Library & Information Science Research 33 (2011) 244–255

Contents lists available at ScienceDirect

Library & Information Science Research

Using emotion recognition technology to assess the effects of different multimedia materials on learning emotion and performance

Chih-Ming Chen [a,*], Hui-Ping Wang [b]

[a] Graduate Institute of Library, Information and Archival Studies, National Chengchi University, No. 64, Sec. 2, ZhiNan Rd., Wenshan District, Taipei City 116, Taiwan, ROC
[b] Department of Applied Electronics Technology, National Taiwan Normal University, No. 162, Sec. 1, HePing East Rd., Taan District, Taipei City 106, Taiwan, ROC

ARTICLE INFO

Available online 30 April 2011

ABSTRACT

With the gradual adoption of multimedia technologies in curriculum designs, the need has increased for in-depth studies that explore how different presentation techniques for multimedia materials affect learner emotions and learner performance. This study employed the *emWave* system, a stress detector for emotional states that was developed by the Institute of HeartMath for measuring changes in learner emotional states when presented with different multimedia materials with the same learning content. By analyzing the collected emotional data and assessment of learning performance, this study explores how different multimedia learning materials affect learning emotions, and ultimately, learning performance. Preliminary results show that the video-based multimedia material generates the best learning performance and most positive emotion among three types of multimedia materials assessed in the study. Moreover, a partial correlation exists between negative learning emotion and learning performance. This study confirms that simultaneously considering pretest score and negative emotion can predict learning performance of learners who use video-based multimedia material for learning. It also finds significant gender difference in learner emotional states while using different multimedia materials for learning: female learners in this study are more easily affected by different multimedia material than male learners.

1. Introduction

Many researchers have argued that affective state (i.e., considering a learner's emotional state) should be an important factor in designing instructional materials, but relatively few empirical studies have focused on learner emotions and how they affect learning performance. Such research could provide a valuable reference when designing learning materials. Innovative multimedia learning materials have emerged to some extent in response to the need for diversity in educational resources. Many studies have contended that a relationship exists among different learning materials, learning performance, cognitive load, and the learning emotional state (Chanlin, 1998; Large, Beheshti, Breuleux, & Renaud, 1994; Um, Song, & Plass, 2007). In response to how different multimedia materials affect learning performance, Chanlin (1998) showed that combining multimedia learning materials with text, animation, and voiceover enhance learner performance. Mousavi, Low, and Sweller (1995) pointed out that multimedia materials containing visual text and auditory narration, known as the split-attention effect, which is a learning effect inherent in some poorly designed instructional materials, results in inefficient learning. Furthermore, studies focused on multimedia-based learning have demonstrated that esthetic designs can induce emotions and that these emotions affect learner performance and cognitive processes (Harp & Mayer, 1997; Mayer & Moreno, 1998; Wolfson & Case, 2000).

Dual-coding theory (Paivio, 1990), a well-known cognitive theory applied to multimedia learning, models different information retrieval and information processes in human cognitive behavior. The dual-coding theory emphasizes that both verbal and visual systems, which are part of the human cognitive system, play important roles in human learning activities. The verbal system processes all verbal information via encoding and storage in the verbal memory area of the brain. The visual system processes all nonverbal information, such as visual, smell, touch, or emotional messages, via encoding and storage in the visual memory area of the brain. Notably, humans have difficulty simultaneously processing multiple auditory or visual cues, and processing effectiveness depends on expertise with a task or prior knowledge of a subject area. Using dual-coding theory, Large et al. (1994) found that learning retention can be enhanced by pictures in two ways to promote activation of dual coding. They gave two supporting reasons, one, that the two separate codes have additive effects such that the likelihood of information being remembered is increased. The other reason is that pictures are more likely than words to be dual-coded; thus, when one memory is lost, the other remains available.

Tractinsky, Katz, and Ikar (2000) and Wolfson and Case (2000) noted that positive emotions were produced by different design characteristics of multimedia elements such as layout, color, and

* Corresponding author.
E-mail address: chencm@nccu.edu.tw (C.-M. Chen).

0740-8188/$ – see front matter © 2011 Elsevier Inc. All rights reserved.
doi:10.1016/j.lisr.2010.09.010

sound. Typically, emotions can be broadly defined as *negative* and *positive* (Um et al., 2007; Zhang & Lee, 2009). Positive emotions have been studied as factors facilitating changes in affective components such as attitude, motivation, creativity, and problem-solving skills (Um et al., 2007). This is consistent with the *facilitation hypothesis of emotions*, which states that positive emotions enhance long-term memory and retrieval, and facilitate working memory processes (Erez & Isen, 2002). Um et al. (2007) studied whether positive emotions experienced during multimedia learning facilitate cognitive processes that lead to enhanced learning performance and satisfaction and found that positive emotions can be generated by instructional designs that may affect learner experience and performance.

Several studies demonstrated the opposite effect for positive emotions, however, and these studies are consistent with the *suppression hypothesis*, which states that mood can require additional task processing or task-irrelevant processing, and negatively impact reasoning and performance (Oaksford, Morris, Grainger, & Williams, 1996; Seibert & Ellis, 1991). This effect of positive emotions can be explained by *cognitive load theory* (Pass, Renkl, & Sweller, 2003), in which emotions experienced during cognitive processing of learning materials imposes an unnecessary load on working memory (i.e., this load can be interpreted as extraneous cognitive load). Conceptually, cognitive load refers to the overall amount of imposed mental activities in the cognitive system generated during learning. Cognitive load can be defined as *intrinsic cognitive load* and *extraneous cognitive load* (Sweller, Van Merrienboer, & Paas, 1998). Intrinsic cognitive load comes solely from the intrinsic characteristics of curricula, such as content that is difficult to learn. Extraneous cognitive load is from poor learning materials, curricula design, or learning activities, but it can be reduced by modifying the design of learning material. Although the facilitation hypothesis is dominant in studies focused on positive emotions, the effects of a learner's positive or negative emotions on the learning process are not well understood (Um et al., 2007). Therefore, exploring how different presentation techniques for multimedia materials affect learner emotions and learner performance is an important research issue, because such research could provide a valuable reference when designing multimedia learning materials.

2. Problem statement

Although many studies have contended that a relationship exists among different learning materials, learning performance, and the learning emotional state (Chanlin, 1998; Chen & Lee, 2011; Large et al., 1994; Um et al., 2007), relatively little empirical research has examined how different multimedia learning materials positively or negatively affect learner emotions, or determined the correlations between learning emotion and learner performance associated with different learning materials. Learning materials with text only are not the concerned issue of the study because curricula presentation is being transformed from text-based materials to multimedia materials in order to increase learner attention and interest in modern education. Identification of the effects of different multimedia materials on learning is definitely needed, however, because many past studies (Narayanan & Hegarty, 2000; Schnotz, Böckheler, & Grzondziel, 1999) have indicated that the instructional effects of different multimedia materials may not always benefit learning. Moreover, many education scholars have pointed out that emotions are directly related to and affect learning performance (Goleman, 1995; Piaget, 1989). But assessing the effects of different multimedia materials on learning emotions has never been investigated.

Based on the essential issues mentioned, the main concern of the study was to examine the correlations between learner emotions and performance when learners are presented with three different multimedia learning materials that are the most frequently used in modern education: static text and image-based multimedia materials, video-based multimedia materials containing moving images with audio, and animated interaction-based multimedia materials, which contain text and animated images and have interactive features. This study also examined the gender differences in learning emotion and performance when learners were presented with three different multimedia learning materials. That is, this study examined the relationships among different multimedia materials, learner emotions, and learning performance, which provides a reference when designing multimedia learning materials. Finally, this study provides useful knowledge in terms of designing an emotion-based adaptive multimedia learning system based on identification of the correlations between learner emotions and performance for supporting personalized learning.

