Learning with Multimedia:

Are Visual Cues and Self-Explanation Prompts Effective?

by

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ABSTRACT

The purpose of this study was to investigate the impacts of visual cues and different types of self-explanation prompts on learning, cognitive load and intrinsic motivation, as well as the potential interaction between the two factors in a multimedia environment that was designed to deliver a computer-based lesson about the human cardiovascular system. A total of 126 college students were randomly assigned in equal numbers ($N = 21$) to one of the six experimental conditions in a 2 X 3 factorial design with visual cueing (visual cues vs. no cues) and type of self-explanation prompts (prediction prompts vs. reflection prompts vs. no prompts) as the between-subjects factors. They completed a pretest, subjective cognitive load questions, intrinsic motivation questions, and a posttest during the course of the experience. A subsample (49 out of 126) of the participants' eye movements were tracked by an eye tracker. The results revealed that (a) participants presented with visually cued animations had significantly higher learning outcome scores than their peers who viewed uncued animations; and (b) cognitive load and intrinsic motivation had different impacts on learning in multimedia due to the moderation effect of visual cueing. There were no other significant findings in terms of learning outcomes, cognitive load, intrinsic motivation, and eye movements. Limitations, implications and future directions are discussed within the framework of cognitive load theory, cognitive theory of multimedia learning and cognitive-affective theory of learning with media.

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INTRODUCTION

Humans' inner cognitive architecture is conceptualized to have two processing channels with limited cognitive capacity (Mayer, 2005). These two channels—one for processing verbal information and the other for processing visual information—complement one with another when delivering information. Based on these assumptions, researchers and educational professionals nowadays tend to believe that people can benefit more from learning a combination of pictures and words than from words alone. This belief is formally referred to as *multimedia principle* (Mayer, 2001; Mayer & Moreno, 2002).

As computer technology advances, graphics become more ubiquitous and accessible to teachers, instructional designers, and other educational professionals than ever before. Consequently, animations or dynamic visualizations continue to gain popularity as one of the instructional tools to support learning in educational settings. Early research (Baek & Layne, 1988; Park & Gittleman, 1992; Rieber, 1990, 1991a, 1991b; Thompson & Riding, 1990) found positive learning effects for animations, which supported the increased use of animations in instructional design and development. For instance, Rieber (1990) provided 119 elementary school students with a computer-based lesson, which used either static or animated graphics to describe concepts of Newton's law of motion. His results revealed that participants in the animated graphics condition developed a better understanding of the concepts and rules of Newton's law than those in the static graphics condition.

These early excitement surrounding the instructional value of animations, however, was subsequently tempered. Tversky, Morrison and Betrancourt (2002) reviewed these early studies and concluded that the results of these studies were not convincing, as more information was delivered via the animations than the static visualizations, making the static-animated comparison inequivalent. The current literature is mixed with regard to whether animations are more effective than static visuals for learning. Some recent studies reveal the advantage of using instructional animations in procedural knowledge (Arguel & Jamet, 2009; Ayres, Marcus, Chan, & Qian, 2009; Michas & Berry, 2000; Wong et al., 2009) and conceptual knowledge (Boucheix & Guignard, 2005; Catrambone & Seay, 2002; Lai, 2000; Large, Beheshti, Breuleux, & Renaud, 1996; Lin & Atkinson, 2011; Yang, Andre, & Greenbowe, 2003). However, other research show the effect of animations and static graphics are equivalent with regard to learning conceptual knowledge, e.g., mechanical systems (Boucheix & Schneider, 2009; Kim, Yoon, Whang, Tversky & Morrison, 2007; Kühl, Scheiter, Gerjets, & Gemballa, 2011; Mayer, Deleeuw, & Ayres, 2007). Moreover, a few studies have even reported finding that static visualizations were superior to animations in terms of supporting learning (Mayer, Hegarty, Mayer & Campbell, 2005). These mixed results suggest research should investigate "what conditions must be in place for dynamic visualizations to be effective in learning" (Hegarty, 2004, p. 344). Two approaches with great potential to serve as instructional aids for learners in multimedia learning environments are visual cueing and prompting self-explanations (Berthold & Renkl, 2009). Cognitive load theory and cognitive theory of multimedia learning are the theoretical frameworks that guide the empirical research in this field.

Theoretical Frameworks

Cognitive load theory (Paas, Renkl, & Sweller, 2003; Schnotz & Kurschner, 2007; Sweller, 1994; Sweller, van Merriënboer, & Paas, 1998) is one of the theoretical frameworks that guide the current empirical research in multimedia learning. Cognitive load is a construct describing “any demands on working memory storage and processing of information” (p. 471, Schnotz & Kurschner, 2007). It is not a unitary construct. Instead, there are three subcomponents of cognitive load—intrinsic cognitive load, extraneous cognitive load and germane cognitive load. Intrinsic cognitive load is determined by the inherent nature of learning materials or tasks. If the elements in the to-be-learned materials have minimal reference with each other (low element interactivity), the level of intrinsic load is low. If there is a high level of element interactivity, the level of intrinsic load is high. Nevertheless, intrinsic load cannot be altered unless the learners’ expertise has changed or the learning materials or tasks have been re-designated. Extraneous cognitive load is the mental effort that is irrelevant and harmful to learning. It is due to the inappropriate instructional design. Germane cognitive load is the mental effort that contributes to the learning-related activities. Consequently, instructional design and development should minimize extraneous cognitive load and foster germane cognitive load so that learners will not experience cognitive overload due to the limitation of working memory.

