Education Tech Research Dev (2020) 68:2215–2237
https://doi.org/10.1007/s11423-020-09765-6

RESEARCH ARTICLE

Measuring performance in leaning process of digital game-based learning and static E-learning

Chih-Hung Wu[1] · Yi-Lin Tzeng[1] · Yueh-Min Huang[2]

Published online: 20 May 2020
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Abstract

This study investigated and compared the effectiveness of both digital game-based learning (DGBL) and static e-learning material for Newton's laws of motion on students' learning attention, affective experiences, cognitive load and academic achievement. Physiological signals and affective techniques were adopted to measure students' learning affective states and cognitive load. After learning, a post-test was then conducted to discover the differences in academic achievement between DGBL and static e-learning. The results showed that the DGBL group displayed greater variance in positive emotion and attention than the traditional e-learning group during the learning process, as well as a greater cognitive load. Based on the timeline measurement of attention and positive emotion patterns in the DGBL and e-learning groups, the largest gap in both attention and positive emotion patterns was found when the DGBL group members were about to finish playing the game. The findings of this study revealed that emotional well-being and increased attention are the key advantages that DGBL learning provides when compared with traditional e-learning approaches.

Keywords Affective computing technique · Digital game-based learning (DGBL) · Learning attention · Affective experiences · Cognitive load · Academic achievement · Physiological signal measurement · Learning performance

✉ Yueh-Min Huang
huang@mail.ncku.edu.tw

Chih-Hung Wu
chwu@mail.ntcu.edu.tw

Yi-Lin Tzeng
bit099101@gm.ntcu.edu.tw

[1] Department of Digital Content and Technology, National Taichung University of Education, Taichung City, Taiwan, ROC

[2] Department of Enginering Science, National Cheng Kung University, Tainan City, Taiwan, ROC

Introduction

Digital Game-Based Learning (DGBL) is an effective tool that can enhance learning experiences (Ak and Kutlu 2015; Connolly et al. 2007; Yeh et al. 2019) and increase student motivation (Liao et al. 2019; Papastergiou 2009). DGBL is defined as "the use of a computer game-based approach to deliver, support, and enhance teaching, learning, assessment, and evaluation" (Connolly et al. 2007; Vlachopoulos and Makri 2017). While it is also widely acknowledged that the use of games has educational advantages (Ak and Kutlu 2015; Lin and Hou 2015), and that they can be motivational and educationally effective, the empirical evidence to support this belief is still limited and contradictory (Marina 2009) despite the many studies that have investigated the effects of DGBL on learning and motivation (Chin et al. 2013; Erhel and Jamet 2013; Hess and Gunter 2013; Ke et al. 2015; Mayer et al. 2014).

In addition, few studies have examined the effects of learner emotions on learning processes and outcomes (Um et al. 2007). Prior research has examined differences between the learning and affective experiences of students playing games in two different countries and found that in both countries, eighth and ninth grade students' learning interest was greatly increased by through the use of playing SURGE games (Clark et al. 2011). In another study, learners' cognitive capacity was shown to be highly engaged during online gamed-based learning (Huang 2011). Although researchers focusing on cognitive load have concluded that an overloaded cognitive capacity can de-motivate learners, almost all studies performed to date have used questionnaire surveys to measure attention, a method which is not very objective.

Major reviews of DGBL have reported either contradictory or ambiguous findings (Papastergiou 2009). While a comparison of the learning achievement and perception in DBGL (2D/3D game) has been investigated (Ak and Kutlu 2015), there remains a lack of research regarding the effectiveness of educational games, and there is thus a need for further investigations to clarify the ambiguous results (Ak and Kutlu 2015; Hess and Gunter 2013). The effects of DGBL on students' academic achievement are still unproven in a robust empirical research setting. Therefore, the first purpose of this study is to explore how different learning methods affect learners' emotions and academic performance. The second goal is to explore and compare the differences in academic achievement, affective experience, and cognitive load in DGBL and traditional e-learning environments.

To examine the possibility of using digital games to learn physics, a quasi-experimental design was used to examine the effectiveness of DGBL and traditional static e-learning on students' learning attention, affective experience, cognitive load, and academic achievement. While the students were learning their eye movement data, brain waves and heart beats were measured to evaluate their learning states. The learners then took a post-test, making it possible to measure the differences in academic achievement between DGBL and static e-learning. Through the use of this approach, the following research questions could be explored:

1. How does DGBL affect learning attention, affective experiences and cognitive load?
2. How different are the effects of the learning environment on students' academic achievement?

Literature review

Digital games are widely used as important form of media to stimulate learner motivation and enhance the effectiveness of learning. Students use games to explore, discover, question, and ultimately construct concepts and relationships in authentic contexts. The concepts of "learning by doing" and "active learning" are important constructivist principles which underlie game-based learning (Yang 2012).

Digital game-based learning, learning attention, affective experiences, and cognitive load

Many studies have investigated the effects of DGBL on learning and motivation (Erhel and Jamet 2013). Learning motivation is composed of four perceptual components: attention, relevance, confidence and satisfaction (Keller 2008). Regarding attention, learners engaged in DGBL start out with successful motivational processing that consists of a high level of attention (Huang et al. 2010). Some features in game development–animated pedagogical agents (APAs) (Chin et al. 2013) and graphic organizers (Cheon et al. 2013) have proven to successfully enhance students' learning motivation and engagement in learning activities. Learners pay more attention and have more motivation to learn in a DGBL environment (Ke et al. 2015; Tüzün et al. 2009). Therefore, previous research has proven that an interesting learning tool, such as DGBL, is likely to enhance learners interest, and thus better hold their attention.

Emotional status and learning effectiveness are highly correlated (Lin et al. 2014). Different learning methods may arouse different emotional responses during the learning process, due to physiological and emotional changes in the learner (Baldaro et al. 2004). Identifying the emotional states of students during learning can facilitate the development of positive learning experiences, and playing games can lead to various affective experiences (Ravaja et al. 2008). However, whether such emotional changes are positive or negative still needs to be further explored. For instance, students who feel these games are interesting may pay more attention to them and experience positive emotional changes. In contrast, those who feel such games are boring are more likely to feel negative emotional changes. Based on these studies, it is proposed herein that DGBL can increase the depth of learners' affective experience. However, whether these emotional changes are positive or negative has yet to be proven.