3. Literature review

3.1. Design issues associated with effective multimedia learning materials

Oliver (1996) indicated that instructional materials in any medium have three discrete elements—content, organization, and an interface. The *content attribute* describes information contained in instructional materials. The *organization attribute* is concerned with how content in learning materials is delivered based on the manner in which it has been stored and represented. The *interface attribute* for learning materials describes the environment in which information is presented. As curricula presentation has become increasingly diversified in modern education, educational materials are not limited to static text; that is, presentation is being transformed from text-based materials to multimedia materials in order to increase learner attention and interest. Multimedia curricula integrate learning materials, which were produced using two or more types of media (Mayer, 1997). Multimedia materials support many different media forms combined in instructional settings, and use computers to present text, audio, video, animation, interactive features, and still images in various combinations made possible by technological advancements. Furthermore, interactivity is an essential feature of technology-supported instructional media. Currently, interactivity tends to be considered the main feature of multimedia materials. Interactivity is a form of communication facilitating dialog between a learner and instructor (Jonassen, 1988). When interaction is planned as part of the learning process, the value and place of instructional media with interactive features should be considered on a higher domain than instructional media of non-interactive features.

Lowe (2003) identified a growing trend across a range of media to use highly illustrated materials for instruction, rather than rely on largely text-based presentations of information. An increasing amount of educational materials include video or animated graphics when possible. Video has the potential to capture many aspects of classroom practice and provide rich and thick representations of practice that leave distinctive mental images in the mind of the viewer through the capability to record visual and aural richness and detail. Video also provides a means by which teachers can have access to teaching that would be difficult to observe in real life; it can enable the manipulation of time by accessing practice through start, pause, and rewind. A successful multimedia model using video as the primary design component is one that creates an environment that connects the content with the viewer on an emotional level, includes related information woven into the experience in a visual way, and is careful not to overload the viewer with too much information (Reiss, 2007). *Animation* is defined here as a series of rapidly changing digital images that represent movement (Rieber & Hannafin, 1988). A number of researchers have described their efforts in using animation to enhance material design and/or education effectiveness (Chang & Chang, 2004; Lowe, 2003). Chang and Chang (2004) demonstrated that student responses were very positive to the use of animation for learning because it provided interesting visual effects, improved communication, and generated high interest levels. Lowe (2003) indicated that animation could provide learners with explicit dynamic information that was either implicit or unavailable in static graphic-based materials. For learners to be successful in constructing high-quality mental models from animated instruction, they must have extracted relevant information thematically from animation and incorporated it into their knowledge structures (Lowe, 2003). Narayanan and Hegarty (2000) provided research evidence, however, that challenged the widespread assumption that animation is intrinsically superior to static graphics. Furthermore, Schnotz et al. (1999) also noted that the instructional effects of animation may not always benefit learning because exploratory learning with interactive, animated pictures is associated with an extraneous cognitive load, and this load can be further increased by the demands of cooperative learning. Therefore, identification of the effects of different multimedia materials on learning is definitely needed.

3.2. Identifying effective learning via emotional states

Many education scholars have pointed out that emotions are directly related to and affect learning performance (e.g., Goleman, 1995; Piaget, 1989). Emotions can affect attention, meaning creation, and the formation of memory channels. Hence, emotional status and learning are strongly correlated (LeDoux, 1994). Kort, Reilly, and Picard (2001) identified the emotional pairs comprised of positive and the corresponding negative emotions, including anxiety–confidence, boredom–fascination, frustration–euphoria, dispirited–encouraged, and terror–enchantment, which were likely relevant to learning. To interact with students effectively in an educational context, teachers frequently try to acquire insight into the emotions and thoughts of students. In learning scenarios, teachers who correctly ascertained the emotional status of students could improve their interactions with students (Kort et al., 2001).

Additionally, many psychologists and neurologists have demonstrated that emotions and motives have important roles in cognitive learning (Izard, 1984). Goleman (1995) noted that students who were depressed, angry, or anxious had trouble learning. According to Piaget (1989), human emotions could arise from or interfere with learning. Izard (1984) analyzed the performance of cognitive activities that were adversely affected by negative emotions, but raised by positive emotions. Coles (1998) argued that teachers could assist and guide students in developing emotions that promoted cognitive development. Identifying these cognitive and emotional states of students during instruction facilitated the development of positive learning experiences for learners (Reilly & Kort, 2004).

Empirical studies on gender and emotion have been conducted by psychologists, who focus on gender differences in their beliefs about emotions, as well as on subjective feelings and expressive behavior among children, adolescents, and young adults (Hochschild, 1975, 1979; Kemper, 1978, 1991; Parsons, 1955, 1964). Studies have found that females are more emotional and emotionally expressive than males, and that males and females differ in their experience and expression of specific emotions (Blier & Blier-Wilson, 1989; Kring & Gordon, 1998). While some studies found that females reported more feelings than males, others found no significant gender differences in experienced emotion (Brody, 1985; Brody & Hall, 1993). Therefore, this study also examined whether learners with different genders reacted differently on emotional states and learning performance to different types of multimedia materials.

Because of the importance of emotional states to learning, many studies (Chen & Lee, 2011; Emmanuel, Pierre, & Claude, 2007; Kiyhoshi & Tomoya, 2006; Mohamed & Mahmoud, 2007; Shaikh, Hua, Ishizuka, & Mostafa, 2005) have attempted to identify learner emotions using artificial intelligence techniques to build appropriate human emotion-recognition models that support effective learning. Generally, the following four methods have been used to recognize learner emotions: (1) voice (prosody) analysis (Kopecek, 2000); (2) observable behavior such as user actions in a system interface (Vicente & Pain, 2002); (3) facial expression analysis (Wehrle & Kaiser, 2000); and, (4) analysis of physiological signs (Picard, Healey, & Vyzas, 2001). Chen and Lee (2011) integrated sensors, signal processing, wireless communication, *system on chip* (SOC) and machine-learning technologies to construct an embedded human-emotion-recognition system; they applied this system to support teachers in reducing the speaking anxiety of English learners while speaking in a Web-based one-to-one synchronous learning environment.

Kiyhoshi and Tomoya (2006) developed a robotic system that identified the emotions of an online student in real time, based on his or her facial expression and biometric signals. Their study confirmed the effectiveness of their proposed multimodal emotion identification system. Emmanuel et al. (2007) examined the use of physiological data for quasi real-time adaptation in Intelligent Tutoring Systems (ITSs). Their study investigated learner reactions using physiological signals generated in a game-like virtual learning environment. These signals were measured by electroencephalographs (EEGs), the galvanic skin response (GSR), and respiration (RESP). To support peer-to-peer e-learning, Mohamed and Mahmoud (2007) designed the Emotional Multi-Agents System, which can recognize learner emotions based on facial expressions. Shaikh et al. (2005) developed an emotion model with eight emotional states and four transitional emotion rules to identify the emotional states of individual learners, and consequently enhanced learning quality and improved accessibility to education and training programs in the e-learning context.

Based on examination of the broad literature survey for this study, assessing the effects of different multimedia materials on learning emotions has never been investigated. Moreover, whether learning emotions are highly related to learning performance when using different multimedia materials needs to be confirmed. Recognizing learner emotions in a real-time learning environment is extremely challenging, however. In recent years, emotion-recognition technologies based on human physiological signals have been developed for practical application (Chen & Lee, 2011; Emmanuel et al., 2007; Kiyhoshi & Tomoya, 2006; Mohamed & Mahmoud, 2007; Shaikh et al., 2005), such that investigating the correlation among different multimedia materials, learner emotional states, and learning performance is now practicable.