Recent development of cognitive load theory emphasized the central role of element interactivity (Sweller, 2010). Not only does it determine intrinsic load, but also underlie extraneous load, based on different learning goals. Furthermore, germane load is also related to element interactivity, as germane load is the mental effort available to handle learning activities. Therefore, an overall cognitive load may theoretically exist to explain the relationships among intrinsic, extraneous and germane load due to the element interactivity. Operationally, it is the load addition of the three subcomponents.

Research in multimedia learning is also guided by the framework of *cognitive theory of multimedia learning* (Mayer, 2005). The theory assumes that humans process information via two complementary channels—visual/pictorial channel and auditory/verbal channel (Mayer, 2005). When a learner receives instructional messages from his/her eyes and ears, one channel will process information presented visually, such as graphics and/or on-screen text, while the other channel will process auditory information, such as narrations. As humans have limited cognitive resources, instructional designs should optimize information processing across the two channels. For instance, in order to avoid overload in the visual channel, results from empirical research supports the approach that instructional explanations should be delivered via audio rather than on-screen text (modality principle, cf. Lowe & Sweller, 2005; Mousavi, Lowe, & Sweller, 1995; Tindall-Ford, Chandler, & Sweller, 1997). In addition to the dual-channel assumption, cognitive theory of multimedia learning also assumes three underlying processes that are essential for active learning—selection, organization and integration. Once a learner selects relevant information by directing attention to it, information is brought into the learner's working memory for further processing. After organizing the selected information into meaningful structures, a learner will integrate it with his/her existing knowledge. The implication is that instructional designs should try every means to avoid a learner's cognitive overload and to foster active learning. Visual cueing and prompting self-explanations are two potentially effective techniques to foster learning and cognition in multimedia environments by enhancing attention and active learning, respectively.

According to self-determination theory (Deci & Ryan, 1985), one way to distinguish motivation is based on different goals that give rise to an action, which lead to the distinction between intrinsic motivation and extrinsic motivation (Ryan & Deci, 2000a). Whereas extrinsic motivation refers to doing an activity that leads to a separate outcome, intrinsic motivation is an individual's inherent tendency towards assimilation, mastery, interest and exploration (Ryan & Deci, 2000b). Theories, along with empirical research findings, have aided in specifying conditions that facilitate or undermine intrinsic motivation. For instance, Fisher (1978) found that the combination of the competence perception and the autonomy sense of enhanced intrinsic motivation. In addition, several studies (e.g., Deci, Nezlek & Sheinman, 1981; Ryan & Grolnick, 1986) revealed that teachers or parents who were supportive of students'/children's internal autonomy promoted their intrinsic motivation.

As motivation impacts learning (Boekaerts, 2007; Husman & Hilpert, 2007), recent theory development has expanded cognitive theory of multimedia learning to include motivational and affective constructs into its learning model (*cognitive-affective theory of learning with media*, cf. Brünken, Plass, & Moreno, 2010; Moreno, 2009; Moreno & Mayer, 2007) so that learning, cognition, motivation, and other affective constructs are integrated into one model to explain learning with different instructional aids. Specifically, in the theoretical model, motivation plays an important role by mediating learning with multimedia.

Visual Cueing as an Aid for Animations

Multimedia learning environments deliver instructional messages by presenting learners with a variety of elements such as graphics, on-screen text, and narrations. Learners may be involved in visual search activities, i.e., searching the relevant information on the visualizations to build connections between what they see and what they hear. This type of activity may cause learners, who have limited working memory capacity, to experience cognitive overload, which prevents learning. In terms of cognitive load theory (Paas, Renkl & Sweller, 2003; Schnotz & Kurschner, 2007; Sweller, van Merriënboer & Paas, 1998), while the intrinsic cognitive load keeps stable for designated learning materials, learners' irrelevant visual search results in a high level of extraneous cognitive load and consequently leads to limited cognitive resources for germane processing. Therefore, specially designed instructional aids should be provided to learners to direct their attention to the thematically important graphical information. Visual cueing is one of the techniques to direct learners' attention in the multimedia environments.

Visual cues, such as arrows, circles, and color coding, are non-content devices that are added to the texts or graphical displays to signal important information. Empirical research has shown that visual cueing devices are effective to guide learners' attention to animations in multimedia environments (de Koning, Tabbers, Rikers & Paas, 2009, 2010a). From a cognitive load perspective, applying cueing devices to visualizations reduces the visual search activities, a source of extraneous load. Learning is, therefore, enhanced by more cognitive resources being freed up for germane processing. As a result, visual cueing has a great potential to facilitate the processes of selecting relevant information, which is one of the essential processes for active learning (Mayer, 2005).