Cognitive load refers to the overall amount of mental activity that occurs in the cognitive system during the learning process (Chen and Wang 2011). The cognitive load of learners is generally greater when facing a more complex learning task. Learners' cognitive capacities are highly engaged during online DGBL, and this thus might overload their cognitive capacity and lead to an unsatisfactory learning experience (Huang 2011) since an overloaded cognitive situation can de-motivate learners. As a learning tool, DGBL is generally more complex than traditional static learning methods, and thus demands a greater cognitive capacity, which may compromise its effectiveness.

Digital game-based learning and academic achievement

The effectiveness of DGBL with regard to students' academic achievement has long been debated, and still needs to be examined in an empirical research setting (Ke et al. 2015; Papastergiou 2009; Wu 2019). Interactive games have been shown to be more effective than traditional classroom instruction with regard to learners' academic achievement and the development of cognitive skills (Vogel et al. 2006). An well designed DGBL environment with the 6E teaching model concept is benefit to improve the learning performance in STEAM (science, technology, engineering, art, and mathematics) education (Wu 2019). The experience of optimal challenge, which is a state of cognitive engagement situated within a playful context, can increase game-based learning engagement. (Ke et al. 2015). However, other studies have found that no differences in student learning can be found between learning environments that involve games and those without game elements (Annetta et al. 2009; Papastergiou 2009). In addition, sixth graders reported higher motivation and engagement levels as a result of playing a science-based game although there was no evidence to show that the game led to learning outcomes that were significantly better than those seen in the traditional classroom (Wrzesien and Alcañiz Raya 2010).

Research design and methodology

This section is organized as follows. In Research hypotheses section, we develop a research framework with four hypotheses to examine the relationships between learning method and attention, affective experience, cognitive load, and academic achievement. In Materials section, the materials used for the pre-test and two groups, a DGBL group and an e-learning group, are described. In Participants and procedure section, the selection of the participants and research procedure are stated. Finally, the physiological signals and sensors adopted in this work are introduced in Physiological signal analysis.

Research hypotheses

Based on a literature review and the research purposes, we proposed the research framework shown in Fig. 1 and developed the related hypotheses as follows. Two learning methods (static e-learning and DGBL) were used in this study. The static e-learning group only read the e-learning materials without playing a game, while the DGBL group played the related game. This work tested the following hypotheses:

H1.The attention score of the DGBL group is significantly higher than that of the traditional static e-learning group.

H2. The affective experiences of the DGBL group are significantly different from those of the traditional static e-learning group.

H3. The cognitive load of the DGBL group is significantly greater than that of the traditional static e-learning group.

H4. The difference in the academic achievement between the DGBL group and the traditional static e-learning group is significant.

To examine these hypotheses, affective computing techniques were employed to evaluate and compare the attention scores, affective experiences, and cognitive loads of learners in the DGBL and traditional static e-learning environments. The learners' attention was measured using NeuroSky, affective experience was measured using emWave, and cognitive load was measured using an eye-tracker. Academic achievement was measured using a pre-test (Force Concept Inventory, FCI) and post-test (Mechanics Baseline Test, MBT). In addition, the following two different learning environments were designed: (1) DGBL, in which learners studied a physics problem using the SURGE physics game and (2)

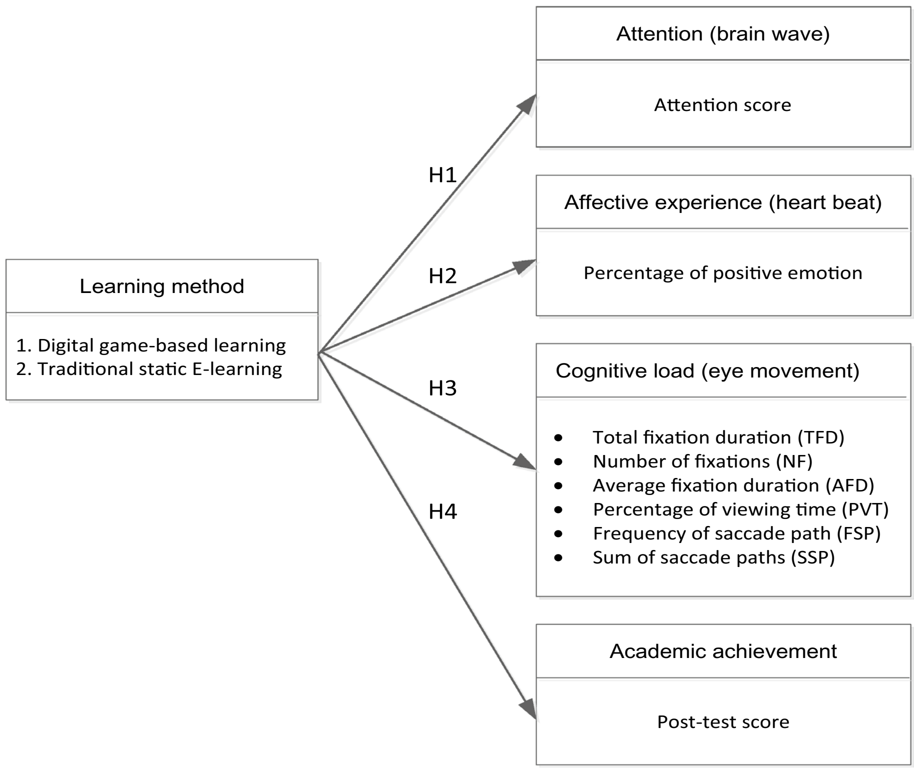

Fig. 1 Research framework

traditional static e-learning, in which the learners studied traditional textual descriptions, coordinates, and formulas.