4. Research procedures

4.1. Research variables and hypotheses

To examine the relationships among different multimedia materials, learner emotions, and learning performance, this study utilized the following three different multimedia materials: static text and image-based multimedia materials containing static text, images, and graphs; video-based multimedia materials containing moving images, audio, and subtitles; and animated interaction-based multimedia materials containing animated pictures, text, and audio. To fairly compare how different multimedia materials affect learning emotions and learning performance, the three learning materials in this study are from the same education units, and have the same learning content and learning objectives; that is, the learning materials are presented in different media formats. The course contents of the three evaluated multimedia materials aim to teach learners how to correctly identify energy types. Learner emotions are recognized by the *emWave* system, which uses human pulse physiological signals to identify three emotional states: positive, peaceful, and negative. Additionally, the assessment of learning performance is based on pretest and posttest results that contain the same questions with different sequences of selecting items in a multiple-choice design. This can reduce the probability of an examinee to give a correct answer based on guessing. Fig. 1 shows the relationship framework of the discussed research variables in this study; the gender differences in learning emotion and performance are also considered. Based on the relationship framework of these research variables, and on the literature review, this study proposes the following research hypotheses, which were tested at the significance level of a statistical hypothesis test $p = 0.05$:

Hypothesis 1. There is a significant relationship between *multimedia material type* and *learning emotion*.

Hypothesis 1.1. There is a significant difference in positive learning emotion while learners are presented with different types of multimedia material for learning.

Hypothesis 1.2. There is a significant difference in negative learning emotion while learners are presented with different types of multimedia material for learning.

Hypothesis 1.3. There is a significant difference in positive learning emotion while different genders are presented with different types of multimedia material for learning.

Hypothesis 1.4. There is a significant difference in negative learning emotion while different genders are presented with different types of multimedia material for learning.

Hypothesis 2. There is a significant relationship between *multimedia material type* and *learning performance*.

Hypothesis 2.1. There is a significant promotion of learning performance while learners are presented with static text and image-based multimedia material for learning.

Hypothesis 2.2. There is a significant promotion of learning performance while learners are presented with video-based multimedia material for learning.

Hypothesis 2.3. There is a significant promotion of learning performance while learners are presented with animated interaction-based multimedia material for learning.

Hypothesis 2.4. There is a significant difference in learning performance between males and females while using static text and image-based multimedia material for learning.

Hypothesis 2.5. There is a significant difference in learning performance between males and females while using video-based multimedia material for learning.

Hypothesis 2.6. There is a significant difference in learning performance between males and females while using animated interaction-based multimedia material for learning.

Hypothesis 3. There is a significant relationship between *learning emotion* and *learning performance*.

Hypothesis 3.1. There is a significant correlation between positive emotion and learning performance.

Hypothesis 3.2. There is a significant correlation between negative emotion and learning performance.

Hypothesis 3.3. There are significant correlations between positive emotion and learning performance of different genders.

Hypothesis 3.4. There are significant correlations between negative emotion and learning performance of different genders.

4.2. Experimental design

To reduce the cognitive loads of difficult learning materials (i.e., *intrinsic cognitive load*), and the efforts required from learners (i.e., *extraneous cognitive load*), this study selected learning materials that had low cognitive loads, including both intrinsic and extraneous cognitive loads. This study assessed the correlations among learning performance and learning emotion states associated with three different multimedia materials. Learning materials for energy education used in this study were designed by members of the National Energy Education Project (http://energy.ie.ntnu.edu.tw/), which was supported by the Bureau of Energy in the Ministry of Economic Affairs of Taiwan. Thus, the effect of learner extraneous cognitive load was reduced as much as possible (Sweller et al., 1998). Additionally, the content of learning materials was set at a basic level, thus minimizing intrinsic cognitive load. The learning objective was simple: Students learned to identify energy types. Figs. 2–4 show the three different multimedia materials for energy education.

The three multimedia materials have the same energy education units, learning content, and learning objectives, but the multimedia techniques differ. This research used the emWave system to identify student emotional status in response to different multimedia materials; it explored the correlations among learning emotions, learning performance, and different multimedia materials, with the goal of contributing to the educational field.

4.3. Research participants and the experimental procedure

Before performing the formal study, a pilot study was conducted in Zihciang Primary School in New Taipei City, Taiwan, in order to identify possible problems with the experimental design and assess whether the intrinsic and extraneous cognitive loads of the learning materials were appropriate for the age group being assessed. The

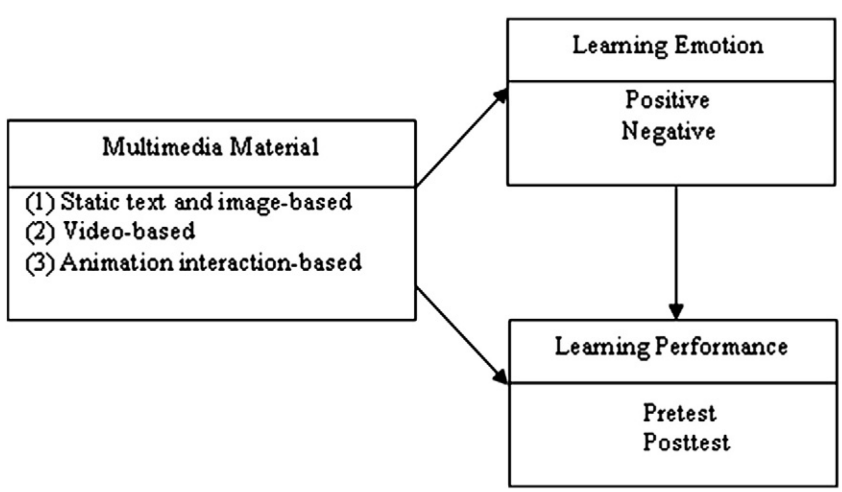

Fig. 1. Relationship framework of the research variables discussed in this study.

Fig. 2. Animation interaction-based multimedia material for energy education.

results of the pilot study confirmed that participants could leisurely view the three different multimedia materials and learn the content within 10 min. They also confirmed that the cognitive load (i.e., intrinsic and extraneous) of the learning materials was appropriate to students in grades three, four, and five, because the learning performance promotion of all participants reached a significant level.

Three factors likely to affect the research results were adjusted before conducting the formal study. First of all, in order to avoid learning interference between participants, each participant in the formal study was given an independent learning space. Second, since research shows that there are significant differences in cognitive skills and affective experiences between different ages (Steinberg, 2005), and the experimental design of the pilot study mixed different age groups and randomly assigned students to three experimental groups, the formal study focused on investigating primary school students of the same age. Finally, in order to promote the experimental reliability, the number of samples was increased and narrowed from 66 third, fourth, and fifth grade students to 170 fifth graders.

The formal study was conducted in Jhuang Jing Primary School in Taoyuan City, Taiwan. In order to address the research ethics of a designed experiment that recorded the emotional states of school children, the children and their parents were given full explanation of the experiment, after which their informed written consent was obtained. To assess the effects of different multimedia materials on learning emotion and performance based on emotion recognition technology, students were randomly divided into three groups for the different multimedia materials—static text and image-based multimedia materials, video-based multimedia materials, and animated interaction-based multimedia materials. Before performing the experiment, the entire learning processes containing pretest, learning, and posttest were explained. In order to insure that both pretest and posttest sheets had the same difficulty, both test sheets had the same questions, and all participating learners knew this in advance. Initially, each participant was given a three-minute pretest. The aim is to ascertain the a priori knowledge of learners about energy types. After the pretest, each learner was given 10 min to view the multimedia materials and learn the content. During this process, learners wore an emWave earplug that collected emotion data. After finishing the assigned unit, learners were required to complete a three-minute posttest to assess their performance. That is, each experimental stage for each learner was approximately 16 min.