A substantial number of studies have found that visual cueing is an effective method to reduce extraneous load in multimedia learning environments (for reviews, see Mayer & Moreno, 2003; Wouters, Paas & van Merriënboer, 2009) and a large number of studies supported the instructional benefits of visual cueing (Amadieu, Mariné, & Laimay, 2011; Atkinson, Lin & Harrison, 2009; Boucheix & Guignard, 2005; de Koning, Tabbers, Rikers & Paas, 2007, 2010b; Jamet, Gavota & Quaireau, 2008; Jeung, Chandler & Sweller, 1997; Kalyuga, Chandler & Sweller, 1999; Lin & Atkinson, 2011; Steinke, Huk, & Floto, 2003). For instance, de Koning et al. (2007) conducted a study to investigate the effectiveness of a cued animated cardiovascular system (using a spotlight cueing effect). The researchers compared learning outcomes for participants who viewed a cued animation with those who viewed the animation without a visual cue. The results showed that participants in the cued animated condition had significantly higher scores on both comprehension and transfer tests. Jamet, Gavota and Quaireau (2008) used a coloring technique as visual cues in their study. They found that participants who studied saliently colored graphics of the human brain performed significantly better than those in the group that viewed non-salient colored graphics. In term of *efficiency* (Paas & van Merriënboer, 1993; van Gog & Paas, 2008), empirical studies (Kalyuga, Chandler, & Sweller, 1999; Lin & Atkinson, 2011) revealed that visual cueing resulted in efficient learning. For instance, Lin and Atkinson (2011) presented visualizations either with or without visual cues (arrows) to 119 college undergraduate students for them to learn about concepts and processes in rock cycle. Those visuals were also manipulated to be either animated or static. The researchers found that learners who studied cued visualizations spent significantly less time to obtain the knowledge than their peers who studied uncued vitalizations.

However, successfully directing learners' attention to the important information on visual displays cannot guarantee enhanced learning, as attention cueing may only facilitate attention and perception but not learners' engagement (de Koning et al., 2009). Learners may passively view visualizations on a surface, perception level without deep cognitive processing (Hegarty, Kriz, & Cate, 2003; Schnotz, & Rasch, 2005). A couple of empirical studies revealed that visual cueing is suboptimal. For instance, Mautone and Mayer (2001) found that cued animations combined with cued narrations (using a lower intonation) did not significantly impacted learning physics. Jeung, Chandler and Sweller (1997) found that flashing part of the diagrams only benefited students' geometry learning with high-visual-search materials, but not those low-visual-search materials. More recently, Boucheix and Lowe (2010) found that, while coloring cues were effective to enhance comprehension, multiple arrow cues were not, compared to an uncued animation showing a piano mechanism. Therefore, supportive techniques that foster germane processing are needed in multimedia learning. Prompting self-explanation is an instructional aid that has the potential to engage learners into deeper level of learning and cognition.

Prompting Self-Explanation to Support Learning

Self-explanation is a domain general activity in which learners explain what they have learned to themselves to monitor their own understanding (Chi, 2000). Consequently, it engages learners in active learning (Roy & Chi, 2005)—actively engaging in construction of coherent mental representations (Mayer, 2005). For instance, Wong, Lawson and Keeves (2002) compared the geometry performance of two groups of middle-school students: one group received self-explanation training while the other did not. They found students trained to use self-explanation strategies performed significantly better than their peers, especially on the transfer test. When it is implemented in a learning environment, self-explanation is often elicited by prompts. Self-explanation prompts are questions that induce the process of self-explanation. Some empirical research has supported the effectiveness of prompting self-explanation. For instance, Chi, de Leeuw and Chiu (1994) found that learners who were prompted to self-explain when reading printed materials about human circulatory system showed greater learning gains than those who studied the same material without prompting. As computer technologies have advanced, a large number of studies, conducted in computer-based multimedia environments, have provided substantial evidence of the effectiveness of self-explanation prompts (e.g., Atkinson, Renkl, & Merrill, 2003; Berthold, Eysink, & Renkl, 2009; Berthold & Renkl, 2009; Mayer, Dow, & Mayer, 2003). Atkinson, Renkl and Merrill (2003) investigated the effect of self-explanation prompts in an example-based computer environment in which knowledge of probability was taught. They found learners provided with prompts (i.e., answering multiple choice questions of probability principles) performed significantly better than their counterparts on near and far transfer tests. Mayer, Dow and Mayer (2003) presented questions (prompts) to learners before they viewed animations about how an electric motor works. They found learners experienced the instructional method outperformed those who were not presented with questions. Therefore, self-explanation elicited by prompts has the potential to promote deep and active learning in multimedia environments (Roy & Chi, 2005). From a cognitive load perspective, self-explanation engages learners in learning related information processing, which is an approach to foster germane cognitive load.

On the other hand, self-explanation may impose considerable cognitive demands on learners. Taking into account humans' limited cognitive resources in their working memory, learners may experience cognitive overload, especially when they are self-explaining in the environments that multiple formats of visual displays along with spoken or on-screen texts are presented. As a result, learning may not be enhanced or may be even prevented because of the heightened cognitive load of the multimedia materials, which is consistent with the results of Gerjets, Scheiter and Catrambone (2006). Participants in their study learned different formats of worked examples (molar vs. modular examples) with either self-explanation prompts or textual instructional explanations. The researchers did not find the superiority of prompting self-explanation. They even found prompting condition deteriorated learning when modular examples were provided to learners. Moreover, additional studies have also documented non-significant effect of self-explanation prompts (de Koning, Tabbers, Rikers, & Paas, 2010b; Große & Renkl, 2006). Their value as instructional aids may be enhanced in combination with other techniques. For instance, an instructional aid such as visual cuing that reduces visual search and enhances attention should be considered to combine with the self-explanation prompting technique to reduce extraneous cognitive load and at the same time foster germane cognitive load.