Materials

Pre-test

The pre-test focused on players' understanding of formal "instructed concepts" based on the FCI (Hestenes and Halloun 1995). The FCI instrument was designed to assess student understanding of the most basic concepts in Newtonian physics. This forced-choice instrument has 30 questions and tests six areas of understanding: kinematics, Newton's First, Second, and Third Laws, the superposition principle, and types of forces (such as gravity and friction). Each question has only one correct Newtonian solution, with common-sense distractors (incorrect possible answers).

DGBL and e-learning materials

This study used the SURGE physics game environment that was proposed and investigated in a previous study (Clark et al. 2011; Wu et al. 2014a). SURGE was developed to connect

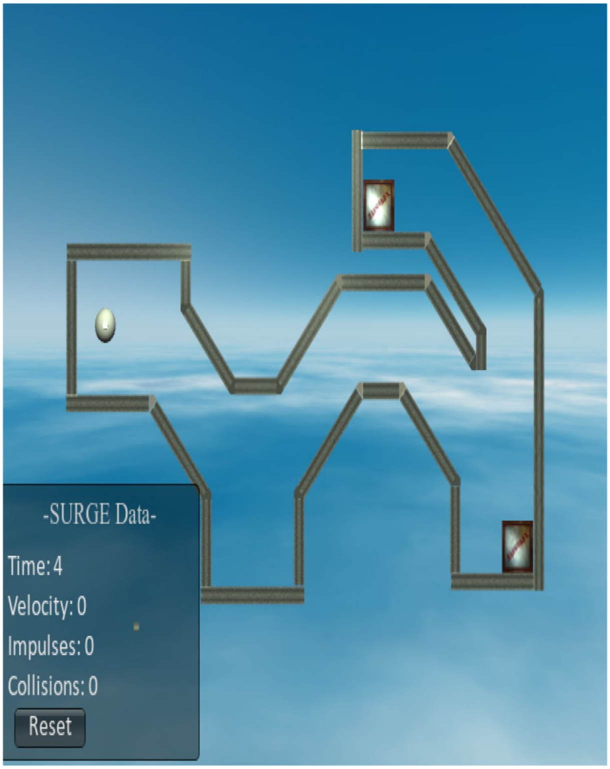

Fig. 2 Easy level of the SURGE game

students' intuitive "spontaneous concepts" about kinematics and Newtonian mechanics. The SURGE game has two modules, as shown in Figs. 2 and 3. The first module used an impulse control system, which each time a student pushed an arrow key then a fixed impulse was applied to Surge's ship (represented by a white ball in the game). The second module used a constant force control system in which students hold down an arrow key to apply a constant force in that direction. Overlaid on the screen were different read-outs of information for the students, including their ship's current speed, the number of impulses they've used, the number of collisions in which Surge's ship hits the walls, and the elapsed time on a given game level. Students were told to minimize their collisions, level completion time, and number of impulses in order to get a high score. The game also include on-screen buttons used to reset or pause the level and to stabilize Surge's ship if it starts moving out of control. A vector representation of velocity was displayed on the screen, showing the player's current speed and direction. Some levels included a Motion Map Region, where students must maintain a constant velocity, increase their speed, or decrease their speed in order to complete at the level.

The content of the static e-learning material was developed based on a senior high school textbook in Taiwan. The content included 10 pages about Newton's three Laws of Motion, with one page of description for each law.

Fig. 3 Difficult level of the SURGE game

Post-test materials

In this study, two problems, one easy and one difficult, were selected from the Mechanics Baseline Test (MBT) for use in the post-test. The test covered concepts related to basic principles (Newton's First, Second, and Third Laws, and the superposition principle) and Special Forces (gravity and friction). The MBT instrument is an advanced companion to the Force Concept Inventory (FCI). The FCI questions were designed for students without formal training in mechanics, so as to meaningfully elicit their preconceptions about the subject in a qualitative way. In contrast, the MBT questions were designed to probe concepts and principles that cannot be grasped without formal knowledge of mechanics. The answers required a quantitative approach that is more involved than plugging numbers into formulas. The two tests together assessed the students' conceptual understanding of basic Newtonian mechanics, including basic principles that are generally covered in an introductory physics course. The forced-choice MBT has 26 questions that were developed based on interviews with students about their misconceptions of basic topics in Newtonian mechanics. The test covers concepts in kinematics (linear and curvilinear motion), basic principles (Newton's First, Second, and Third Laws, and the superposition principle, energy conservation, impulse-momentum, and work) and Special Forces (gravity and friction).

In problem 1, a diagram (Fig. 4) depicts a hockey puck moving across a horizontal, frictionless surface in the direction of the dashed arrow. (Answer: 2 or 3).

Problem 1.

The right diagram depicts a hockey puck moving across a horizontal, frictionless surface in the direction of the dashed arrow. A constant force F, shown in the diagram, is acting on the puck. For the puck to experience a net force in the direction of the dashed arrow, another force must be acting in which of the directions labeled 1, 2, 3, 4, 5?

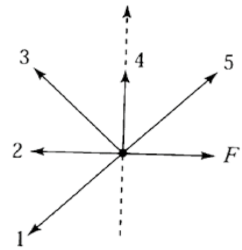

Fig. 4 Post-test problem 1 (easy level)

Problem 2.

A person pulls a block across a rough horizontal surface at a constant speed by applying a force F. The arrows in the right diagram correctly indicate the directions, but not necessarily the magnitudes of the various forces on the block. Which of the following relations among the force magnitudes W, k, N, and F must be true?

1. F = K & N = W 2. F = k & N > W
3. F > k & N < W 4. F < k & N = W
5. None of the above

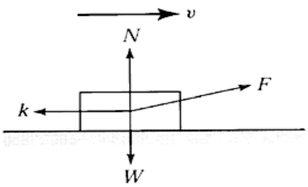

Fig. 5 Post-test problem 2 (difficult level)

In problem 2 (as shown in Fig. 5), a person is pulling a block across a rough horizontal surface at a constant speed by applying a force F. (Answer: 3).