Fig. 3. Video-based multimedia material for energy education.

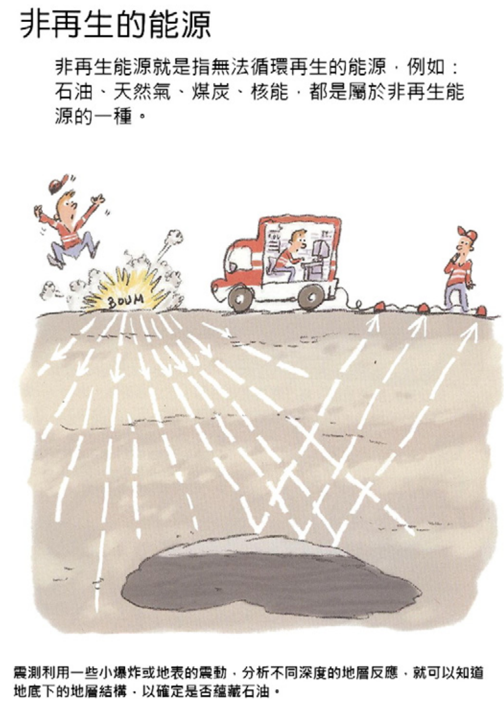

Fig. 4. Static text and image-based multimedia material for energy education.

4.4. Emotion recognition by the emWave system during the learning process

Research has shown that heart rate variability (HRV) patterns, also known as heart rhythms, are directly responsive to changes in emotional states (McCraty, Atkinson, Tiller, Rein, & Watkins, 1995; Tiller, McCraty, & Atkinson, 1996). The emWave technology is a computer-based heart rhythm coherence feedback system designed to facilitate acquisition and internalization of the emotional self-regulation skills taught in HeartMath programs. McCraty (2005) applied this technology in educational settings to facilitate social, emotional, and academic learning, and indicated that classroom-based programs incorporating this intervention can facilitate improvements in emotional health, social behaviors, and academic performance in diverse student populations. Climov (2008) designed an experiment to evaluate whether applying relaxation associated with HRV biofeedback from emWave could reduce stress, negative affectivity, and social inhibition for graduate students. The results showed a positive and significant impact on all three psychometric variables. The emWave system uses an ear sensor to determine HRV, based on human pulse signals, in order to identify human emotion (Fig. 5). The emWave system has an easy-to-use software program with a heart rhythm monitor and an emotion-recognition algorithm for identifying emotional states (Fig. 6). With this system, one can look at user-friendly graphics displayed on a computer monitor to assess how human emotions affect HRV. When stressed, heart rhythms have an

Fig. 5. Ear sensor used in emWave PC stress relief system for human pulse signal detection.

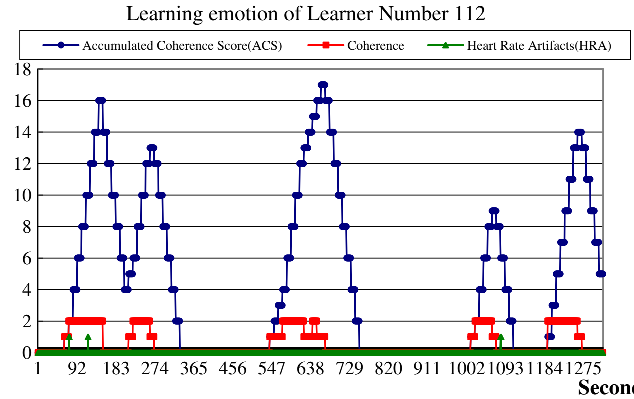

Fig. 7. Example of recognizing emotional states of Learner Number 112 during a learning process.

irregular, jagged pattern. Conversely, the heart rhythm pattern is a smoother, wave-like pattern when human emotion shifts to a positive emotional state.

The emWave system uses heart rate power spectral density analysis to identify human emotional states (McCraty et al., 1995). Fig. 6 shows the heart rate as a curve of cumulative heartbeats per minute; below is Coherence Ratio, derived from the power spectral density analysis of heart rate. Per this analysis, the Coherence Ratio corresponding to different coherent states can be identified as three color-rendered indexes. The red part is the low-frequency zone of the power spectral density, which represents a change in sympathetic activity; according to analytical results, it also represents a negative emotional state. The blue part is the medium-frequency zone of the power spectral density, representing changes in parasympathetic nervous activity, or a peaceful emotional state. The green part is the high-frequency zone of the power spectral density, representing parasympathetic nervous activity changes, or a positive emotional state.

When an emotion arises, the emWave system calculates the Coherence Ratio of these three color indexes, presents them as a percentage of a learner's emotional state, and maps them as the Accumulated Coherence Score (ACS) (bottom left in Fig. 6). The curve of the ACS with a positive slope indicates that the learner relaxed and had a positive emotional state. When the curve slope is negative, the learner is feeling pressured and in a negative emotional state. The ideal state is when the slope remains positive.

Fig. 7 shows an example of the emotional states of Learner Number 112, as assessed by the EmWave system during learning. Based on the distribution of frequency zones, the coherence states are represented as zero, one, or two when a learner's emotional state is negative (i.e., the low-frequency zone of the power spectral density), peaceful (i.e., the medium-frequency zone of the power spectral density), or positive (i.e., the high-frequency zone of the power spectral density) during learning, respectively. The value of Heart Rate Artifacts (HRAs) is zero when the human emotion detected is in normal situations, whereas the value of HRAs is one when the human emotion is detected in abnormal situations. The ACS is the sum of each coherence value over time.

The method for computing the percentage of positive and negative emotions based on the coherence value, the ACS and HRA detected by

Fig. 6. Emotion analysis interface of the emWave PC stress relief system based on human physiological signals.

the emWave system, is utilized to assess the emotional state of individual learners during learning. The sampling time for the emWave system for detecting HRV is set at 0.5 s. Emotional states are recognized after accumulating 10 states of HRV; that is, the emWave system identifies learner emotional states every 5 s. In this study, identifying the percentages spent in positive or negative emotions was applied to assess the effects of the various multimedia materials on learning emotions. In computing the percentages of positive and negative emotions, the ACS has the key role, whereas the method for computing ACS based on different coherence states and HRAs is as follows:

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

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 times of emotional states that are recognized.

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

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

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

Taking the recognizing emotional states of Learner Number 112, as shown in Fig. 7, as an example, the accumulated ACS of the positive emotions under Coherence(t) = 2 and HRA(t) = 0 can be calculated as follows:

$$\begin{aligned}\text{ACS of Positive Emotion}(\%)\\&=\sum_{t-1}^{m} CV(t)\\&=(2+2+2+2+2+2+2)+\ldots+(2+2+2+2+2+2)\\&=56\end{aligned} \tag{7}$$

The accumulated ACS of the peaceful emotions under Coherence(t) = 1 and HRA(t) = 0 can be calculated as follows:

$$\begin{aligned}\text{ACS of Peaceful Emotion}(\%)\\&=\sum_{t-1}^{m} CV(t)\\&=(1+1+1+1+1)+\ldots+(1+1+1+1)\\&=13\end{aligned} \tag{8}$$

Similarly, the accumulated ACS of negative emotion under Coherence(t) = −1 and HRA(t) = 0 can be calculated as follows:

$$\begin{aligned}\text{ACS of Negative Emotion}(\%)\\&=\left|\sum_{t-1}^{m} CV(t)\right|\\&=|(-2-2-2-2-2-2-2)+\ldots+(-1-2-2-2-2-2)|\\&=58\end{aligned} \tag{9}$$

Thus, the occupied percentage of positive and negative emotions in this example can be respectively obtained as follows:

$$\text{Positive emotion}=\frac{56}{56+13+58}\times 100=44.1 \tag{10}$$

$$\text{Negative emotion}=\frac{58}{56+13+58}\times 100=45.7 \tag{11}$$

5. Experimental analysis

This section assesses the three research hypotheses (Section 4.1) based on a statistical test. Section 5.1 assesses whether learning emotion is significantly changed while learners view different multimedia materials. Section 5.2 confirms whether learning performance is significantly changed while learners view different multimedia materials. Section 5.3 evaluates whether learner performance is significantly changed while learners have different emotions.