When self-explanation prompts are implemented by computer programs, one issue arises: when to prompt learners to self-explain during instruction. Some empirical studies (Hegarty, Kriz, & Cate, 2003; Mayer, Dow, & Mayer, 2003; Moreno, 2009) investigated prediction prompts—presenting prompting questions right before the related instruction was delivered. The rationale for implementing prediction prompts is that learners' prior knowledge may be activated by these prompts in the self-explaining process, which facilitates the integration of incoming information with existing knowledge. The results of those studies revealed the relative benefits of the prediction prompts, compared to no prompts. For instance, Hegarty, Kriz and Cate (2003) provided learners five prediction questions before they viewed a graphical representation of a mechanical system. The researchers compared the performance between learners who were prompted to predict the behavior of the mechanical system and those who were not in a learning environment that presented either animation or static pictures. They found that these prediction questions had a positive, significant impact on learners' understanding of the system in two experiments. On the other hand, reflection prompts—questions that are administered right after the related instruction or ask learners to explain their actions—are also used to elicit self-explanation. This is based on the assumption that reflection-induced self-explanations can foster deep learning (Moreno & Mayer, 2010). Moreno and Mayer (Experiment 3, 2005) investigated the cognitive function of reflection prompts, along with guidance, in a multimedia game augmented with an animated pedagogical agent. They found that there was a reflection-prompt effect on retention and transfer tests in a non-interactive environment but not in an interactive environment. Further, they found that reflection was effective when learners were asked to reflect on the correct information. Other researchers (Wouters, Paas, & van Merriënboer, 2009) found that the effect of reflection prompts interacted with the modality effect (i.e., spoken explanations vs. written explanations) in an agent-based multimedia environment—written explanations combined with reflection prompts yielded better transfer performance than the same format of explanations with no prompts; this effect disappeared when explanations were spoken narrations. It is of note that past research only investigated the learning and cognitive benefits of self-explanation prompts compared to no prompts. No empirical study has dived into the issue of when to implement self-explanation prompts in computer-based instruction. As a result, it remains to be seen whether prediction prompts and reflection prompts are equally effective to learning or one is more effective than the other. Therefore, based on the timing of prompting self-explanation, the present study specified two types of self-explanation prompts—prediction prompts and reflection prompts. The potential effect of these prompts was considered in investigating the benefit of visual cues and self-explanation prompts in a multimedia environment.

Eye Tracking Technology

Past research in reading revealed that eye movement reflects visual attention (Klein, 1980; Rayner, 1998). Eye tracking is an approach that traces learners' learning processes by recording their eye movements. This methodology assumes that what the eyes are fixating is an indication of what the mind is processing (eye-mind assumption, Just & Carpenter, 1980). As a result, learners' eye movements parameters identified by Rayner (1998), such as total fixation duration and the number of fixations in the areas of interest (AOIs), can provide moment-to-moment information about cognitive processes induced by the visual cuing effect or the self-explanation prompting effect. Therefore, eye tracking technique can make unique contributions to research in multimedia learning by providing "online" measures complementary to "offline" measures (Mayer, 2010; van Gog & Scheiter, 2010).

Recent empirical research utilizing eye tracking technique shows that visual cueing enhances learners' attention (Boucheix & Lowe, 2010; de Koning et al., 2010a; Ozcelik, Arslan-Ari, & Cagiltay, 2010; Ozcelik, Karakus, Kursun, & Cagiltay, 2009). For instance, de Koning et al. (2010) found that a higher proportion of number of fixations and a higher proportion of fixation durations on the cued part(s) of an animation compared to the uncued animation. Ozcelik, Arslan-Ari and Cagiltay (2010) found similar results—the number of fixations on visually cued text labels and pictures was more than that on the uncued labels and pictures. However, these studies revealed a weak attention-directing effect of visual cueing based on learners' eye movement. Lowe and Bouchneix (2011) even found no significant effect of cueing to direct attention in a domain of mechanical system. Therefore, the generalizability and plausibility of this visual cueing effect is still questionable. The current study intended to further interrogate attention-directing effect in a multimedia environment, in which not only visual cues, a surface level supporting aid, but also self-explanation prompts, a deep level supporting aid, were provided.

Overview of the Study

The main purpose of the study was to investigate the potential impacts of visual cueing and different types of self-explanation prompts on learning, cognitive load and intrinsic motivation, as well as the interplay between these two instructional aids in a context of multimedia environment that delivered a lesson about the human cardiovascular system by utilizing a series of animations accompanied by human narrations. The study, as well as the design and development of the learning environment, was guided by cognitive load theory, cognitive theory of multimedia learning and its extended cognitive-affective theory of learning with media. Specifically, the study addressed the following research questions:

(a) Is visual cueing an effective technique to direct learners' attention in a multimedia environment?