Participants and procedure

The experimental data was derived from our previous study (Wu et al. 2014a). The participants comprised 32 university students, aged 19 to 26, 18 of whom were female and 14 of whom were males. These students were randomly assigned to either the DGBL group or the static e-learning group (Wu et al. 2014a). All participants had good vision and passed the eye-tracking calibration tests were tested individually. On arrival, they completed the FCI pre-test, and after physiological sensors had been attached to measure their physiological signals, the participants were told that the experiment included two phases, a learning phase and a post-test phase. Before the learning phase began, all of the participants had to complete the eye-tracking, NeuroSky, and emWave sensors calibration. Next, the learning phase began, where participants were randomly assigned to either the DGBL group or the static e-learning group. The learning phase lasted approximately 10 min. After the learning phase, the post-test phase began, and the eye movement data were recorded while participants were solving the problems. In addition, the participants were asked to think aloud while solving the problems. In this way we were able to record the participants' reasons for selecting their answers. A think-aloud training exercise was conducted before the experiment started. The post-test phase lasted approximately 10 min. The participants' eye movement data and question responses were recorded.

Physiological signal analysis

Multiple physiological signals have been used to improve the accuracy of evaluating learning performance (Wu et al. 2014a, b, 2015). In this study, eye movements, heart rates, and brain waves were adopted to measure the learners' attention, affective experiences, and cognitive load.

Eye movement variables

Five eye-movement measures including total fixation duration (TFD), number of fixations (NF), and average fixation duration (AFD), percentage of viewing time (PVT) and frequency of saccade path (FSP) were used to analyze the eye movement patterns in each learning environment (Yang et al. 2013). This eye movement information measure the cognitive load related to reading, comprehension, and attention while learning in our experiment. In brief, the fixation measures, such as NF, FC and TFD, indicated the period of time required to acquire new information (Rayner 2009). The AFD, while revealing the time needed for information processing, can be influenced by the nature of the task given to participants (Rayner 2009). The times of saccade paths, which indicate the back-and-forth scanning between different zones, were also recorded. These times can reveal the integration processes of among different modes of information (Holsanova et al. 2009).

Emotion variables

When a learner's emotional state is negative, peaceful or positive, the Coherence score will be calculated as 0, 1, and 2, respectively. The value of Heart Rate Artifacts (HRAs) is zero when a normal human emotion is detected, whereas the HRAs value is one when the abnormal emotion is detected. The emWave system was adopted in this study to identify the emotional states of the learners every 5 s. The Accumulated Coherence Score (ACS) was used to calculate the percentage of positive and negative emotions, where the method for computing the ACS was based on different coherence states and HRAs as follows (Chen and Wang 2011):

$$CV(t) = \begin{cases} 0, \text{if Coherence(t)} = 0 \ \textit{and} \ HRA(t) = 0 \ \text{(negative emotion)} \\ 1, \text{if Coherence(t)} = 1 \ \textit{and} \ HRA(t) = 0 \ \text{(peaceful emotion)} \\ 2, \text{if Coherence(t)} = 2 \ \textit{and} \ HRA(t) = 0 \ \text{(positive emotion)} \end{cases}, CV(0) = 0, t = 0, 1, 2, \ldots m, \tag{1}$$

where $CV(t)$ is the coherence value at the ith sampling time. Coherence (t) is the coherence state at the tth sampling time; HRA(t) is the HRA value at the tth sampling time; and m is the number of times the emotional states are recognized.

Based on the CVs obtained using Eq. (1), the ACSs of positive, peaceful, and negative emotions during learning can be formulated as follows:

$$\text{ACS of Positive Emotion} = \sum_{t-1}^{m} CV(t),\ \text{if Coherence}(t) = 2 \text{ and HRA}(t) = 0 \tag{2}$$

$$\text{ACS of Peaceful Emotion} = \sum_{t-1}^{m} CV(t),\ \text{if Coherence}(t) = 1 \text{ and HRA}(t) = 0 \tag{3}$$

$$\text{ACS of Negative Emotion} = \left|\sum_{t-1}^{m} CV(t)\right|,\ \text{if Coherence}(t) = 0 \text{ and HRA}(t) = 0 \tag{4}$$

Therefore, the percentage of time spent in positive and negative emotional states can be formulated as follows:

Positive Emotion

$$= \frac{\text{ACS of Positive Emotion}}{\text{ACS of Positive Emotion} + \text{ACS of Peaceful Emotion} + \text{ACS of Negative Emotion}} \times 100\% \tag{5}$$

Negative Emotion

$$= \frac{\text{ACS of Negative Emotion}}{\text{ACS ofPositive Emotion} + \text{ACS of Peaceful Emotion} + \text{ACS of Negative Emotion}} \times 100\% \tag{6}$$

By employing Eqs. (5) and (6), the percentage of positive and negative emotions during learning can be obtained, respectively.

Variable measurements

To measure the motivation score using physiological signals in order to compare the motivation, affective experiences and cognitive load of learners in the DGBL and traditional static e-learning environments, the attention score was measured with NeuroSky, which was adopted and tested in prior DGBL studies (Liarokapis et al. 2014; Vourvopoulos and Liarokapis 2014).

(a) EmWave **(b)** Eye Tracker

Fig. 6 Emotion device: emWave hardware

Table 1 Physiological signal variables

Physiological signal variables	Definition	Reference
Brain wave variable	Learning attention	A higher AT level indicates increased learning motivation. (Derbali and Frasson 2010)
Attention score (AT)	The attention score ranged from is 1 to 100; 1 = very low attention level and 100 = very high attention level	
Emotion variable	Affective experience	When PE gets bigger, affective experiences also get stronger. (Chen and Wang 2011)
Percentage of positive emotions (PE)	Time spent feeling positive emotions divided by the total time spent feeling emotions (%)	
Eye movement variables	Cognitive load	When these variables get bigger, cognitive load also gets higher. (Yang et al. 2013)
Total fixation duration (TFD)	Duration of all fixations with an AOI (areas of interest). (millisecond, ms)	
Number of fixations (NF)	Sum of the number of all fixation points	
Average fixation duration (AFD)	Average duration at a fixation points. (millisecond, ms)	
Percentage of viewing time (PVT)	Duration of total fixation/total time (%)	
Frequency of saccade path (FSP)	Saccade times/total time tracked (piece)	

