A COMPUTER-ASSISTED LEARNING MODEL BASED ON THE DIGITAL GAME EXPONENTIAL REWARD SYSTEM

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ABSTRACT
The aim of this research was to construct a motivational model which would stimulate voluntary and proactive learning using digital game methods offering players more freedom and control. The theoretical framework of this research lays the foundation for a pedagogical learning model based on digital games. We analyzed the game reward system, which is recognized as one of the most important mechanisms to engage players in active sustainable digital game playing. In general, the reward system is designed similar to an exponential learning model. This paper compares the reward systems of four typical digital games which have more than 10 million school-age players around the world. Based on the results, we propose a computer-assisted exponential learning model similar to that applied in digital game based learning models. By applying these results to educational algorithms associated with the field of artificial intelligence, we are able to motivate emergent learning. Using the proposed method, it is possible to form a model of computer-assisted learning, adequate for all learning levels.
Keywords: digital game reward system, exponential learning model, computer–assisted learning model

INTRODUCTION
This research analyzes enthusiasm towards digital games and questions whether teenagers are capable of applying the motivation mechanisms activated by digital games to education situations.

With advancements in digital technology, digital games are now enmeshed in popular culture (Oblinger, 2004). The feature which most distinguishes digital games from cinema or other media is the fact that players need to intervene to interactively solve issues according to provided rules (Juul, 2002; Moreno, 2006). The inter-activeness of digital games is not only a result of a gathering of players, it requires discovering and learning certain rules contained within the game text and actively organizing while experiencing the game (Kiili, 2005a; Koc & Bakir, 2010; Prensky, 2001; Teo, 2009b; Tutgun & Deniz, 2010).

In newer digital games, cutting-edge psychological and artistic techniques are being applied in addition to various information processing technologies including artificial intelligence. These processes are intended to captivating interest and further promote the emotional satisfaction of the players by maximizing the interactive elements. Although negative aspects are highlighted at times, the emotion based technologies used in digital games are being applied in various parts of our lives through their convergence with cognitive science and information technology.

Most digital games are designed so players must actively complete quests based on a reward system (Koster, 2005). Players accumulate skill points through the process of collecting and discerning information required for creative reconstruction. This framework is very similar to the problem base learning model (Colby & Colby, 2008; Rosinski & Squire, 2009). Such methods of digital gameplay are one reason why it is being regarded by many in the field of education as an appealing interface to maximizing learning.

The learning method applied in digital games is an ideal mechanism in which anyone can proactively participate even at a very early age in the ‘interest element’ of ‘play’ through the virtual world. Furthermore, it has the advantage of being able to naturally induce problem solving capabilities and social learning (Browne, 2003; Calendra & Lee, 2005; Campos, 2005; Finneran & Zhang, 2003; İşman & Çelikli, 2009; Jonassen, 2006; Juul, 2002; Perkins, 1991; Prensky, 2001; Radford, 2001; Stevenson, 2007; Vygotsky, 1986). Accordingly, many educators have long recognized the value of the digital game based learning model as an effective framework allowing users to creatively construct opinions and realize self-organized learning.

Furthermore, the gameplay model, which uses concepts similar to the learning model commonly designed in the field by educators such as chatting, writing, speaking and team-playing, is being frequently applied in the latest digital games. Accordingly, many educators are trying to apply such digital gameplay examples to various types of pedagogical learning models including those in the field of emergent learning (Kiili, 2005a; Papastergiou, 2009; Pilke, 2004).

Arguably, the young student generation forms the major age group of digital games users on a global level. We, accordingly, reviewed the reason for their interest in digital games and the possibility of designing a learning model based on the reward system used to induce play. From this perspective, functional mechanisms of the reward system in digital games were comparatively analyzed. Furthermore, based on the exponential learning equation model proposed by educators we suggest a computer-assisted learning model design.

Based upon information from previous studies, we present a set of designs for an effective digital pedagogy which takes the important step of analyzing the level-based ‘experience point’ (EXP) reward system as the main factor responsible for continuous, active commitment of players to digital games. To ensure objectivity, this work focused on two types of digital games made in South Korea and the USA for comparative analysis.

The first game type includes two cases of ‘education-emphasized digital games’ (EEDG) made in South Korea, which are available to all ages and have over 10 million student-age players around the world. The other game type includes two cases representative of massive multiplayer online role-playing games (MMORPG) of ‘amusement-emphasized digital games’ (AEDG) available to those 15 years of age and older.

Data from the analysis was examined through a process known as normalized evaluation. Experimental results suggested that the pedagogical function formula and the computer–assisted learning model which digital games are based on are very similar to the active absorption factor inherent in games played voluntarily by teenagers.

LITERATURE REVIEW

Learning Model Function

Along with the recent advancements in computer technology, there are many international cases in which functional formulas have been applied to motivational learning model studies of computer-assisted education such as emergent learning. We concentrated on several researchers which have proposed exponential learning equation models from a mathematical perspective similar to that suggested by this study.

In academia, various methods have been proposed in studies that apply functional formulas as a way to increase learning effects in the field of education. Actually, several creative educators have proposed models adjustable according to the learning environment and the disposition of learners for the purpose of enhancing learning effectiveness.