5.1. Statistical tests of hypotheses 1

Table 1 shows the descriptive statistics of all participating learners' emotions as they corresponded to the three different multimedia materials. Based on the descriptive statistics listed in Table 1, this study used one-way analysis of variance (ANOVA) to assess the difference of emotional states for all learners, who were tested on three different multimedia materials. The results show that the difference of emotional states for all learners reached significant levels whether the emotional state was positive (F = 3.517, Sig. = 0.032 < 0.05) or negative (F = 3.720, Sig. = 0.026 < 0.05). This study also analyzed the impact between positive emotions and negative emotions associated with each multimedia material by the Scheffe test of one-way ANOVA with post hoc multiple comparison for Hypothesis 1. Table 2 shows the results. The results confirm that the video-based multimedia material had a greater effect on keeping emotions positive when learners were in a positive emotional state than the static text and image-based multimedia and animated interaction-based multimedia materials; however, which of these materials was better at keeping emotional states positive cannot be identified. When learners were in a negative emotional state, the static text and image-based and animated interaction-based multimedia materials had greater significant effects on generating negative emotion than the video-based multimedia material. These analytical results suggest the video-based multimedia material generated the most positive emotion for learners, while the static text and image-based and animated interaction-based multimedia materials generated more negative emotions in learners.

Table 1
Descriptive statistics of all participating learners' emotions, corresponding to three different multimedia materials.

Type of learning emotion	Type of multimedia material	Number of learners (male, female)	Emotion mean	Emotion std. dev.
Positive emotion	Static text and image-based multimedia material	57(31, 26)	14.45	15.24
	Video-based multimedia material	55(30, 25)	20.69	15.49
	Animation interaction-based multimedia material	58(26, 32)	14.11	13.53
Negative emotion	Static text and image-based multimedia material	57(31, 26)	74.06	17.47
	Video-based multimedia material	55(30, 25)	66.21	16.96
	Animation interaction-based multimedia material	58(26, 32)	73.08	15.21

Table 2
Learning emotion comparison, using the Scheffe test of one-way ANOVA with post hoc multiple comparison, for all participating learners who were given three different multimedia materials.

Type of learning emotion	Type of multimedia material (I)	Type of multimedia material (J)	Mean difference (I−J)	Sig.	Result
Positive emotion	Static text and image-based	Video-based	−6.24	0.027*	Video-based > Static text and image-based
		Animation interaction-based	0.34	0.902	
	Video-based	Static text and image-based	6.24	0.027*	Video-based > Static text and image-based
		Animation interaction-based	6.58	0.019*	Video-based > Animation interaction-based
	Animation interaction-based	Static text and image-based	−0.34	0.902	
		Video-based	−6.58	0.019*	Video-based > Animation interaction-based
Negative emotion	Static text and image-based	Video-based	7.85	0.013*	Static text and image-based > Video-based
		Animation interaction-based	0.98	0.752	
	Video-based	Static text and image-based	−7.85	0.013*	Static text and image-based > Video-based
		Animation interaction-based	−6.87	0.029*	Animation interaction-based > Video-based
	Animation interaction-based	Static text and image-based	−0.98	0.752	
		Video-based	6.87	0.029*	Animation interaction-based > Video-based

* Indicates Sig. (2-tailed) < 0.05.

The study also analyzed the difference in emotional states of learners categorized by gender, who learned various types of multimedia materials for energy education, based on the one-way ANOVA. Table 3 shows the descriptive statistics of male and female learners' emotions as they corresponded to different multimedia materials. The results indicate that the difference in emotional states did not reach significant levels in male learners with either positive emotion ($F = 0.949$, $p = 0.391 > 0.05$) or negative emotion ($F = 1.083$, $p = 0.343 > 0.05$). By contrast, female learners with positive emotion ($F = 3.273$, $p = 0.043 < 0.05$) and negative emotion ($F = 3.387$, $p = 0.039 < 0.05$) did reach significant levels. The results confirm that the emotional states of female learners were more easily affected by different multimedia materials than the male learners during their learning processes. Next, the Scheffe test of one-way ANOVA with post hoc multiple comparison was used to analyze the difference of emotional states for the female learners, who were given different multimedia materials. Table 4 shows the results, which are completely the same in the case of all participating learners. That is, the video-based multimedia material had a greater effect on maintaining the positive emotion of female learners than the static text and image-based multimedia material and animated interaction-based multimedia material. Moreover, the static text and image-based and animated interaction-based multimedia materials had greater significant effects on generating the negative emotion of female learners than the video-based multimedia material.

5.2. Statistical test of hypothesis 2

To identify the correlation between learning performance and three different types of multimedia materials, as stated in Hypothesis 2, this study analyzed data using the paired sample t-test. Table 5 shows the summary results of all participating learners. The results confirm that three types of multimedia materials all had significant effects (Sig. = 0.035 < 0.05, Sig. = 0.000 < 0.05, and Sig. = 0.001 < 0.05) on learning performance. This implies that the three types of multimedia materials met the preset educational objective for overall energy education. Obviously, no split attention effect or cognitive load occurred in the three types of multimedia materials. But when comparing the significant levels of the learning performance on the three types of multimedia materials, the video-based multimedia material had the best learning performance, followed by the animated interaction-based multimedia material, and then the static text and image-based multimedia material. In other words, the dynamic multimedia

Table 3
Descriptive statistics of male and female learners' emotions, as corresponded to three different multimedia materials.

Gender	Type of learning emotion	Type of multimedia material	Number of learners	Emotion mean	Emotion std. dev.
Male	Positive emotion	Static text and image-based multimedia material	31	15.01	16.51
		Video-based multimedia material	30	20.52	16.63
		Animation interaction-based multimedia material	26	15.86	16.90
	Negative emotion	Static text and image-based multimedia material	31	73.82	19.25
		Video-based multimedia material	30	66.98	18.23
		Animation interaction-based multimedia material	26	71.17	17.09
Female	Positive emotion	Static text and image-based multimedia material	26	13.79	13.59
		Video-based multimedia material	25	20.90	14.34
		Animation interaction-based multimedia material	32	12.70	10.09
	Negative emotion	Static text and image-based multimedia material	26	73.34	15.44
		Video-based multimedia material	25	65.29	15.61
		Animation interaction-based multimedia material	32	74.63	13.58

Table 4
Learning emotion comparison, by the Scheffe test of one-way ANOVA with post hoc multiple comparison, for the female learners who were given three different multimedia materials.