The affective experiences were measured using emWave (Fig. 6a), and the cognitive load was measured using an eye-tracker (Fig. 6b). The learner's attention score was obtained by using the NeuroSky system's Attention & Meditation eSense algorithms. The attention score ranged from 1 to 100 (1 = very low attention level and 100 = very high attention level). The learner's affective experiences were recognized by the emWave system, which uses human pulse measurements to generate a Coherence score every 5 s. Coherence scores can be either 0, 1 or 2 (0 = negative emotion, 1 = peaceful, and 2 = positive emotion). Descriptive statistics and a one-way ANOVA were then conducted to test the proposed hypotheses. In addition, post-test scores were analyzed using an ANCOVA, in which the learning method (DGBL vs. static e-learning) was the between-groups factor, and the pre-test scores were treated as covariates to control for the effects of pre-existing between-group differences. Cognitive load is determined by the eye tracker's five eye-movement measures, including TFD, NF, AFD, PVT and FSP. The physiological signals variables are shown in Table 1.

Physiological signal analysis based on timeline

Emotions are normally associated with physiological changes, which can be measured through some non-intrusive affective computing techniques (Huang et al. 2014; Wu et al. 2015). One major advantage of using affective computing in education is that the learner's physiological status can be observed continuously while the learning process. Therefore, we examined the differences (brain wave attention and positive emotion) between the e-learning and DGBL learners. In the e-learning group, the learners had to study the e-learning physics material for ten minutes. In the DGBL group, the learners had to finish the easy level and then the difficult level of the SURGE game, and were given five minutes for each task (i.e. a total of 10 min).

Table 2 Independent samples t-test of physiological signals between the static and DGBL learners

Test item	Static ($n = 16$)		DGBL ($n = 14$)		t	Significance (*two tailed*)
	Mean	(SD)	Mean	(SD)		
Learning attention						
Attention score	44.48	(7.40)	45.37	(15.34)	−0.196	0.847
Affective experiences						
Positive emotion	0.1823	(.156)	0.1856	(.265)	−0.041	.968
Cognitive load						
TFD	440,204.00	(88,490.73)	244,923.00	(84,290.83)	6.185	.000
NF	1845.69	(457.15)	550.86	(229.06)	9.987	.000
AFD	250.20	(57.64)	464.38	(91.97)	−7.517	.000
PVT	733.67	(147.48)	1561.75	(415.49)	−7.077	.000
FSP	2.86	(.88)	4.50	(3.46)	−1.727	.105

Data analysis

Difference analysis of attention, affective experiences and cognitive load between e-learning and DGBL

A one-way ANOVA was used to examine the difference between traditional static e-learning and DGBL. The results showed that there were significant differences in the TFD ($t=6.185$, $p<0.001$), NF ($t=9.987$, $p<0.001$), AFD ($t=-7.517$, $p<0.001$), and PVT ($t=-7.077$, $p<0.001$) across the two learning environments. However, attention, percentage of positive emotion, FSP and SSP all showed statistically non-significant differences (Table 2).

Although the DGBL group had a higher attention (AT) score than the static e-learning group, no significant differences were found. Learners who start out with successful motivational processing exhibited a higher attention levels in game-based learning, as found in an earlier work using the questionnaire measurements (Huang et al. 2010). Past studies have also reported that students demonstrate statistically and significantly higher intrinsic motivation and statistically and significantly lower extrinsic motivation when learning in a game-based environment (Tüzün et al. 2009). Because the link between attention and motivation is extremely close (Crookes and Schmidt 1991), this indirectly supports the idea that game-based learning has a positive impact on attention. Although past studies have argued that learners pay more attention in a DGBL environment, according to the questionnaire measurements, the findings of the current study, based on scientific evident from physiological measurements, did not support this, and thus Hypothesis 1 was rejected.

According to the positive emotion (PE) score, the DGBL group did not have better affective experiences (i.e. percentage of positive emotion) as compared to the traditional static e-learning group, so hypothesis 2 was also rejected. The cognitive load was measured using five eye-movement measurement indices. Significant differences were found in TFD, NF, AFD, and PVT. The DGBL group had lower scores than the static e-learning group in TFD and NF. However, for the AFD and PVT data, the DGBL group scored higher than the static e-learning group. The results showed that the DGBL group had a significantly greater cognitive load than the traditional static e-learning group, and thus Hypothesis 3 was supported.

Fig. 7 The pre-test and post-test (static e-learning vs. DGBL)

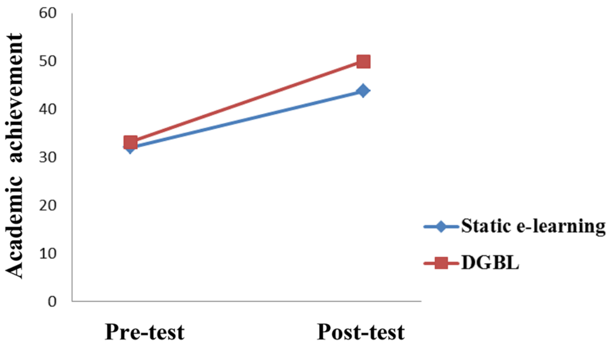

Table 3 ANOCVA for academic achievement

		SS	*df*	*MS*	*F*	*p*
Covariance	Pre-test	174.58	1	174.58	.209	.651
Between-groups	Learning environment	291.49	1	291.49	.349	.559
Within-group	Error	24,200.42	29	834.49		

Comparison analysis of academic achievement for e-learning and DGBL

The FCI test score was used as the pre-test, with results of 32.08 ($SD = 12.64$) and 32.62 ($SD = 12.28$) for the static e-learning and DGBL groups, respectively. In addition to the pre-test, a post-test was also conducted, with mean scores of 43.75 ($SD = 25.00$) and 53.57 ($SD = 30.79$) for the static e-learning and DGBL groups, respectively. The differences in the pre- and post-test scores for the two learning environments (static e-learning vs. DGBL) are shown in Fig. 7.