Carroll proposed a standardized functional formula related to the school learning effect (1963). In this model by Carroll, important factors that affect various types of school learning were extracted and an effective learning plan based on the interrelation of these factors was devised. This model is a very important teaching/learning model in the sense that a practical method for increasing school learning efficiency was presented through a specific functional formula. The model by Carroll proposed that learning efficacy is determined by the actual amount of time needed by a learner to accomplish a given assignment. The functional formula proposed is as follows:

$$Learning = F\left(\frac{\text{time actually spent}}{\text{time needed}}\right)$$

In this model, the learning effect is determined by the ‘time actually spent’ and ‘time needed’. The ‘time actually spent’, indicates the time of active concentration by the learner required to perform a learning assignment. Generally, the time spent passively by the learner during the learning process is excluded from the time spent learning. Carroll emphasized the fact that this time may be affected by elements such as perseverance, learning opportunities, etc., and is therefore important to consider. The ‘time needed’, indicates the time required by the learner to reach the teaching objective. This element includes aptitude, quality of instruction, etc. This model is a concept which simultaneously emphasized the importance of considering individual learner differences and

environmental characteristics in teaching design. Furthermore, the model of school learning devised by Carroll also provided the theoretical foundation for mastery learning presented by Bloom (1976).
Johnston and Aldridge suggested an effective teaching/learning design that considered learner characteristics such as individual abilities and motivation through a functional formula in addition to learning effect (1985). In their exponential learning model, efficacy is determined by considering learner level and the amount of time spent problem solving. The formula for the exponential function learning model devised by Johnston and Aldridge is:

$$L = 100[1 - e^{-k(t+t_0)}]$$

where L =learning effects, t = learning time, t_0 = time spent on the subject before beginning to learn it, $k=cm$ where c = ability and m = motivation, and e =logarithm.

In this functional formula, L is a constant which can be converted into a percentage and $e^{-k(t+t_0)}$ is a function of the absolute effect on learning efficacy which increases as this value decreases. In other words, this formula takes into account not only internal elements such as the attitude of the learner during the learning process but also environmental elements such as the level of difficulty appropriate for the learner and the clarity of the objective.

According to Johnston and Aldridge, this functional formula considers exponential growth. They emphasized the fact that the learning effect can change based upon elements such as time, abilities of learner and teacher, environment, and motivation. The exponential learning equation models proposed by Carroll (1963, 1989) and Johnston and Aldridge (1985) were applied by Hwang who proposed a learning dynamic model based on the Newton mechanism (Hwang et al., 2004).

Hwang et al. (2004) proposed methodology that could increase learning efficacy by adding learning dynamics and learning energy. This exponential learning model referred to as a Learning Response Dynamic Model applies the theory of Newtonian mechanics. In addition, learning dynamics, energy, speed, force, and acceleration were considered as important elements to increase learning efficacy in digital-based network learning circumstances.

The majority of researchers emphasize the fact that a functional mechanism produces exponential growth which is not linear in form (Hwang et al., 2004). Theoretically, this functional mechanism has a very similar structure to the reward system of digital games. It is an established theory that most digital games have been designed with a logarithm structure where attaining the next level is relatively easy during initial gameplay to increase motivation but gradually becomes more and more difficult.

Accordingly, it is highly likely that the learning model presented in this study can also be applied to the digital game-based learning model design since the digital environment is mostly exponential in function with a nonlinear framework. In other words, setting the appropriate difficulty level according to learner level by controlling the function and motivational elements is feasible.

We examined the reasons why a majority of student-age individuals are attracted to digital games and explored the possibility of applying the game reward system which they are currently familiar with to learning model applications.

The digital game reward system based on an exponential mechanism
Generally, the reward system in digital games is classified as one of the most important elements in game structure responsible for stimulating active and sustained game playing. The reward system is designed to function similar to the learning model and is adjusted according to players' capabilities in diverse levels of difficulty which are assessed with several open test processes.

The reward system is divided into three types: 'level-based progression', 'skill-based progression' and 'freeform advancement'; however, gameplay is conducted based on experience points (EXPs) attained in all areas.

EXPs are a numerical display denoting the problem solving skills of game players (Koster, 2005) which can be compared to learning environments where credit is awarded according to the efforts of students. The reward system of digital games is assumed to have originated from the level up system of 'Dungeon' perceived as a traditional role-playing game model (Koster, 2005) which entails increasing levels attained by moving from point A to B to a complex type of mission where various items must be obtained in a given time.

Unlike the general case related to the game character, there are also instances that have been designed to change EXPs throughout the game map. However, most digital games have been designed so that progression to the next level is based on the accumulation of EXPs. As for the gameplay method, most cases use the quest performance method which entails defeating monsters or obstacles using the game character. However, there are also cases in certain games such as 'GURPG' and 'World of Darkness' that change according to the method of solving the mission. Such methods transform in various ways according to the game genre or platform.

In most cases, the reward system of digital games has been designed so players receive EXPs in gradation according to their individual efforts and capabilities. Furthermore, this mechanism is connected to various fun elements of the game domain thereby enticing continuous play.

Arguably, such digital game reward system mechanisms have a very similar functional structure to the exponential learning equation model proposed by Johnston and Aldridge. In other words, the reward system of digital games has also been designed with an exponential equation as a function of time and motivational elements according to player level similar to the exponential learning equation model (Koster, 2005) and as such, is very similar to the learning model commonly used in the field by educators despite being electronic.

Accordingly, it is highly possible that the reward system of digital games can be applied to an effective learning model that can be adjusted in gradation according to learner level for elements directly responsible for learning efficacy such as difficulty level and motivation in a computer-assisted learning model environment.