Type of learning emotion	Type of multimedia material (I)	Type of multimedia material (J)	Mean difference (I − J)	Sig.	Result
Positive	Static text and image-based	Video-based	−7.11	0.049*	Video-based > Static text and image-based
		Animation interaction-based	1.09	0.745	
	Video-based	Static text and image-based	7.11	0.049*	Video-based > Static text and image-based
		Animation interaction-based	8.20	0.018*	Video-based > Animation interaction-based
	Animation interaction-based	Static text and image-based	−1.09	0.745	
		Video-based	−8.20	0.018*	Video-based > Animation interaction-based
Negative	Static text and image-based	Video-based	9.05	0.032*	Static text and image-based > Video-based
		Animation interaction-based	−0.29	0.941	
	Video-based	Static text and image-based	−9.05	0.032*	Static text and image-based > Video-based
		Animation interaction-based	−9.34	0.020*	Animation interaction-based > Video-based
	Animation interaction-based	Static text and image-based	0.29	0.941	
		Video-based	9.34	0.020*	Animation interaction-based > Video-based

* Indicates Sig. (2-tailed) < 0.05.

materials, such as video-based and animated interaction-based multimedia materials, were superior to static multimedia material, such as static text and image-based multimedia material. This study also analyzed the difference of learning performance by gender, based on the pair sample *t*-test. The results show no matter which gender the learners were, the learning performance on the static text and image-based multimedia material failed to reach statistical significance. In contrast with the static text and image-based multimedia material, no matter which gender the learners were, the learning performance on the video-based and animated interaction-based multimedia materials all reached significant levels.

5.3. Statistical test of hypothesis 3

Table 6 summarizes the correlations by Pearson correlation coefficient analysis for Hypothesis 3 between learning emotions and learning performance for all learners who were given three different types of multimedia materials. The results showed that only the learners who were given the video-based multimedia material for energy education learning had significant correlation (positive emotion, Sig. = 0.039 < 0.05; negative emotion, Sig. = 0.012 < 0.05) between learning emotions and learning performance. The correlations of the static text and image-based and animated interaction-based multimedia materials, however, could not be identified. After finding these results, researchers performed the stepwise multiple regression analysis using the pretest score, positive emotion, and negative emotion as independent variables, and the posttest score as a dependent variable. Table 7 shows the results. The results confirm that only using the pretest score ($R = 0.647$, Sig. = 0.000 < 0.001) or simultaneously considering the pretest score and negative emotion ($R = 0.679$, Sig. = 0.000 < 0.001) could predict the learning performance of the learners who used the video-based multimedia material for energy education learning. Based on the variables of pretest score and negative emotion for forecasting the learning performance, the explained variance on the video-based multimedia material was 46.1%. The primary prediction variable was the pretest score ($\beta = 0.603$, Sig. = 0.000 < 0.001), and the secondary prediction variable was the negative emotion ($\beta = -0.210$, Sig. = 0.049 < 0.05).

Researchers also analyzed the difference of correlations, based on the Pearson correlation coefficient analysis, between learning emotions and learning performance for the male and female learners who learned various types of multimedia materials for energy education. The study found that only the correlation of the female learners, who used video-based multimedia material for energy education learning, reached significant level. The other correlations could not be identified. Table 8 reveals the correlation between learning performance and learning emotion for the female learners who were given the video-based multimedia material for learning. Based on these, the researchers then performed the stepwise multiple regression analysis using the pretest score, positive emotion, and negative emotion as independent variables, and the posttest score as a dependent variable. Table 9 shows the results, which confirm that using the pretest score ($R = 0.714$, Sig. = 0.001 < 0.01) only, or simultaneously using the pretest score and negative emotion ($R = 0.712$, Sig. = 0.000 < 0.001) could predict the learning performance of female learners using the video-based multimedia material for energy education learning. Based on both the variables of pretest score and negative emotion for forecasting the learning performance, the explained variance on the video-based multimedia material was 50.6%. The primary prediction variable was the pretest score ($\beta = 0.537$, Sig. = 0.003 < 0.01), and the secondary prediction variable was the negative emotion ($\beta = -0.330$, Sig. = 0.048 < 0.05).

Table 5
Summary results of learning performance assessment, by pair sample *t*-test, for all participating learners who were given three different types of multimedia materials.

	Performing evaluation	Number of learners	Mean	Std. dev.	Sig (2-tailed)
Static text and image-based multimedia material	Pretest	57	8.07	1.67	0.035*
	Posttest	57	8.51	1.62	
Video-based multimedia material	Pretest	55	7.84	1.64	0.000***
	Posttest	55	8.69	1.35	
Animation interaction-based multimedia material	Pretest	58	7.66	2.07	0.001**
	Posttest	58	8.50	1.73	

* Indicates Sig. (2-tailed) < 0.05.
** Indicates Sig. (2-tailed) < 0.01.
*** Indicates Sig. (2-tailed) < 0.001.

6. Discussion

First, the experimental results confirm that the video-based multimedia material had the best learning performance and generated the most positive emotions among the three types of multimedia materials assessed in the study. Although learning performance with the static text and image-based, and animated interaction-based multimedia materials reached significant levels, they led to a stronger negative learning emotion and weaker positive learning emotion than the video-based multimedia material. Mayer (2001) and Reiss's (2007) findings also confirmed the instructional effects of video-based multimedia material in learning. Mayer (2001) indicated that spoken narration combined with an onscreen visual guide did not split the attention of the learner, and even enhanced the experience, in certain instances. Reiss (2007) also argued that the standard video player was the most effective overall, which suggests that media designs are able to control the focus of a learner's attention to one specific stream of information. A single-stream focused approach may be the most effective way to present

Table 6
Correlation between learning performance and learning emotion, by Pearson correlation coefficient analysis, for all learners who were given three different types of multimedia materials.

			Positive emotion	Negative emotion	Posttest
Static text and image-based multimedia material	Posttest	Pearson correlation	−0.062	0.054	1
		Sig.(2-tailed)	0.647	0.688	
		Sum of squares and cross-products	−85.523	86.049	146.246
		Covariance	−1.527	1.537	2.612
		Number of learners	57	57	57
Video-based multimedia material	Posttest	Pearson correlation	0.279	−0.338	1
		Sig.(2-tailed)	0.039*	0.012*	
		Sum of squares and cross-products	313.882	−415.922	97.745
		Covariance	5.813	−7.702	1.810
		Number of learners	55	55	55
Animation interaction-based multimedia material	Posttest	Pearson correlation	0.070	0.050	1
		Sig.(2-tailed)	0.603	0.711	
		Sum of squares and cross-products	92.945	74.651	170.500
		Covariance	1.631	1.310	2.991
		Number of learners	58	58	58

* Indicates Sig. (2-tailed) < 0.05.

Table 7
Results of stepwise multiple regression analysis for all learners who were given video-based multimedia material, using the pretest score and negative emotion as independent variables, and the posttest score as a dependent variable.

Group	Model summary				ANOVA		Standardized coefficients		
	Model	Selected variable	R	R^2	F	Sig.	β distribution	t	Sig.
Video-based multimedia material	1	Pretest	0.647	0.419	38.250	0.000	0.647	6.185	0.000***
	2	Pretest	0.679	0.461	22.259	0.000	0.603	5.79	0.000***
		Negative emotion					−0.210	−2.015	0.049*

* Indicates Sig. (2-tailed) < 0.05.
*** Indicates Sig. (2-tailed) < 0.001.

media-based content. Although animated interaction-based multimedia material may have advantages, such as improved visual effects and communication, and the ability to generate high interest levels (Chang & Chang, 2004), the instructional effects of animation may not always benefit learning because of likely occurring extraneous cognitive load from exploratory learning with interactive, animated pictures (Schnotz et al., 1999). This study found the video-based multimedia material was superior to the animated interaction-based multimedia material on learning performance and emotion when incorporated in the right multimedia design.