The post-test scores were analyzed using an ANCOVA, in which the learning environment (static e-learning vs. DGBL) was the between-groups factor, and the pre-test scores were treated as covariates in order to control for the effects of pre-existing between-group differences on subsequent analysis. Before the ANCOVA analysis was conducted, the Kolmogorov–Smirnova method was used to test the normality of academic achievement data in this study, where a non-significant result ($p < 0.001$) indicated that the data were non-normally distributed. Additionally, Levene's test of equality of error variance for homogeneity of variance was conducted, and the results revealed no significant effect, F (1, 28) = 0.166, $p = 0.687$. That is, the data met the requirement for homogeneity of variance. No statistically significant effect was found for learning environment, F (1, 27) = 0.883, $p = 0.356$, as shown in Table 3.

Interactive games have been shown to be more effective than traditional classroom instruction with regard to enhancing learning outcomes and the development of cognitive skills (Vogel et al. 2006). As shown by the results, no differences in student learning could be found between learning environments with or without game elements, as shown in Fig. 9. In other words, in comparison to the traditional static e-learning group, the DGBL group had better academic achievement in the post-test (43.75 vs. 53.57), although there was no statistically significant difference.

Physiological signal analysis based on timeline

Table 4 shows the descriptive statistics of the participants' performance in DGBL. The average times for finishing the easy and difficult levels of game were 0.76 m (std. dev.

Table 4 Descriptive statistics of the DGBL participant's performance

	Time in finish (s)		Number of collisions	
	Easy	Difficult	Easy	Difficult
Average	45.86 s = 0.76 m	120.79 s = 2.01 m	17.29	179.21
Std. dev	20.59 s	45.34 s	13.65	171.86

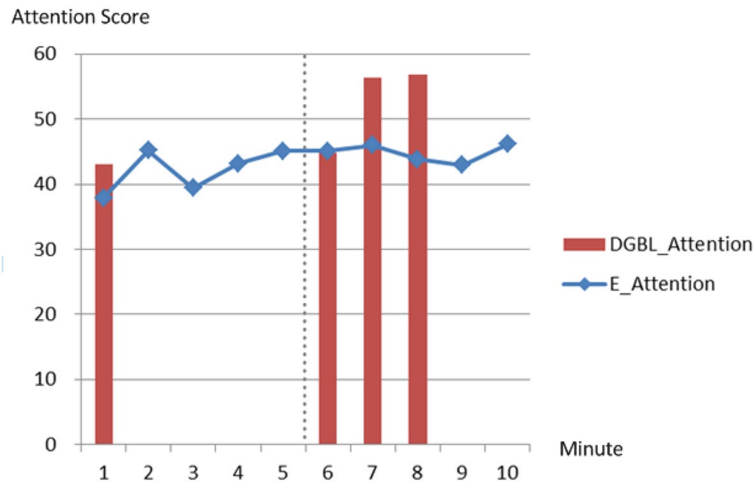

Fig. 8 Trend of changes in attention by minute. (E-learning: 1–10 min for studying; DGBL: 1–5 min for easy level; 6–10 min for difficult level). DGBL time needed to complete the task: Easy level (avg. in 0.76 m); difficult level (avg. in 8.01 m)

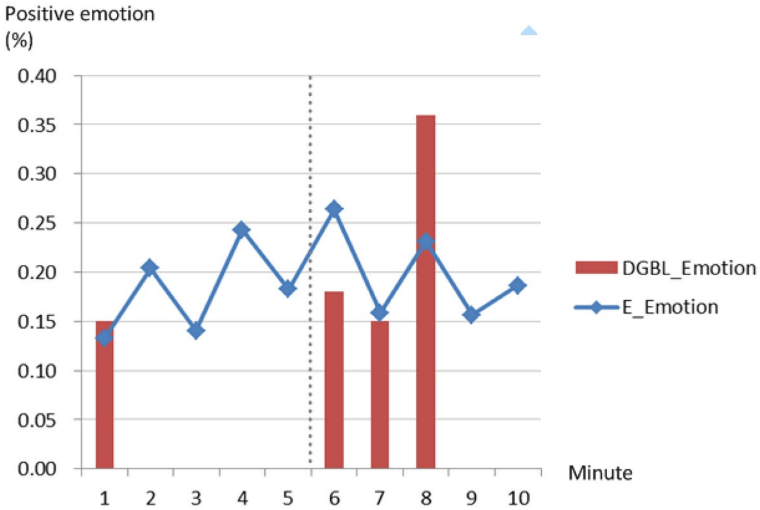

Fig. 9 Trends of changes in positive emotion in each minute. (static e-learning: 1–10 min for studying; DGBL: Easy level of game (1–5 min); difficult level of game (6–10 min). DGBL Time need to finish the game: Easy level (avg. in 0.76 m); difficult level (avg. in 8.01 m)

20.59 s) and 2.01 m (std. dev. 45.3 s), respectively. The ship hit the walls 17.29 times and 179.21 times (i.e. the number of collisions) at the easy and difficult levels, respectively. The descriptive statistics showed that all the participants were able to master and finish the game when playing the easy and difficult levels, and thus, the average time for finishing the easy level was significantly less than the time required for the difficult level (0.76 min vs. 2.01 min), whereas the average number of collisions at the difficult level was significantly higher than at the easy level (17.29 vs. 179.21). The greater number of collisions means the participants had many more instances of trial-and-error while attempting to complete the difficult level of the game.

The trends in the changes in attention per minute for e-learning and DGBL are shown in Fig. 8, where the blue line and red vertical bars denote the e-learning and DGBL learners' attention scores, as determined by our physiological sensors, respectively. For the easy level of the game, all of the DGBL learners finished their work within two minutes, so only the data collected in the first minute was analyzed. However, the learners spent three more minutes, on average, to finish the difficult level, so the data generated in the first three minutes is analyzed for this. Several interesting things were found in the timeline based on physiological signal analysis. First, the data showed that the pattern of the DGBL learners' attention was significantly different from the pattern of the e-learning learners' attention, although the difference between the two groups' average attention scores was statistically insignificant. The pattern showed that the DGBL learners had to pay more attention to finishing their task than the e-learning learners. Second, attention at the beginning stage of playing the game (easy level and difficult level) was low (points 1 and 6 on the *x-axis*), but it increased and peaked as the learners finished the game (points 7 and 8 on the *x-axis*). In contrast to the DGBL group, the average attention of the e-learning learners remained relatively stable.