METHDOLOGY

Research Design

We analyzed the reward system of digital games, which is an element that makes teenagers become immersed in game-playing. To investigate the possibility of its application in learning model applications, the following areas were examined during the experimental process:

- a level-based comparison of EXPs between Education-Emphasized Digital Games (EEDG) and Amusement-Emphasized Digital Games (AEDG);
- an analysis of major stages in the game-playing process in EEDG and AEDG;
- derivation of the functional formula of digital game reward systems;
- applicability of a learning model based on EEDG;
- differences in exponential curves based on motivational parameters from the normalized data fit;
- feasibility of a computer-assisted learning model, applied to exponential-learning, based on the digital game reward system.

Data Collection

Digital games sampled in this research are based on two types of massive multi-player online role-playing games (MMORPG): EEDG and AEDG. The first type stresses both playing and studying while the latter emphasizes only playing. These digital games are known to have more than 10 million members worldwide, the majority of which are students. Based on our evaluation of the characteristics of EEDG and AEDG, we propose that the particular mechanisms which attract players to these games may have applications in educational learning models.

Data from Tables 1 to 4 are based on open sources provided by each digital game production company. While the general digital game level-up system is designed by mathematical formulas, it is often customized by manufacturing companies to meet their needs. The digital game level-up system is available to the public to help players advance in the games and is reviewed by expert online sites related to digital game analysis as well.

To obtain the most appropriate data, we selected 40 players and divided them into 10 categories, from novices who have played each game for only a year to experienced players who have played each game for more than three years. We had them play at five levels lower than what they typically played. As a result, we confirmed four cases of EXP data provided by the game production company that agreed with the actual process of playing and subsequently collect these as samples.

Digital games in Tables 1 and 2 are popular across generations. *Maple Story* in Table 1 features exploration of an imaginary world in adventure form. *Tales Runner* in Table 2 is a racing game integrating athletic sports with an imaginary fairy-tale world. Tables 1 and 2 list level-based EXPs appearing in both games. Figure 2 shows the graphs produced from the data in Tables 1 through 4.

The level-up systems in these games actually include up to approximately 130 levels, but for experimental effectiveness the graphs show only 50 levels. Furthermore, *Maple Story* and *Tales Runner* emphasize learning differently from other digital games which are violent in nature. These digital games were selected as suitable to be used for statistical research in relation to digital pedagogy, as they are voluntarily played by young people all over the world.

It should be noted that level-based EXP values may be compromised through the process of repeated testing with common users. For example, *Maple Story* in Table 1 has been enjoyed by over 50 million members from over 10 countries including Korea, Japan, China, Taiwan, Thailand, Singapore, Malaysia, America, Canada, and EU since it was released in Korea in 2003. The game, on average, has approximately 210,000 simultaneously connected users.

Tables 3 and 4 show EXP data from *Suddenattack* produced by GAMEHI & CJ Internet Company and *World of Warcraft* (*WoW*) an iconic digital game for entertainment available around the world to anyone over 15 years of age, manufactured by BLIZZARD Entertainment Company.

Data Analysis

Comparative Analysis of Level-Based EXPs in a Reward System

There are two common characteristics of EEDG summarized in Tables 1 and 2. One is the fact that level-up is easily achieved through a small amount of effort until levels 15 to 20 which correspond to the powerful level-up areas in Figure 2 (a) and (b).The other is that when players reach certain stages as a result of their own will and effort, level-up becomes more difficult due to the fact that the digital game system is designed based upon a logarithm which makes it difficult to achieve level-up at certain times and in certain situations.

In comparative analysis of two AEDG and two EEDG, the emphasis on motivation which consisted of three different areas—powerful level-up, adjustment level-up, and level-up—was found to be similar to learning theories related to step learning in constructivist educational pedagogy.

The degree of difficulty is designed by dividing game sections into stages, as shown in Figure 2 (a) and (b). This form is common to all general EEDG. This design style is thought of as similar to the traditional theory related to constructivist pedagogy, that is to say, that learning with media should provide motivation and opportunity in an active and voluntary way, fertilizing the fields of motivation.

Tables 3 and 4 are expressed as graphs in Figure 2 (c) and (d). The model of AEDG depicted in Figure 2 (c) and (d) shows short-term lines in the powerful level-up area providing players with motivation. This feature is very different from Figure 2 (a) and (b) where the line can be seen rapidly increasing.

Figure 2 (c) and (d) depict typical models of extreme forms of digital games with goals of entertainment. Some structures which make it irresistible and urgent to get rewards, may cause social problems as players develop an excessive desire for compensation. The areas in the circles in Figure 2 (b) and (c) denote the possibility of various scenarios occurring within the game. The irregular lines reflect this aspect which is intended to prevent player anxiety or boredom.

Table 1. *Maple Story* level-based EXP

EXP	Level	EXP	Level
15	1	54900	26
34	2	63666	27
57	3	73080	28
92	4	83720	29
135	5	95700	30
372	6	108480	31
560	7	122760	32
840	8	138666	33
1242	9	155540	34
1716	10	174216	35
2360	11	194832	36
3216	12	216600	37
4200	13	240500	38
5460	14	266682	39
7050	15	294216	40
8840	16	324240	41
11040	17	356916	42
13716	18	391160	43
16680	19	428280	44
20216	20	468450	45
24402	21	510420	46
28980	22	555680	47
34320	23	604416	48
40512	24	655200	49
47216	25	709716	50