(b) Is visual cueing effective to enhance learning?

(c) Do different types of self-explanation prompts have any impact on learning, cognitive load, and intrinsic motivation?

(d) Do learners in the uncued-animations/no-prompts condition need visual cues or self-explanation prompts to support learning?

(e) What are the relationships among learning, cognitive load, and intrinsic motivation in the multimedia environment?

Two independent variables were manipulated in the study, i.e., visual cueing (cues vs. no cues) and prompting self-explanation (no prompts vs. prediction prompts vs. reflection prompts). Other variables, such as the presentation format of the graphics, the level of learner control and the number of presentation segments were controlled to be constant. The study incorporated a number of dependent variables as "offline" measures, including 40 learning outcomes measures (20 for pretest and 20 for posttest), five self-report cognitive load measures and 21 self-report intrinsic motivation measures. The total fixation duration and the total fixation count, indentified as eye movement parameters by

Rayner (1998), were collected as an “online” measure of the learning process. Learning time was recorded and included as an en-route variable.

In addition to the main purpose and major research questions, the study also intended to address two supplemental research questions:

(f) Based on the collected data, what is the construct structure of cognitive load?

(g) What is the construct structure of intrinsic motivation?

Chapter 2

METHOD

Participants & Design

A total of 126 participants were recruited from a large southwestern university in the US to participate in the study. They were undergraduate students enrolled either in a computer literacy course in the Teachers College or an introductory psychology course in the Department of Psychology. They participated in the study to earn course credits. They were all over 18 years old, and their average age was 21.69 (*SD* = 5.73). Among these participants, 53 (42.1%) were males. With regard to the ethnicity, 11 of the participants were African Americans, 18 Asians, 71 Caucasians, 18 Hispanics, 2 Native Americans and 6 Others.

This study used a pretest-posttest, 2 (cues vs. no cues) x 3 (no prompts vs. prediction prompts vs. reflection prompts), between-subjects design, in which participants were randomly assigned in equal numbers (*N* = 21) to one of the six conditions:

(a) uncued-animations/no-prompts,

(b) cued-animations/no-prompts,

(c) uncued-animations/prediction-self-explanation-prompts,

(d) cued-animations/prediction-self-explanation-prompts,

(e) uncued-animations/reflection-self-explanation-prompts,

(f) cued-animations/reflection-self-explanation-prompts.

Measures & Instruments

A pretest, including 20 multiple choice questions, was administered to measure participants' prior knowledge about the content—the human cardiovascular system. Each question in the pretest was scored 0 points for the incorrect answer or 1 point for the correct answer by the computer program automatically. Therefore, a maximum of 20 points can be achieved in the pretest. A 20-item posttest was used to measure participants' comprehension of the content after instruction. The posttest had the same format and followed the same scoring procedures as the pretest, but the questions in the pretest and posttest were different. Cronbach's alphas for the pretest and posttest were .80 and .81, respectively. The correlation between the pretest and posttest was .61 ($p < .01$).

Five subjective questions (i.e., task demands, effort, navigational demands, perceived success, and stress, see Table 1) were used to measure learners' perceived cognitive load. They were adapted from the NASA-TLX (Hart & Staveland, 1988), and were described in the previous studies (Gerjets, Scheiter & Catrambone, 2004, 2006). Each of the questions was administered on an 8-point Likert scale.

Participants' intrinsic motivation was also measured using an 8-point Likert scale ranging from "1" (*not at all true*) to "8" (*very true*). There were a total of 21 statements, adapted from Ryan (Ryan, 1982) and McAuley, Duncan, and Tammen (1989), assessing intrinsic motivation with six subscales—interest, competence, value, effort, pressure, and choice (see Table 2).

Eye Tracking Equipment

A 24-inch display Tobii eye tracker (see Figure 1) was used to record learners' eye movements. This eye tracker operates at a sampling rate of 60Hz, and has a spatial resolution of less than 0.5 degrees. The system consists of a flat-panel monitor with a built-in eye tracking camera, and infrared light emitting diodes mounted inside the monitor bezel. The camera's viewing angle is 44 x 22 x 70 cm, allowing head movement from a distance from 50 to 80 cm. No device was attached to participants.