The positive emotion data from both groups is presented in Fig. 9. The trends in the emotion data showed that the behavioral pattern of DGBL learners' average percentage of positive emotion for the DGBL learners was different from that of the e-learning participants. For the DGBL learners, the level of positive emotion at the beginning stage of the easy level of the game was slightly higher than that of e-learning learners (point 1 on the *x-axis*) but was lower for the more difficult level (point 6 on the *x-axis*). The positive emotion apparently decreased in the DGBL group when faced with the beginning of the difficult game. This was perhaps to be expected since more difficult level might have been less enjoyable to complete as the length of time playing the game became longer. The DGBL learners' positive emotion decreased even further during the next minute (point 7 on the *x-axis*), but it reached a peak when they finished the game (point 8 on the *x-axis*). The result showed that the difficult task decreased and then increased the positive emotion effect, which indicated a certain level of learning difficulty for experiencing the game and then excitement as the learners completed it. In contrast to DGBL, the average percentage of positive emotion among the e-learning students remained relatively stable.

Discussion and conclusion

Multi-channel physiological signal measurements were adopted in this study to measure cognitive load and to reveal the detailed learning behavioral patterns in the e-learning and DGBL groups. In contrast to direct/subjective measures, an eye-tracking analysis can provide an objective measurement of cognitive load (Brunken et al. 2003; Liu et al. 2014; Paas et al. 2003; Spann et al. 2019; Yang et al. 2013; Wu et al. 2014a) and learning performance (Giannakos et al. 2019; Wu et al. 2014a; Wu 2019). Additionally, cognitive load can be measured by physiological signals, such as heart rate (Paas and Merrienboer 1994), pupil dilation (Beatty 1982), visual attention (fixations, duration, and saccade) (Wu et al. 2014a), and electroencephalography (EEG) (Wu et al. 2014a; Giannakos et al. 2019; Vasiljevic and de Miranda 2019). The physiological signal analysis can reflect details regarding the learner's behavioral patterns (Giannakos et al. 2019, which are an indirect causal link to cognitive load. Therefore, our results can be treated as indirect and objective measures in the field of multimedia learning when investigating the effects of cognitive load on performance outcomes.

Implication for researchers

In the past decades, researchers have been using eye movement devices to measure cognitive process (Liu et al. 2014; Rayner 1998; Rayner and Duffy 1986; Simonsen 2017; Tono 2011; Yang et al. 2013). Based on the eye-mind assumption in one of the psychological theories, the eye gaze time represents the eyes being fixed on a target as long as the target is being processed, so the gaze time can be used to reflect how much cognitive effort learners are putting into a specific task (Just and Carpenter 1980). In a theory of reading, eye fixations can be used to understand the comprehension cognitive process, where the cognitive process can be represented through the following gaze behaviors in eye movements: (1) attention to the target features can be assessed through fixation duration on target tasks, (2) repeated exposure can be measured through fixation frequency on target tasks, and (3) deep cognitive process can be measured through target search duration and total fixation duration and time spent on relevant tasks. Therefore, the gaze behaviors in the eye-tracking measurement can be represented by an effective and objective cognitive load measurement of learning process (Just and Carpenter 1980; Liu et al. 2014). Based on the above-mentioned arguments, several eye-movement behaviors (TFD, NF, AFD, PVT, and FSP) were adopted in this study that have been used in a previous study (Yang et al. 2013) for cognitive load measurement during learning.

Recently, a large part of educational research concerned with embodied learning relates the findings of cognitive study to CLT (cognitive load theory) (Skulmowski and Rey 2017). Multimedia learning studies have adopted a wide array of measures in order to assess the cognitive demands in learning (Brunken et al. 2003). Therefore, progress in cognitive load measurement is regarded to be important for the future of the CLT (Paas et al. 2003; Skulmowski and Rey 2017). Cognitive load measurement for embodied learning can be classified into three types of methods: subjective methods (e.g. self-reported assessment and survey-based NASA-TLX questionnaires) and behavioral measures such as eye tracking, dual-task performance, and response latency), and physiological measures (e.g., electroencephalography (EEG), heart rate, pupil dilation, and pupillometric measurement). Among these measurement methods, behavioral and physiological measures of cognitive load are considered to be objective alternatives to subjective cognitive load surveys (Brunken et al. 2003, 2013). Physiological measurement has an enormous potential in three types of cognitive measurements for educational research (Skulmowski and Rey 2017). In the review paper of cognitive measurement (Skulmowski and Rey 2017), eye movements were used as an indicator of cognitive activity occurring during learning (Pouw et al. 2016). However, none of these studies claimed what types of cognitive load could be measured. Therefore, the methods for measuring different cognitive load types can be investigated in future studies.

The attention trends and patterns for the e-learning and DGBL groups were different. In contrast to DGBL, the e-learning learners exhibited a relatively stable attention pattern while studying the learning material. Overall, the DGBL group demonstrated higher attention than the e-learning group during the learning process, indicating that the game enhanced their degree of attention. In particular, in the final stage of finishing the game the DGBL learners' attention scores were very pronounced. As for the positive emotion pattern, it appeared to be more discrepant than that of attention. This implied that the participants' emotions fluctuated along with playing the game, particularly during the more challenging parts of the game as well as at the moment the more difficult level was completed. DGBL is regarded as an useful learning method because it has the advantage to make learning academic subjects more learner-orientated, easier, more funny and more interesting, and this is supported by the scientific evidence provided by this study.

As for learning effectiveness, no significant difference between the two groups were found based on the pre- and post-test measurements of the subjects' understanding of Newton's laws of motion. This is in contrast to the results for cognitive load, which was slightly higher for the DGBL group than the e-learning group. This suggests that a certain amount of the cognitive load in this activity was due to the game itself. Although many studies argue that learners, on average, demonstrate better attention and learning motivation in a DGBL environment, these results are based on self-report questionnaires. Our findings, based on affective computing techniques, do not fully support this position although it was supported during the final stage during which the game was completed. One contribution of this study is thus to provide scientific evidence that puts the status of the entire learning process into perspective.