Table 2. *Tales Runner* level-based EXP

EXP	Level	EXP	Level
0	1	143400	26
600	2	167400	27
1200	3	191400	28
1800	4	215400	29
2700	5	265400	30
3600	6	365400	31
4500	7	465400	32
5400	8	565400	33
6900	9	665400	34
8400	10	765400	35
9900	11	865400	36
11400	12	1065400	37
14400	13	1315400	38
17400	14	1665400	39
20400	15	2015400	40
23400	16	2415400	41
29400	17	2865400	42
35400	18	3365400	43
41400	19	4365400	44
47400	20	5365400	45
59400	21	6365400	46
71400	22	7365400	47
83400	23	8365400	48
95400	24	9365400	49
119400	25	10365400	50

Table 3. *Suddenattack* level-based EXP

EXP	Level	EXP	Level
2,999	1	1524999	26
8,999	2	1674999	27
17999	3	1824999	28
29999	4	1974999	29
44999	5	2174999	30
64999	6	2374999	31
84999	7	2574999	32
104999	8	2774999	33
134999	9	2974999	34
164999	10	3174999	35
194999	11	3474999	36
224999	12	3774999	37
274999	13	4074999	38
324999	14	4374999	39
374999	15	4674999	40
424999	16	4974999	41
474999	17	5374999	42
574999	18	5774999	43
674999	19	6174999	44
774999	20	6574999	45
874999	21	6974999	46
974999	22	7374999	47
1074999	23	7874999	48
1224999	24	8374999	49
1374999	25	8874999	50

Table 4. *WoW* level-based EXP

EXP	Level	EXP	Level
0	1	338000	26
400	2	374400	27
1300	3	413300	28
2700	4	454700	29
4800	5	499000	30
7600	6	546400	31
11200	7	597200	32
15700	8	651700	33
21100	9	710300	34
27600	10	773100	35
35200	11	840200	36
44000	12	911800	37
54100	13	987900	38
65500	14	1068700	39
78400	15	1154400	40
92800	16	1245100	41
108800	17	1340900	42
126500	18	1441900	43
145900	19	1548200	44
167200	20	1660000	45
190400	21	1777500	46
215600	22	1900700	47
242900	23	2029800	48
272300	24	2164900	49
304000	25	2306100	50

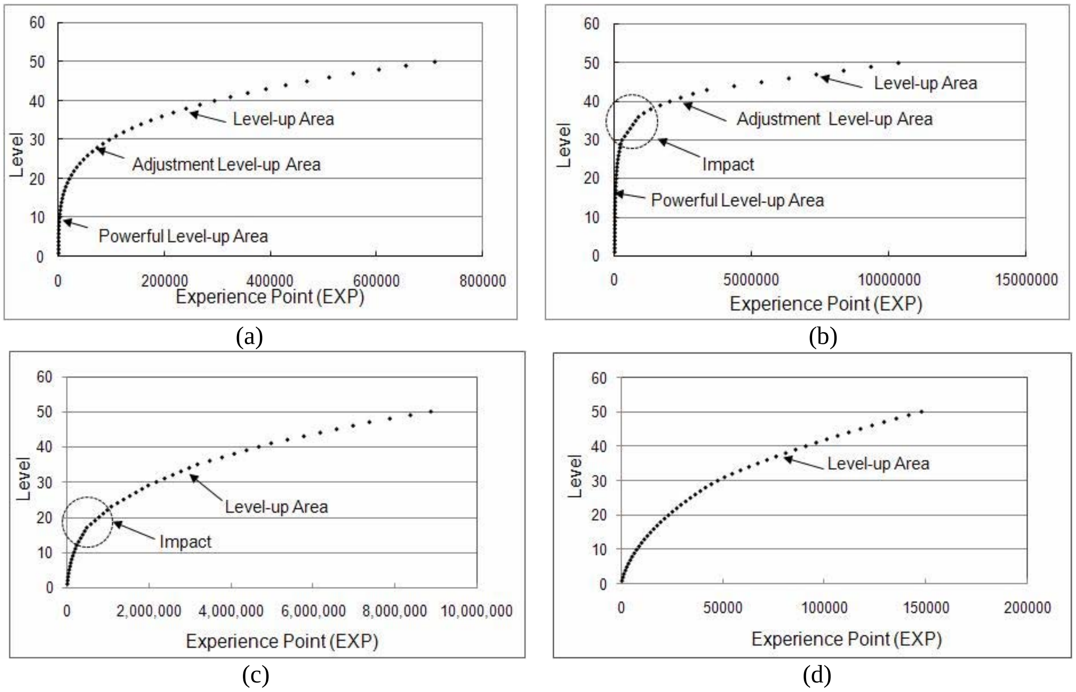


Figure 2. Level-up curve, (a) *Maple Story*, (b) *Tales Runner*, (c) *Suddenattack*, (d) *WoW*

Game Playing Procedure Stages

Figure 3 depicts a model of the step-by-step course in playing the digital games presented in Figure 2. Motivation is the focus of the powerful level-up area. Players experience motivation (a) and show will (b) in the course of adjustment. Players with this background are well-developed to commit to action (c) with their own skills, knowing that they are going to be faced with difficult problems to solve in certain situations.

