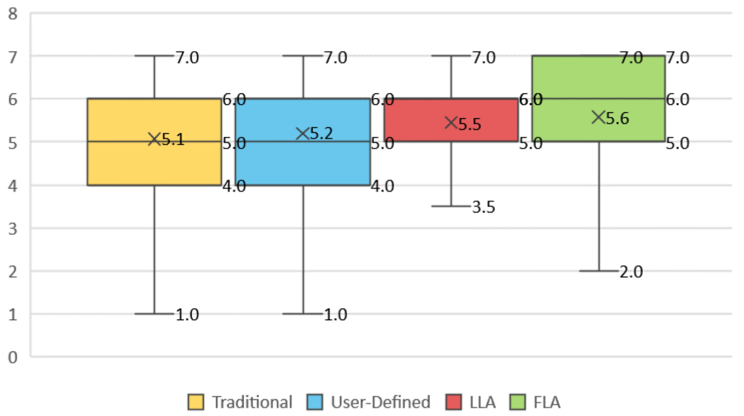

Figure 14. Novelty (NO) factor box plot.

The FI factor has the same low-reliability value as the previous factor. The four scenarios are engaging, according to the FI factor that measures the players' enjoyment. The LLA scenario, in particular, makes the gameplay the most engaging. Figure 15 shows that there aren't many differences in the value of each scenario. This implies that all four scenarios are entertaining to consider. Contrary to the earlier analysis, the box plot reveals that FLA's Q3 has a greater value than the others at 6.8. This demonstrates that many players agreed that FLA was enjoyable to play. This was in line with the claim that DDA affects enjoyment [43].

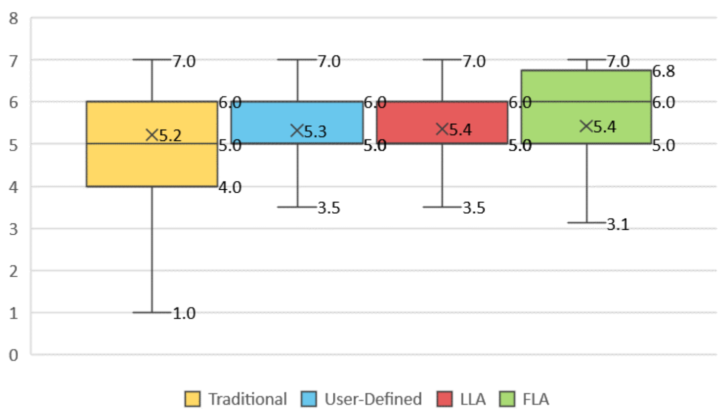

Figure 15. Felt Involvement (FI) factor box plot.

The final factor was AE which is the aesthetic factor of the visualization of the game. The game visualization presented for the four scenarios was the same. So even though FLA was superior at several points in Figure 10 and Figure 16, the difference between the four scenarios was insignificant. The difference in the visualization was only in the complexity of the maze given. Drastic level jumps to make the complexity of the given maze higher than in other scenarios. Therefore, playing with this maze's complex shape was more engaging than playing with simple shapes.

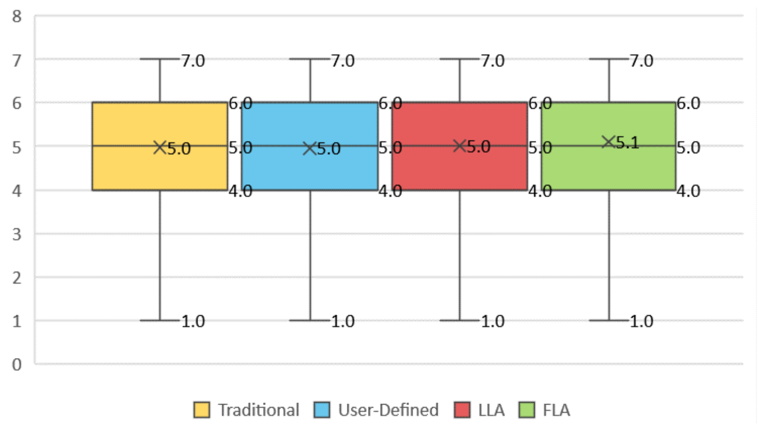

Figure 16. Aesthetic (AE) factor box plot.

Analysis of level achievement shows that two players reached the highest point in level 117 after being reduced by standard deviation. The achievement of these two players was the highest compared to the others in FLA so it can be said to have the best performance. However, it was necessary to analyze whether, with this high performance, players could still feel engaged or even make players feel stressed. The results of the t-test showed that there was no significant difference between the two players.

In the FA factor, both players showed a positive average score. Both players tended to play with a high focus. In the PU Factor, the two players had slightly different tendencies. One player tended to feel a low level of stress because the level given followed their cognitive abilities. At the same time, one other player felt quite desperate when it was difficult to complete a level with high complexity. However, even though they were quite burdened, the EN factor showed that according to him the experience of playing in FLA was worth it. Both players considered the playing experience a success. The NO factor showed that both players were motivated to play because of high curiosity. The FI factor showed that both players were quite happy to play FLA even though they played with high performance. Finally, for the AE factor, the two players on average gave a neutral answer to the visualization of the game. The analysis of each factor shows the positive contribution of FLA to the player's deep engagement. This shows that DDA was able to optimize player engagement, which was also consistent with previous studies [42]–[44].

4. Conclusion

In this study, an adaptive and non-linear game level adjustment based on the player's ability and the Fibonacci sequence was proposed. The proposed game adjustment method was compared with a conventional linear growth scenario and a user-defined scenario. Analysis of the ANOVA test results indicates that there was a significant difference between each scenario. The analysis shows that the proposed FLA has a better impact on optimizing the ability of the player than the other three scenarios. The FLA has a clear advantage over the user-defined scenario in that the experiments show that the users often cannot objectively assess their abilities, resulting in non-optimal achievements. Under traditional scenarios and LLA, the linearity of the level adjustment often does not match the users' improvements and thus hampering their growth. The results show that FLA also demonstrates a clear advantage over LLA.

Measurement of player engagement using the UES questionnaire produces promising results as well. Under FLA two players reached the maximum level of 117. These two players demonstrated high performances while also feeling a high level of engagement, although one of them felt there was a level that was quite burdensome. However, on all factors, it was shown that both players had a positive playing experience.

For further research, this method can be applied to various fields, not limited to computer games. For example, the application of FLA in a serious game to basic education with programs that are oriented toward the abilities of each student. FLA can help provide dynamic, personalized learning. Evaluation of personalized learning by FLA can eventually be combined with educational data mining approaches for enhanced decision-making. This method can also be applied to serious games for personal trainer programs in sports and various types of independent courses or popular topics such as biodiversity conservation. This is possible to gamify more case studies using the game object used in this study.

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