Moreover, many education scholars have demonstrated that emotions are directly related to and affect learning performance (Goleman, 1995; Piaget, 1989), a view of this study also partially supported. Particularly, the study confirmed that simultaneously using the pretest score and negative emotion could predict the learning performance of learners who were given the video-based multimedia material. That is, this study found that learner negative emotions affected learning performances more than positive emotions on video-based multimedia material. Therefore, the negative emotion (stress) may have been a necessary factor in the learning process, but giving learners too much stress may have resulted in an unchanged learning performance. Also, the experimental results indicate that the emotional states of female learners were more easily affected by different multimedia materials than the male learners during their learning processes. The results also confirm that females are more emotional and emotionally expressive than males (Blier & Blier-Wilson, 1989; Kring & Gordon, 1998).

Table 8
Correlation between learning performance and learning emotion, by Pearson correlation coefficient analysis, for the female learners who were distributed to the video-based multimedia material.

			Positive emotion	Negative emotion	Posttest
Video-based multimedia material	Posttest	Pearson correlation	0.424	−0.495	1
		Sig. (2-tailed)	0.035*	0.012*	
		Sum of squares and cross-products	193.008	−245.547	42.000
		Covariance	8.042	−10.231	1.750
		Number of learners	25	25	25

* Indicates Sig. (2-tailed) < 0.05.

Additional studies are warranted. First of all, the likely reason for this partial correlation between learning performance and learning emotion may be that some learning situations must be simultaneously included, except when considering single learning emotion factors. For instance, a learner with positive emotion who is concentrating on learning may achieve a good learning performance. Concentration can be potentially assessed by a monitoring system of human–computer interaction, such as the eye-tracking system (Mayer, 2010). This research issue has been considered as our future work. Furthermore, besides realizing the relationship between learning performance and learning emotion, a future study should explore the relationship between learning emotion and cognitive load for a relatively more in-depth and multi-dimensional understanding. Based on understanding the relationships among learning performance, learning emotion, and cognitive load, an emotion-based adaptive learning system can be developed for supporting personalized learning.

Finally, some limitations of the study merit further consideration. First, it relies on a single learning topic and a single set of multimedia materials, so the research results cannot be readily inferred to the other related learning topics, and the specific instances of multimedia materials. Second, the study only focused on a particular age group of children to assess the effects of different multimedia materials on learning emotion and performance. Thus, the research results cannot be inferred to other age groups of children with different cognitive skills and affective experiences.

Table 9
Results of stepwise multiple regression analysis for the female learners who were given the video-based multimedia materials, using the pretest score and negative emotion as independent variables, and the posttest score as a dependent variable.

Group	Model summary				ANOVA		Standardized coefficients		
	Model	Selected variable	*R*	R^2	*F*	Sig.	β distribution	*t*	Sig.
Video-based multimedia material	1	Pretest	0.714	0.510	15.825	0.001	0.638	3.978	0.001**
	2	Pretest	0.712	0.506	11.281	0.000	0.537	3.409	0.003**
		Negative emotion					−0.330	−2.097	0.048*

* Indicates Sig. (2-tailed) < 0.05.
** Indicates Sig. (2-tailed) < 0.01.

7. Conclusion

This study applied the human emotion monitoring system for measuring and recording changes in human emotion in order to assess relationships among learning performance, different multimedia materials, and learning emotions. It determined that among the three types of assessed multimedia materials, video-based multimedia material generated the most positive emotion in learners, and improved learning performance. It found that the characteristics of video-based multimedia material, which is time-based, allowed learners to act as active information receivers through controlling playback functions via the standard video player controls, such as start, pause, and rewind. Meanwhile, video-based multimedia material could create an environment that connected the content with the learner on an emotional level. Although the static text and image-based and animated interaction-based multimedia materials also improved learning performance, they generated negative emotions more often than positive emotions, indicating that learner interest was relatively lower than that for video-based multimedia material. Based on the above-mentioned results, one conclusion drawn from this study is that a well-produced video-based multimedia material can be a powerful learning tool that provides learners with a rich and rewarding experience when incorporated in the right multimedia design.

This study also confirmed the correlation between learning emotion and learning performance. Although many studies claimed that the learning emotion affected learning performance, analytical results show that the effectiveness was only partially supported in the negative emotion case. This study determined that simultaneously considering pretest score and negative emotion could predict learning performance of learners who use video-based multimedia material for learning. Meanwhile, the gender difference in learner emotional states existed when using different multimedia materials for learning. The female learners were more easily affected by different multimedia materials than the male learners.