Implication for practitioners

While many learners used in playing the exciting games in learning, researchers have to be aware that learners may lose the opportunities to pay more attention to learning content such as the Newton's law formulas. As noted in a prior study (Huckin and Coady 1999), if learning requires a precise and effortful coordination of form and meaning, a game design intended to increase germane cognitive load should avoid the learners to bypass such precision and mental effort, it caused no significant in learning performance improvement. Thus, such games should be designed to help learners focus on the learning content and thus to perform deep cognitive processing that improves their learning performance.

Therefore, the research results of the learning achievements of the DGBL group with a higher cognitive load and the conventional e-learning group with a lower cognitive load were not significantly different and can be explained by cognitive load theory (CLT) (Sweller et al. 1998). The CLT theory categorizes cognitive load into three types: intrinsic, extraneous, and germane. Our results were consistent with the results of a prior study measuring cognitive load during second language learning (Liu et al. 2014). Although the DGBL group experienced a higher cognitive load than the conventional e-learning group, the game design may not increase the germane cognitive load and then to improve learning performance. Based on the CLT, only germane cognitive load benefits to improve learning performance.

In addition, computer game benefits to increase users' average attention over time. However, the performance of subjects has been found to have no statistically significant improvement without appropriate visual feedback and design (Vasiljevic and de Miranda 2019). The overly difficult, inappropriate, or boring game design may cause learners experienced negative affective status such as high frustration. Further, additional cognitive efforts can disrupt cognitive processing (Lieberman et al. 2007).

Therefore, an appropriate game design should be created to attract the attention of earners to the learning content and to increase their germane cognitive load (Wu 2019). Gamification designs provide cognition and emotional interaction that creates positive as well as negative emotions in users related to the outcome of gamification (Mullins and Sabherwal 2018). Researchers should create a game design that provides a suitable interface and contents in order to engage students in active learning and exploration of core science concepts.

Implications and suggestions for future work

The research results showed that the difficulty of the game is a crucial factor in game-based learning. The easy level of the game used in this study did not enhance the learners' attention and emotion, since it may not have been challenging, and some of the participants may have felt bored (Liu et al. 2011). Unlike the easy level, the difficult level challenged the learners and held their attention. However, it apparently did not engage the emotions of the learners, as they seemed to experience a relatively low degree of excitement until the very end of the playing time, at which point they became more excited. Prior research has also suggested that an optimal level of challenge can best increase learner motivation and engagement (Ke et al. 2015). In contrast, in this study, students who felt bored when playing the game only learned to solve the problem at a superficial level. Thus, instructors should apply some strategies to engage students in in-depth reasoning related to their solutions (Liu et al. 2011). For instance, teachers may try to increase the level of appropriate challenge, enabling learners to experience feelings of self-efficacy, and encouraging them to analyze potential solutions more critically in order to solve the problem. The DGBL strategy was clearly effective in promoting the students' problem-solving skills, but the full development of skills requires a longer period of time. Indeed, as a higher order thinking skill, problem-solving requires a full semester to develop (Yang 2012), and it is not possible to evaluate the learning effects of DGBL using only one game. Therefore, long-term observation is suggested in any future studies.

In addition, our findings reveal that the learners' attention and emotional states were easily increased by the rich visuals, animations, and sound effects in the game. However, their attention and emotional states declined quicker than was the case with the static e-learning group. In light of this, designers should work to set an appropriate level of difficulty in their games to avoid any frustration and heavy cognitive load from arising, as this may reduce the benefits of DGBL. Due to a lock of available time and resources, the experiment was limited to Newton's laws of motion. Future research can investigate the effects of adopting digital game-based learning and learners' portfolio information in the science or social science domain. In addition, sophisticated data mining schemes such as multimedia data mining of use of eye-tracking information for sequential analysis, web/text mining for unstructured and semi-structured questionnaire data could be a focus of future works.

Acknowledgements Funding for this research work was partly provided by the Ministry of Science and Technology (MOST), Taiwan, under grant numbers: MOST 104–2410-H-142–017-MY2, and MOST 106–2511-S-142–006-MY2.

Compliance with ethical standards

Conflict of interest The authors declare that they have no conflict of interest.

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Publisher's Note Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.

Chih-Hung Wu is a Professor of the Department of Digital Content and Technology in the National Taichung University of Education, Taichung, Taiwan. He received his Ph.D. in the Department of Business Administration, National Taipei University, specializing in information technology and finance management. His research interests include information technology, affective computing, affective learning and qualitative research in digital learning, digital game based learning, and technology-mediated education in various fields and at various levels. He has published over 40 refereed journal papers.

Yi-Lin Tzeng is a master graduate of Nation Taichung University of Education. His research focuses on artificial intelligence and eye tracking technology, examining the effectiveness of Digital Game-based Learning (DGBL) on learning or relationships between DGBL and learners' physiological state based on solid objective evidence, such as physiological signals. His recent publication can be found in Journal of Computers in Education and International Journal of Mobile Learning and Organization.

Yueh-Min Huang is a Chair Professor in Department of Engineering Science, National Cheng-Kung University, Taiwan. His research interests include e-Learning, multimedia communications, and artificial intelligence. He received his MS and Ph.D. degrees in Electrical Engineering from the University of Arizona in 1988 and 1991 respectively. He has co-authored 3 books and has published more than 280 refereed journal research papers. Dr. Huang has received many research awards, such as Taiwan's National Outstanding Research Award in 2011/2014, as well as 2017 Taiwan Outstanding IT Elite Award. He has completed over 60 Ph.D. and 300 MS thesis students. Dr. Huang is in the editorial board of several international journals in the area of educational technology, computer communications, and web intelligence. Dr. Huang is also the funding chair of International Symposium of Emerging Technologies for Education (SETE) and International Conference of Innovative Technologies and Learning (ICITL). Dr. Huang is a senior member of the IEEE and became Fellow of British Computer Society in 2011.