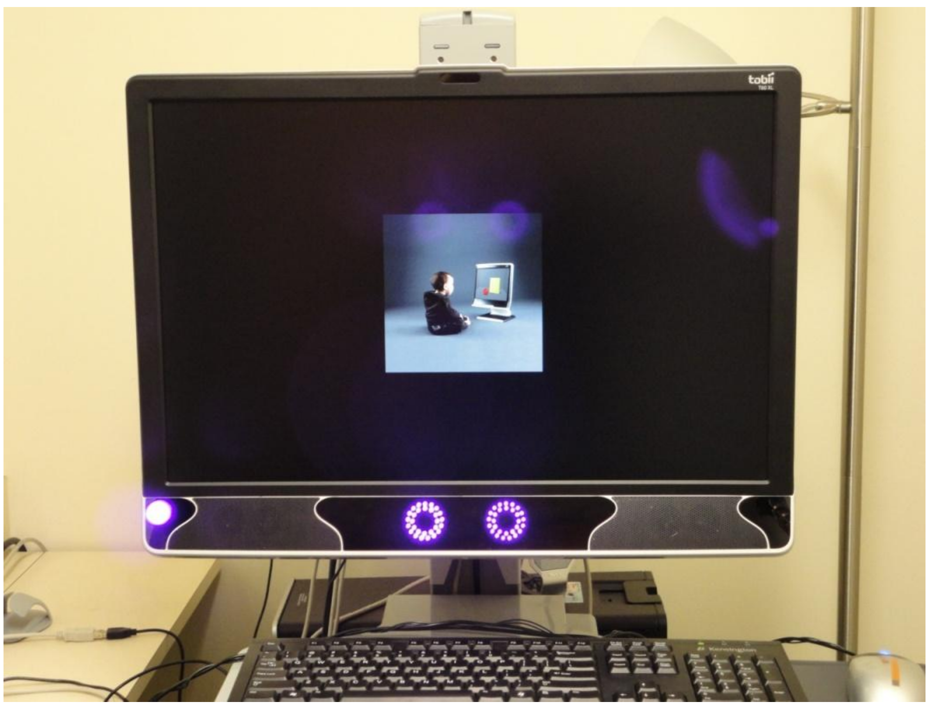

Figure 1. Tobii Eye Tracker Utilized in the Study

Tobii Studio was the software used to record eye movements, operate the calibration process, replay the recordings of participants' eye movements, define areas of interest, and generate data for analysis. The software was installed on a PC with Windows XP. All icons and running program windows, except for the computer program used in the study, were removed from participants' PC desktop. Five points with medium speed were used in the calibration process. This study used the total fixation duration (in seconds) and the total fixation count (in frequencies) as eye movement data.

Computer-Based Multimedia Environment

The computer-based instructional materials intended to deliver an instructional unit about the human cardiovascular system. Specifically, they covered the following topics in a sequence: the structure and function of the heart, the blood and blood vessels, the circulatory pathway of blood vessels, and the material exchange in the human body. The learning environment was created by Visual Basic, and was embedded with 2-D graphics created by Adobe Flash. In the uncued-animation/no-prompts condition (see Figure 2), participants viewed 24 screens of presentation, each including one segment of animations describing the human cardiovascular system. No visual cues were added to these uncued animations. In the cued-animations/no-prompts condition (see Figure 3), the same number of the segmented animations were presented to the participants except that the animations were cued using arrows. The uncued-animations/prediction-prompts condition was almost identical to the uncued-animations/no-prompts condition with only one exception: four prompting questions (see Table 3) were inserted into the computer-based lesson to elicit self-explanations (see Figure 4). The wording of these prompts was originally from a list of content-free prompts (Chi, Siler, Jeong, Yamauchi, & Hausmann, 2001) and was rephrased to be content specific. These prediction prompts appeared between Screen 4 and 5, 7 and 8, 13 and 14, and 19 and 20 respectively, i.e., they preceded the presentation of the related instructions. For instance, after they were presented with the first prediction question "*Could you explain the function of blood in your own words?*", the participants viewed three screens of the uncued animations (Screen 5, 6, and 7) accompanied by narrations, explaining the blood's function in the cardiovascular system. The uncued-animations/reflection-prompts condition was almost identical to the uncued-animations/prediction-prompts condition with one exception: the identical four prompting questions appeared after the related instructions were presented, i.e., between Screen 7 and 8, 13 and 14, 19 and 20, and after Screen 24. For instance, after the participants received instruction from the uncued animations from Screen 5, 6, and 7, they were provided with the question "*Could you explain the function of blood in your own words?*" The cued-animations/prediction-prompts condition was almost identical to the uncued-animations/prediction-prompts condition except that arrows were added to the animations in the cued-animations/prediction-prompts condition. Similarly in the cued-animations/reflection-prompts condition, all other elements were identical except that arrows were added to the animations, whereas no visual cueing devices were used in the uncued-animations/reflection-prompts condition.