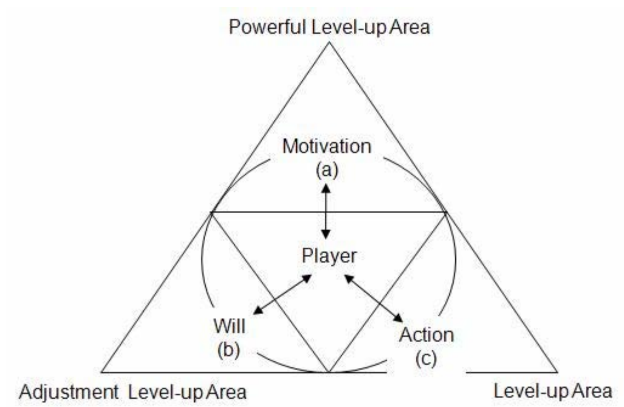


Figure 3. Game playing procedure and elements

The adjustment level-up area has the support functions and knowledge for skill accumulation useful in gaining an edge against fellow players. Motivation and will, presented in Figure 3 (a) and (b), can be thought of as mental attributes providing players in the powerful level-up and adjustment level-up areas the means to attain educational goals. Players can attain the confidence necessary to navigate these courses successfully. The level-up area, common in both EEDG and AEDG, offers limited rewards compared to effort required; however, it is possible to design other fun types of level-up systems like that depicted in Figure 2 (d) to motivate players to actively partake in the games.

Level-Based EXP Data Modeling

Figure 4 depicts a form of modeling used to derive the functional formula indicated in Figure 2. It shows that it is easy to increase from level E_1 to E_3 on the x-axis, identifiable as a gentle slope from A of E_3 on the x-axis according to the degree of difficulty. The model depicted in Figure 4 can be constructed using the formula:

$$Level = K \log_e EXP$$

$Level$ = game level, K = a constant (the degree of difficulty in digital games), e = exponential, EXP = Experience Point.

According to Figure 2, in the case of Figure 4 being designed with a fan-shaped structure in which the levels on the y-axis increase consistently, it is very easy for players to lose interest and experience anxiety or boredom. However, players who experience E_1 to E_3 accumulate a certain amount of skills gained from 1 to A and are therefore continuously challenged by the possibility of attaining high numerical points.

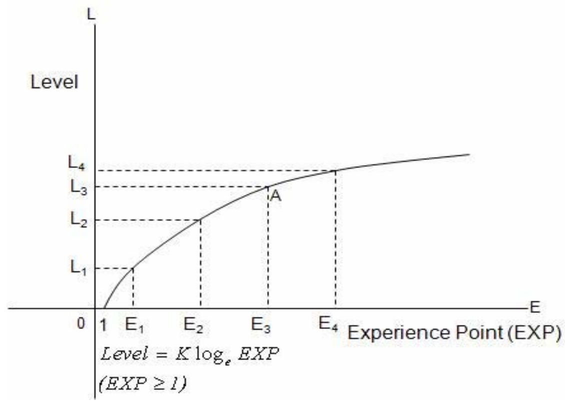


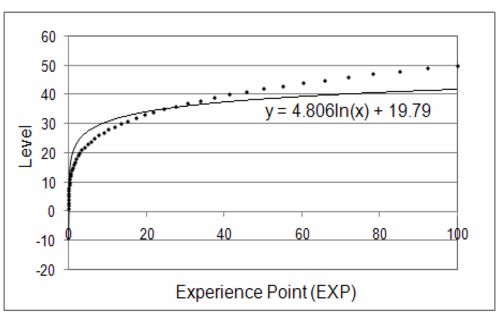
Figure 4. Experience Point Data Modeling

DATA FITTING OF THE REWARD SYSTEM

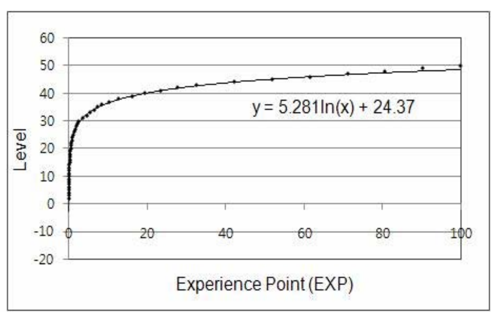
Data Normalizations and Fit

The level data from four digital games (Tables 1-4) were subjected to the process of normalization as a percentage, resulting in the fit model of Figure 5. The main characteristics of each group based upon comparative analysis of the fit model of four cases of EEDG and AEDG in Figure 5 are as follows:

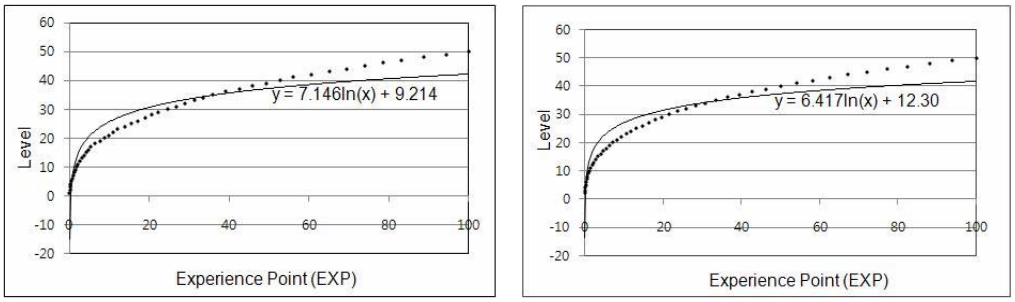
- Data obtained from the normalization is similar in form to Figure 2; however, in drawing the trend line, Figure 5 (a) and (b) in the fit model emphasize the powerful level-up area devoted to motivation.
- A section of powerful level-up area appears clearly and distinctly in two cases of EEDG (Fig. 5 a, b), but a powerful level-up area can only be drawn short-term or not at all in two cases of AEDG (Fig. 5 c, d).
- The fit graph shows concretely that Figure 5 (c) and (d) reach above Figure 5 (a) and (b), corresponding to the changes at the x-axis in the gradual process of the level- up area.
- The functional values of EEDG and AEDG differ from each other in functional formulas based on trend lines.