References

Blier, M. J., & Blier-Wilson, L. A. (1989). Gender differences in self-rated emotional expressiveness. *Sex Roles*, *21*(3–4), 287–295.
Brody, L. R. (1985). Gender differences in emotional development: A review of theories and research. *Journal of Personality*, *53*(2), 102–149.
Brody, L. R., & Hall, J. (1993). Gender and emotion. In M. Lewis, & J. Haviland (Eds.), *Handbook of emotions* (pp. 447–460). New York: Guilford Press.
Chang, T., & Chang, D. (2004, October). *Enhancing learning experience with dynamic animation.* Paper presented at the International Conference on Engineering Education, University of Florida.
Chanlin, L. J. (1998). Animation to teach students of different knowledge levels. *Journal of Instructional Psychology*, *25*(3), 166–175.
Chen, C. -M., & Lee, T. -H. (2011). Emotion recognition and communication for reducing second-language speaking anxiety in a web-based one-to-one synchronous learning environment. *British Journal of Educational Technology*, *42*(3), 417–440.
Climov, D. (2008). *Results of a stress management program for graduate students based on relaxation associated with HRV biofeedback.* Retrieved from http://www.heartmath.org/templates/ihm/downloads/pdf/research/publications/stress-management-relaxation-with-hrv-biofeedback.pdf
Coles, G. (1998). *Reading lessons: The debate over literacy*. New York: Hill & Wang.
Emmanuel, B., Pierre, C., & Claude, F. (2007, July). *Towards advanced learner modeling: Discussions on quasi real-time adaptation with physiological data.* Paper presented at the Seventh IEEE International Conference on Advanced Learning Technologies (ICALT), Niigata, Japan.
Erez, A., & Isen, A. M. (2002). The influence of positive affect on the components of expectancy motivation. *The Journal of Applied Psychology*, *87*(6), 1055–1067.
Goleman, D. (1995). *Emotional intelligence.* New York: Bantam Books.
Harp, S. F., & Mayer, R. E. (1997). The role of interest in learning from scientific text and illustrations: On the distinction between emotional interest and cognitive interest. *Journal of Educational Psychology*, *89*(1), 92–102.
Hochschild, A. R. (1975). The sociology of feeling and emotion: Selected possibilities. In M. Millman, & R. M. Kantor (Eds.), *Another voice: Feminist perspectives on social life and social science* (pp. 208–307). New York: Anchor Books.
Hochschild, A. R. (1979). Emotion work, feeling rules, and social structure. *The American Journal of Sociology*, *85*, 551–575.
Izard, C. E. (1984). Emotion-cognition relationships and human development. In C. E. Izard, J. Kagan, & R. B. Zajonc (Eds.), *Emotions, cognition and behavior.* New York: Cambridge University Press.
Jonassen, D. (1988). *Instructional designs for microcomputer courseware.* Hillsdale, NJ: Lawrence Erlbaum.
Kemper, T. D. (1978). *A social interactional theory of emotions.* New York: Wiley.
Kemper, T. D. (1991). Predicting emotions from social relations. *Social Psychology Quarterly*, *54*, 330–342.
Kiyhoshi, N., & Tomoya, K. (2006, August). *A multi-modal emotion-diagnosis system to support e-learning.* Paper presented at the First International Conference on Innovative Computing, Information and Control (ICICIC), Beijing, China.
Kopecek, I. (2000, September). *Emotions and prosody in dialogues: An algebraic approach based on user modelling.* Paper presented at the ISCA Workshop on Speech and Emotions, Newcastle, Northern Ireland.
Kort, B., Reilly, R., & Picard, R. W. (2001, August). *An affective model of interplay between emotions and learning: Reengineering educational pedagogy-building a learning companion.* Paper presented at the IEEE International Conference on Advanced Learning Technologies, Madison, USA.
Kring, A. M., & Gordon, A. H. (1998). Sex differences in emotion: Expression, experience, and physiology. *Journal of Personality and Social Psychology*, *74*, 686–703.
Large, A., Beheshti, J., Breuleux, A., & Renaud, A. (1994). Multimedia and comprehension: A cognitive study. *Journal of the American Society for Information Science*, *45*(7), 515–528.
LeDoux, J. (1994). Emotion, memory, and the brain. *Scientific American*, *270*, 50–57.
Lowe, R. K. (2003). Animation and learning: Selective processing of information in dynamic graphics. *Learning and Instruction*, *13*(2), 157–176.
Mayer, R. E. (1997). Multimedia learning: Are we asking the right questions? *Educational Psychologist*, *32*(1), 1–19.
Mayer, R. E. (2001). *Multi-media learning.* Cambridge: Cambridge University Press.
Mayer, R. E. (2010). Unique contributions of eye-tracking research to the study of learning with graphics. *Learning and Instruction*, *20*(2), 167–171.
Mayer, R. E., & Moreno, R. (1998). A split-attention effect in multimedia learning: Evidence for dual processing systems in working memory. *Journal of Educational Psychology*, *90*, 312–320.
McCraty, R., Atkinson, M., Tiller, W. A., Rein, G., & Watkins, A. D. (1995). The effects of emotions on short-term power spectrum analysis of heart rate variability. *The American Journal of Cardiology*, *76*(14), 1089–1093.
McCraty, R. (2005). Enhancing emotional, social and academic learning with heart rhythm coherence feedback. *Biofeedback*, *33*(4), 130–134.
Mohamed, B. A., & Mahmou, N. (2007, July). *EMASPEL (emotional multi-agents systemfor peer to peer e-learning).* Paper presented at the Seventh IEEE International Conference on Advanced Learning Technologies (ICALT), Niigata, Japan.
Mousavi, S. Y., Low, R., & Sweller, J. (1995). Reducing cognitive load by mixing auditory and visual presentation modes. *Journal of Educational Psychology*, *87*(2), 319–334.
Narayanan, N. H., & Hegarty, M. (2000). *Communicating dynamic behaviors: Are interactive multimedia presentations better than static mixed-mode presentations?* Paper presented at the Diagrams 2000 Conference, University of Edinburgh, Scotland.
Oaksford, M., Morris, F., Grainger, B., & Williams, J. M. G. (1996). Mood, reasoning, and central executive process. *Journal of Experimental Psychology. Learning, Memory, and Cognition*, *22*, 477–493.
Oliver, R. (1996, January). *Interactions in multimedia learning materials: The things that matter.* Paper presented at the 3rd International Interactive Multimedia Symposium Perth, Western Australia.
Paivio, A. (1990). *Mental representations: A dual coding approach.* Oxford, England: Oxford University Press Book.
Parsons, T. (1955). *Family socialization and interaction processes.* Glencoe, IL: Free Press.
Parsons, T. (1964). *Social structure and personality.* Glencoe, IL: Free Press.
Pass, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent development. *Educational Psychologist*, *38*(1), 1–4.

Piaget, J. (1989). Les relations entre l'intelligence et l'affectivité dans le developpement de l'enfant [The relationship between intelligence and affectivity in the development of the child.]. In B. Rimé, & K. Scherer (Eds.), *Les émotions. Textes de base en psychologie*. (pp. 75–95) Paris: Delachaux et Niestlé.

Picard, R. W., Healey, J., & Vyzas, E. (2001). Toward machine emotional intelligence: Analysis of affective physiological state. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *23*(10), 1175–1191.

Rieber, L. P., & Hannafin, M. J. (1988). Effects of textual and animated orienting activities and practice on learning from computer-based instruction. *Computers in the Schools*, *5*, 77–89.

Reilly, R., & Kort, B. (2004, March). *The science behind the art of teaching science: Emotional state and learning.* Paper presented at the International Conference on Society for Information Technology and Teacher Education, Atlanta, GA, USA.

Reiss, D. (2007). Video-based multimedia designs. A research study testing learning effectiveness. *Canadian Journal of Learning and Technology*, *33*(3). Retrieved from http://www.cjlt.ca/index.php/cjlt/article/viewArticle/164/154.

Schnotz, W., Böckheler, J., & Grzondziel, H. (1999). Individual and co-operative learning with interactive animated pictures. *European Journal of Psychology of Education*, *14*, 245–265.

Seibert, P. S., & Ellis, H. C. (1991). Irrelevant thoughts, emotional mood states, and cognitive task performance. *Memory & Cognition*, *19*, 507–513.

Shaikh, M. A. M., Hua, W., Ishizuka, M., & Mostafa, A. M. (2005, December). *Modeling an affectionate virtual teacher for e-learning underpinning 3-dimensional emotion model.* Paper presented at the 8th International Conference on Computer and Information Technology (ICCIT), Islamic University of Technology (IUT), Dhaka, Bangladesh.

Steinberg, L. (2005). Cognitive and affective development in adolescence. *Trends in Cognitive Sciences*, *9*(2), 69–74.

Sweller, J., Van Merrienboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, *10*(3), 251–297.

Tractinsky, N., Katz, A. S., & Ikar, D. (2000). What is beautiful is usable. *Interacting with Computers*, *13*, 127–145.

Tiller, W. A., McCraty, R., & Atkinson, M. (1996). Cardiac coherence: A new, noninvasive measure of autonomic nervous system order. *Alternative Therapies in Health and Medicine*, *2*(1), 52–65.

Um, E. R., Song, H., & Plass, J. (2007, June). *The effect of positive emotions on multimedia learning.* Paper presented at the World Conference on Educational Mutlimedia, Hypermedia and Telecommunications, Vancouver, Canada.

Vicente, A. D., & Pain, H. (2002, June). *Informing the detection of the students' motivational state: An empirical study*. Paper presented at the 6th international Conference on intelligent Tutoring Systems, Biarritz, France and San Sebastian, Spain.

Wehrle, T., & Kaiser, S. (2000). Emotion and facial expression. In A. Paiva (Ed.), *Affect in interactions: Towards a new generation of interfaces* (pp. 49–63). Heidelberg, Germany: Springer.

Wolfson, S., & Case, G. (2000). The effects of sound and color on responses to a computer game. *Interacting with Computers*, *13*, 183–192.

Zhang, Q., & Lee, M. (2009). Analysis of positive and negative emotions in natural scene using brain activity and GIST. *Neurocomputing*, *72*(4–6), 1302–1306.

Chih-Ming Chen is currently a professor in the Graduate Institute of Library, Information and Archival Studies at National Chengchi University, Taipei, Taiwan. He received B.Sc. and M.Sc. degrees from the Department of Industrial Education at National Taiwan Normal University in 1992 and 1997, and his Ph.D. from the Department of Electronic Engineering at National Taiwan University of Science and Technology in 2002. His research interests include digital libraries, e-learning, data mining, machine learning, and intelligent agents on the web.

Hui-Ping Wang is currently a practice teacher at Taipei Municipal Da-An Vocational High School, Taipei, Taiwan. She received her B.Sc. and M.Sc. degrees from the Department of Industrial Education and Department of Applied Electronics Technology at National Taiwan Normal University in 2008 and 2010, respectively. Her research interests include e-learning and data mining.