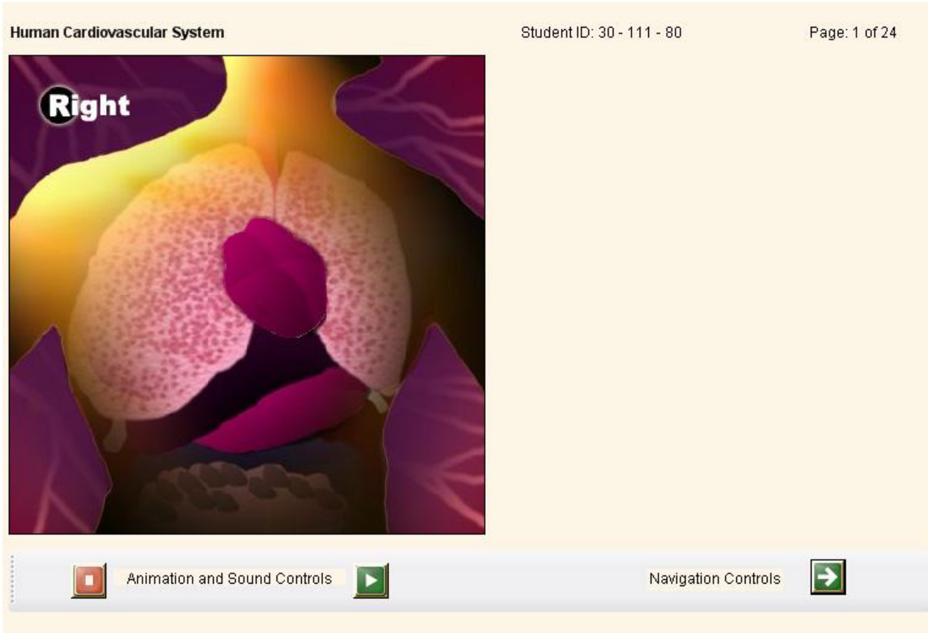

Figure 2. A Sample Screen of Uncued Animations

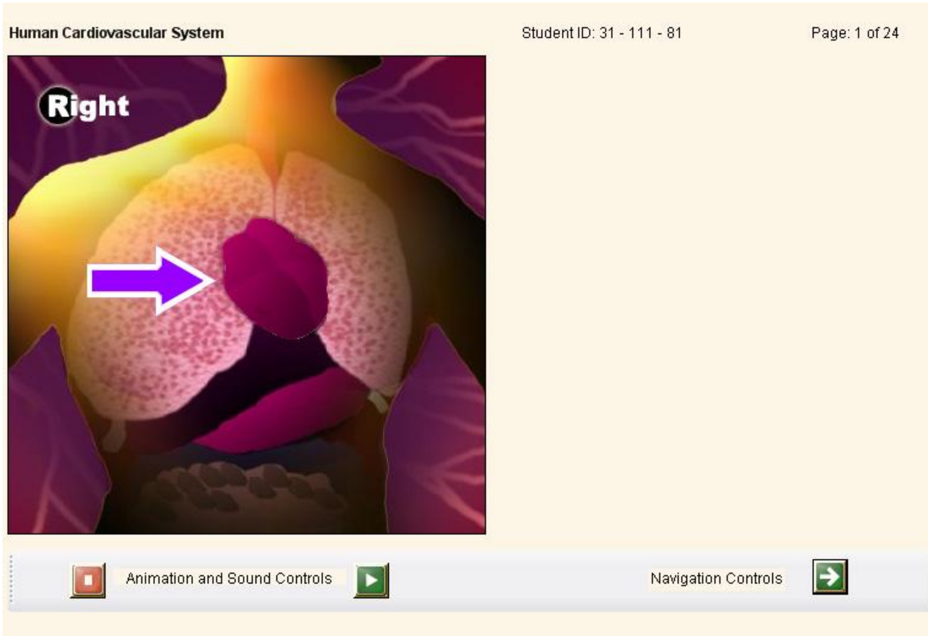

Figure 3. A Sample Screen of Cued Animations

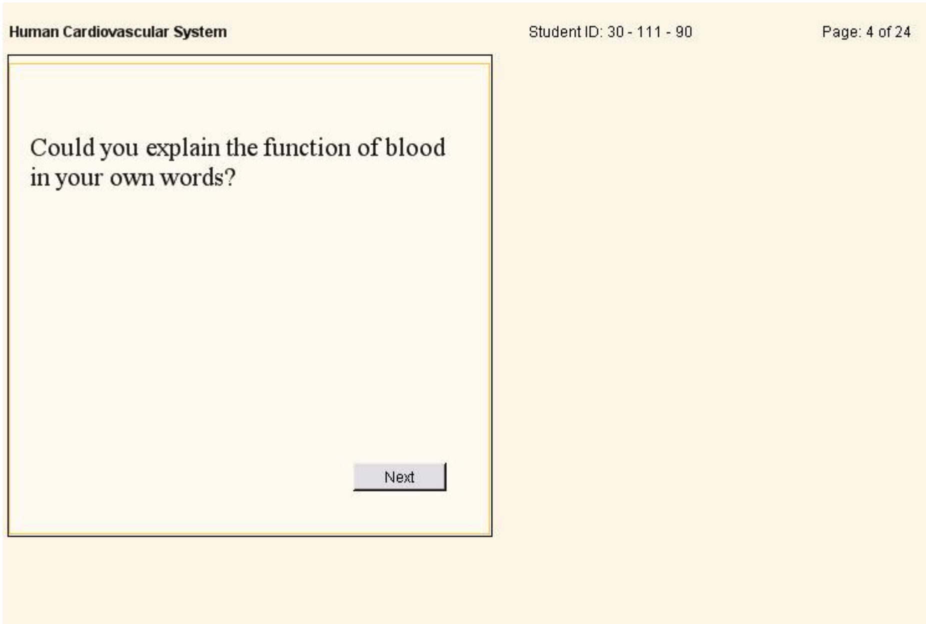

Figure 4. A Sample Prompting Question

Procedure

The study was conducted in a laboratory setting. At the beginning of the study, a researcher asked participants to sign a consent form for participation. Next, the researcher randomly selected a subsample of participants (49 out of 126, see Table 4) to have their eye movements recorded by the eye tracker. Each of the participants who were not selected to record their eye movements were seated at an individual cubicle, facing a computer, and were debriefed by the researcher about the procedure of the study. Then, they started the pretest on the computer with no time limit. After the completion of the pretest, he/she was provided with a randomly assigned experiment ID number to start the computer-based lesson. The purpose of using the experiment ID number was (a) to randomly assign each participant into one of the six experimental conditions, and (b) to preserve the anonymity of each participant. Once the participants completed the instruction, the attitude questionnaire were administered followed by the posttest. No activity had a time limit. The questionnaire had two parts: subjective cognitive load measures and intrinsic motivation measures. Upon completion of the questionnaire and the posttest, the participants were thanked. Each of the participants, who were randomly selected to have their eye movements recorded, was seated in a cubic, facing the eye tracker. The researcher utilized the Tobii Studio software to calibrate each individual's eyes with the eye tracker. After the calibration process, the procedure that the participant went through was identical to those individuals who were not eye-tracked. The participants, regardless of whether their eye movements were recorded, needed approximately 35 minutes to complete the entire study.

Chapter 3

RESULTS

Family-wise type I error rate was set at .05 level. Cohen's *f* or Cohen's *d* was used as an effect size index. Accordingly, .10, .25 and .40 are considered as the *f* values for small, medium and large effect sizes, and .20, .50 and .80 are considered as the *d* values for small, medium and large effect sizes (Cohen, 1988). All learning outcome scores were converted to percentage scores.

A subsample of the participants (49 out of 126, see Table 4) was randomly selected to participate in the study while seated at the eye tracker. Eye movement data were collected for these individuals. Eye movement data were not collected for the remaining individuals.

Learning Time

A two-way analysis of variance (ANOVA) was conducted to evaluate the potential effects of prompting and cueing on learning time. There were no main effects of prompting or cueing; nor was there any interaction (all Fs < 1.00, and all ps $> .30$).

Prior Knowledge

A two-way ANOVA was conducted to evaluate whether participants' prior knowledge differed across the six conditions. The results showed that there was no significant difference between the cueing conditions and no-cueing conditions, $F\ (1, 120) = 1.19$, $MSE = 9.11$, $p = .28$, $f = .10$, or the three prompting conditions (i.e., prediction-prompts conditions, reflection-prompts conditions, and no-prompts conditions), $F\ (2, 120) = .52$, $p = .60$, $f = .10$; nor was there any interaction, F (2, 120) = 2.36, p = .10, f = .20. Means and standard deviations (SDs) were presented in Table 5.