(a)



(b)



(c) (d)

Figure 5. Data fit (a) *Maple story*, (b) *Tales Runner*, (c) *Suddenattack*, (d) *WoW*

Table 5 shows the functional formulas deduced by means of a trend line. A functional formula derived by the trend line does not always indicate accurate normalized values in the parameters, but values and a functional formula can be deduced, thereby enabling understanding, i.e.

$$Level = K \ln EXP \pm W$$

where $Level$ = game level, K = a constant, that is the degree of difficulty in digital games, $\ln$ = logarithm, EXP = Experience Point, and W = motivational element constant.

Table 5. Function formulas derived from data fit

	K W
Figure 5 (a)	$Level$=4.806*ln EXP+19.79
Figure 5 (b)	$Level$=5.281*ln EXP+24.37
Figure 5 (c)	$Level$=7.146*ln EXP+9.214
Figure 5 (d)	$Level$=6.417*ln EXP+12.30

Compared to the EEDG group, the AEDG group (Fig. 5 c, d) has a constant K which is highly expressed and defines the width of its graph. The structure in the AEDG group is designed so the line radically heads upward as game playing progresses. The constant K in the EEDG group is relatively lower, with values of 4.806 and 5.281, compared to the constant K in AEDG, which is set higher at 7.146 and 6.417.

The values 19.79, 24.37, 9.214, and 12.30 correspond to the first, second, third, and fourth entries of W in Table 5. The functional formulas are the constants that influence the width in motivation which is reflected in the design with the purpose of increasing motivation in players in the powerful level-up area. When W is high, as in the first and second entries in Table 5, the graph moves towards the left indicating a long and active powerful level-up area (Fig. 5 a, b). On the other hand, when the value is low, as in the third and fourth entries in Table 5, the powerful level-up area is short and slightly expressed (Fig. 5 c, d). W as well as K have distinct differences in each group.

These differences make it easy to distinguish between EEDG and AEDG which has been difficult to achieve in an academic way until now. Furthermore, these results could be adapted for the possible construction of models with adjustments to the functional values that would enable effective computer–assisted learning programs suitable for each age level.

RESULTS

Figure 6 is derived from the process of plotting the functional formula deduced from Table 5 using MATLAB™. The groups of EEDG and AEDG take a common form as a logarithm; however, it is easy to see that there are differences in the fan-shaped lines of all groups plotted.

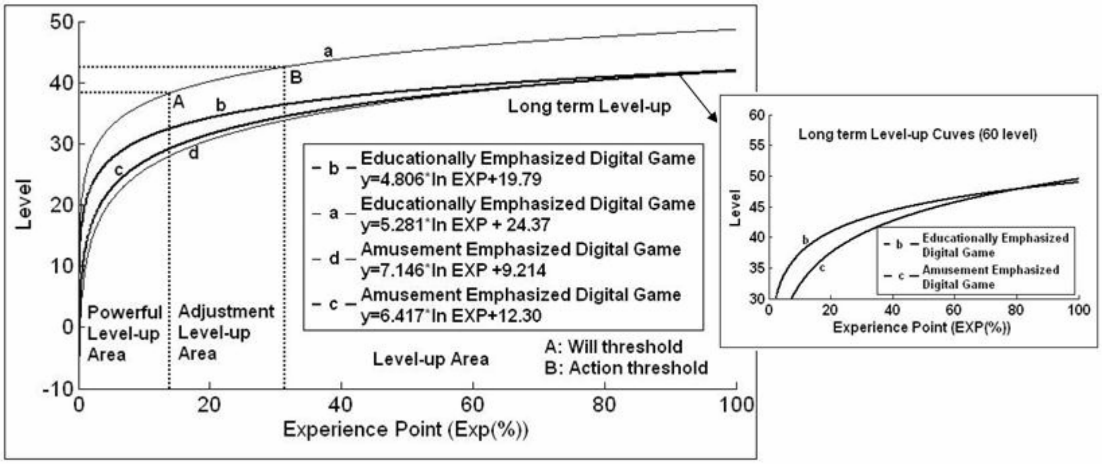


Figure 6. Plotting results: exponential curves of function formulas

The 'a' and 'b' lines in Figure 6 represent EEDG, while the 'c' and 'd' lines depict AEDG. The 'b' and 'c' lines are drawn in bold for typical samples that demonstrate a clear difference between the two groups. EEDG consist of three areas, namely powerful level-up, adjustment level-up, and level-up, which are the same as in the fit results from Figure 2. AEDG are designed with short sections, or without sections and at the same time designed to go upward to increase time spent. The inset graph (small box) demonstrates the clear difference between 'b' and 'c' lines.

Label A in Figure 6 indicates the will threshold step for learners who are able to change themselves very actively after they've experienced the first step of the powerful level-up area. Label B in Figure 6 denotes the action threshold step for learners who experienced a will threshold so that they could actively accomplish the learning steps in the long term. The functional formula in Table 5, verifies the flexibility between the two groups in that EEDG and AEDG are determined by a constant K, and depending on the value of K, they can differ from one another.

The constant W determines the width in motivation at the powerful level-up area. It also differs between the two groups. Evaluation of Figure 6 demonstrates the possibility of adjusting entertaining materials to educational ones with a computer–assisted learning model framework based on domains in digital games, and the possibility of designing the structure of educational methods that bring about accomplishments in each learning phase through a step-by-step process according to the learner's level.

DISCUSSION

The Exponential Learning Model

As mentioned previously, digital games are based on a functional formula in relation to an educational model wherein a schema can be defined as a log-function. A functional formula derived from Figure 5 and Table 5 can be applied as follows where $Level \approx$ Learning Level, and $Exp \approx Schema$:

$$L = k \log_e Schema \pm w$$

L = the accumulated learning level; k = a constant (the degree of difficulty in the computer–assisted learning model; the amusement, learning usability level); e = educational exponential; w = a constant (learning motivation elements); $Schema$ = accumulated learning skill.

It is possible to design various educational models appropriate for various learning capacities and ages through a process of adjustments in the constants k and w which consist of certain factors possessing several particularities. The functional formula of the constant k includes many parts: rules, competition, compensation, degree of freedom, and community (Colby & Colby, 2008), while w includes motivation. The addition of an alternate expression of players' personal capacities, such as computer competency and learning attitudes, might improve educational benefits. According to this research, it is possible to establish a boundary in digital games which can be divided into two parts, one for educational purposes and one for entertaining purposes, depending on the numerical values of k and w.

The computer–assisted learning model can be effective if factors involved in gameplay are permitted to function through several processes. However, learners' efforts may not always come to fruition. If the powerful level-up area does not function distinctively or if irregular events happen without any relation to education it would be difficult to accomplish the primary goal of learning with this system.

A Computer-Assisted Learning Model
When the main characteristics resulting from the analysis in this experiment are put together with the theory of educational models (Davidovitch et al., 2008), a computer–assisted learning model can be constructed. This is similar to an instructive educational model designed to accomplish learning step-by-step based upon the constructive educational theory via digital games. From a theoretical aspect, by using EEDG in association with the educational principles of constructivism, various forms of active models can be designed to motivate learning voluntarily by means of amusement. This is depicted in the example of a powerful level-up area as seen in Figure 7.

The adjustment level-up area causes learners to concentrate on the learning process with self-examination and co-operation. Learners in this area commit themselves to systematic thoughts, achieving their goals by solving problems. At the same time they can examine their knowledge and capacities through interaction with fellow learners.

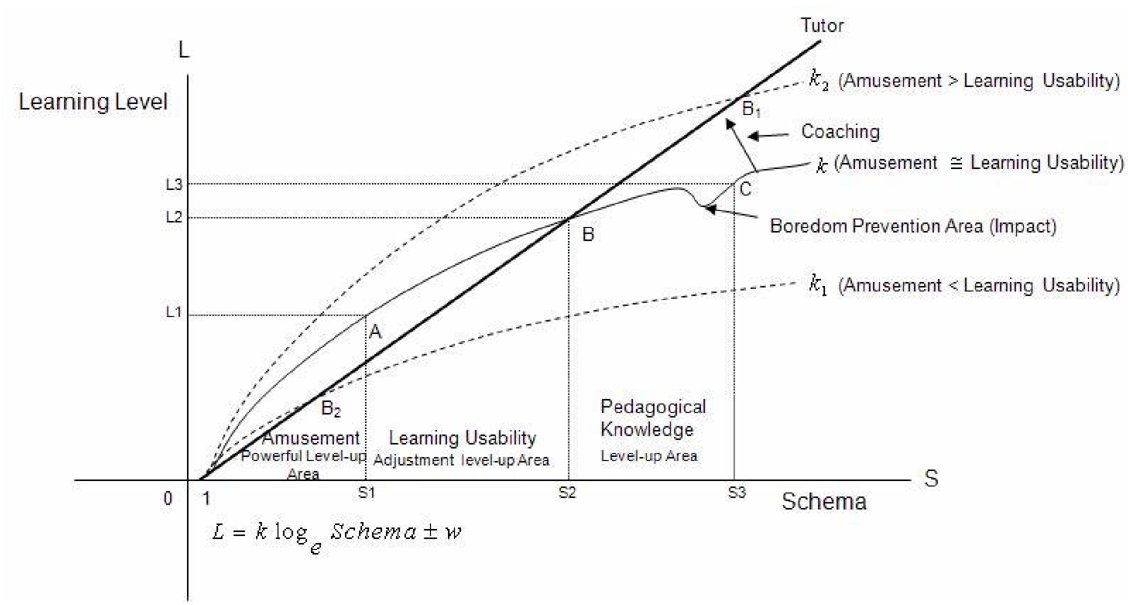


Figure 7. Proposed computer–assisted learning model

The level-up area helps learners attain pedagogical knowledge. This area offers creative materials in affective and cognitive aspects by tutoring, creating situated learning and a cognitive apprenticeship (Seufert, 2003). The function of the tutor in the level-up area is considered to be important for enhancing creative activities to prevent the learner from falling into a state of boredom

The slope of schema increase curve in Figure 7 would be determined with the values of k in a logarithm function. The schema of the x-axis in the modeling function consists of amusement, learning usability, and pedagogical knowledge. According to the research results shown in Figure 6, k line is one of the most ideal types. In Figure 7, if k_2 at point B_1crosses the tutor line, the condition of amusement is larger than learning usability so that it becomes a model similar to AEDG placing more weight on amusement than education. When k_1 crosses the tutor line at point B_2relatively early, learning usability is greater than amusement, pointing out that learners do not find learning interesting without amusement. Therefore, the most ideal model of computer–assisted learning could theoretically be achieved if amusement$\cong$ learning usability, with the k line presented above.

A section of A (S_1, L_1) on k line indicates amusement and a section of B (S_2, L_2) shows the process of learning usability. The section of C (S_3, L_3) is the step entering into pedagogical knowledge. Learners entering into pedagogical knowledge proceed to learning very actively because they have already accumulated knowledge and schema as shown in section C (S , L).

An area drawn irregularly on the k line indicates boredom prevention, derived from the event effects used in the reward system (Fig. 2 b, c). The framework of the reward system of (b) and (c) in Figure 2 provides players with various events that play an important role in helping and encouraging them to commit consistently to games that are fun. This fact makes it possible to effectively design many diverse models related to impact learning (Papastergiou, 2009), which prevent users from entering a state of boredom. From the viewpoint of cognitive apprenticeship, the area of coaching is the space that provides learners with outside assistance such as hints and feedback by experts and tutors observing the learners' activities during their tasks (Gee, 2003; Hayes et al., 2008; Zeichner, 2007; Zwart et al., 2008).

CONCLUSIONS

It has been determined on an international level that the majority of digital game users are of student-age. Most voluntarily participate in digital games and together with their online buddies, they collect, discern, and creatively reconstruction information. During this process, they discover the rules in the game space and repeat a self-organizing learning process.

Similar framework to the self-regulated learning constantly emphasized by educators in the field is actually occurring naturally during digital gameplay. Accordingly, many educators have attempted to apply the flow induction mechanisms of digital games to the educational learning model design (Csikszentmihalyi, 1990; Finneran & Zhang, 2003; Kiili, 2005a; Pilke, 2004).

As shown in the results of this study, the core device of the mechanism that constantly induces the flow of users to digital games is the reward system. In most cases, the reward system of digital games is designed in slightly different ways according to the genre (learning game, entertainment game, etc.) and the age of user. Additionally, it naturally induces flow through the use of fun elements based on a reward system.

Since the majority of digital game users are of school-age, there is a high possibility, in theory, that the learning efficiency of students can be naturally increased through this model. From this perspective, we analyzed the reward system, which is the core device for inducing user flow to digital games, and examined the possibility of applying it to a learning model.

The study results revealed that the two models contain common functional mechanisms. Appropriate compensation was provided through this functional mechanism according to the players' level in the gameplay process. In addition, it induced continuous gameplay and level up progression through the use of fun elements. As we expected, these results demonstrate a high possibility of designing a learning model which applies the reward system employed so effectively in digital games.

In addition, it was discovered that the EEDG group sampled has been designed to enable powerful level-up with less effort during initial gameplay compared to AEDG. This design method was commonly encountered in the EEDG group sample. This model is similar to the motivated learning model commonly applied in the field by educators. Accordingly, the emphasis on learning in EEDG is a design for inducing continuous gameplay by providing motivation to users.

Through the shape of the exponential curve trend line, it was also confirmed that digital games are designed differently according to genre and objective. The functional formula proposed in this study was deduced based upon the exponential curve which is the modeling result of EXP data. Based on this functional formula, we propose an exponential model that can be applied to a computer-assisted learning and a learning model design method.

The most distinguishing characteristic of this functional formula is the fact that it enables design of a learning model which considers the learner's level. This formula is basically similar to the exponential learning model of Johnston and Aldridge (1985) which is adjustable according to the individual characteristics of learners such as ability and motivation. However, the functional formula proposed in this study is considered to be more applicable to the actual field since it clearly classifies the constants which determine learning difficulty level and motivation.

In academia, many types of learning activities and materials are affected by the motivational curve of the exponential equation model similar to that for players in the digital gaming environment. The exponential learning equation model proposed by previous researchers is still being applied in various areas in the field. It is thought that the proposed exponential learning model can maximize learning efficacy by enabling the application of motivational materials differentiated according to the personalities or individual characteristics of students by adjusting the constants.

In addition, we propose a computer-assisted learning model design method based on the exponential learning equation model explained in this study. This model has been designed based on comparative analysis of the level up system of EEDG and AEDG. Accordingly, the curve can be adjusted with the constants of the exponential learning equation model proposed in this study. In other words, we present a concrete method for a design adjustable to meet the needs of particular learners or learning environments through adjustment of motivation and learning efficacy elements. The significance of this model lies in the fact that it presents a design method to effectively enhance performance learning through specific functions.

Appropriately providing motivational elements in the learning environment has an absolute effect on learning, which is a concern shared by most educators. Accordingly, the intensity of the motivational elements needed in a particular learning environment for individual learners can be predicted and adjusted by gradation in the learning model design used in this method. Studies of learning models applied to digital games are being conducted very actively on an international level. However, there are hardly any cases that evaluate the functional mechanism in the digital game domain and apply it to an exponential learning equation model in specific ways.

The exponential mechanism of digital games is automatically integrated and controlled through digital technologies including artificial intelligence technology. The functional formula and learning model design method proposed in this study are considered applicable in various types of computer-assisted learning methods, and considered important in the ‘impact learning model’ and ‘emergent learning model’, when integrated with technologies in the digital-based learning environment.

This is only the initial phase of this innovative idea. It is necessary to thoroughly review its application in the field. Accordingly, we will be conducting actual field tests based on the functional formula proposed in this study. We propose that this issue presents important possibilities in the area of education and is worth exploring through further research.

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