Learning Outcomes

A two-way analysis of covariance (ANCOVA) was conducted to evaluate the potential effects of prompting and cueing on the posttest percentage scores. Both learning time and the pretest percentage scores were used as the covariates to control for the potential effects learning time and prior knowledge on learning outcomes. As the correlation between learning time and the pretest percentage scores was not substantial (r = -.19, p = .04), multicollinearity was not a concern in the conducted ANCOVA. The homogeneity-of-slope assumption was evaluated. All interactions between the independent variables and the covariates were non-significant (Fs < 1.00 and ps > .30), except for the cueing by learning time interaction, F (1, 117) = 1.39, MSE = .02, p = .03. However, a two-way ANCOVA was conducted, taking into account that (a) the size of this significant effect was small (f = .21); (b) the significance test had relatively low power (power = .64); and (c) the difference of the adjusted means between cueing and no-cueing conditions was maintained at the mean, one SD above and below the mean of learning time (see plots in Figure 5). There was a significant main effect of visual cueing, F (1, 118) = 12.60, MSE = .02, p = .001, with a medium-to-large effect size, f = .33, power = .96. Participants assigned to the cueing conditions (adjusted Mean = .76, standard error = .02) scored significantly higher on the posttest than their peers who were assigned to no-cueing conditions (adjusted Mean = .68, standard error = .02), taking into account the effect of pretest and learning time. However, the main effect of prompting and the interaction effect of prompting-by-cueing were non-significant; prompting main effect, F (1, 118) = 1.15, p = .32, f = .14, prompting by cueing interaction, F (1, 118) = .67, p = .52, f = .11. Descriptive statistics were presented in Table 5.

It is of note that the participants who viewed the uncued animations and were not prompted had the lowest (adjusted and unadjusted) posttest scores. Therefore, a series of two-group comparisons, controlling for the pretest percentage scores and learning time, were conducted to determine whether the uncued- animations/no-prompts condition was the worst condition, compared to the other five conditions. To control for the type I error, the Bonferroni procedure was used and the alpha level for each comparison was set at .01 (.05/5). Significant differences were found between the uncued- animations/no-prompts condition and (a) the cued-animations/prediction-prompts condition, t(40) = 3.31, p = .001, Cohen's d = 1.02; (b) the cued-animations/no-prompts condition, t(40) = 2.79, p = .006, Cohen's d = .86; and (c) the cued-animations/reflection-prompts condition, t(40) = 2.92, p = .004, Cohen's d = .90. Non-significant differences were found between the uncued- animations/no-prompts condition and (a) the uncued-animations/prediction-prompts condition, t(40) = 1.18, p = .24, Cohen's d = .36, and (b) the uncued-animations/reflection-prompts condition, t(40) = 1.79, p = .08, Cohen's d = .55.

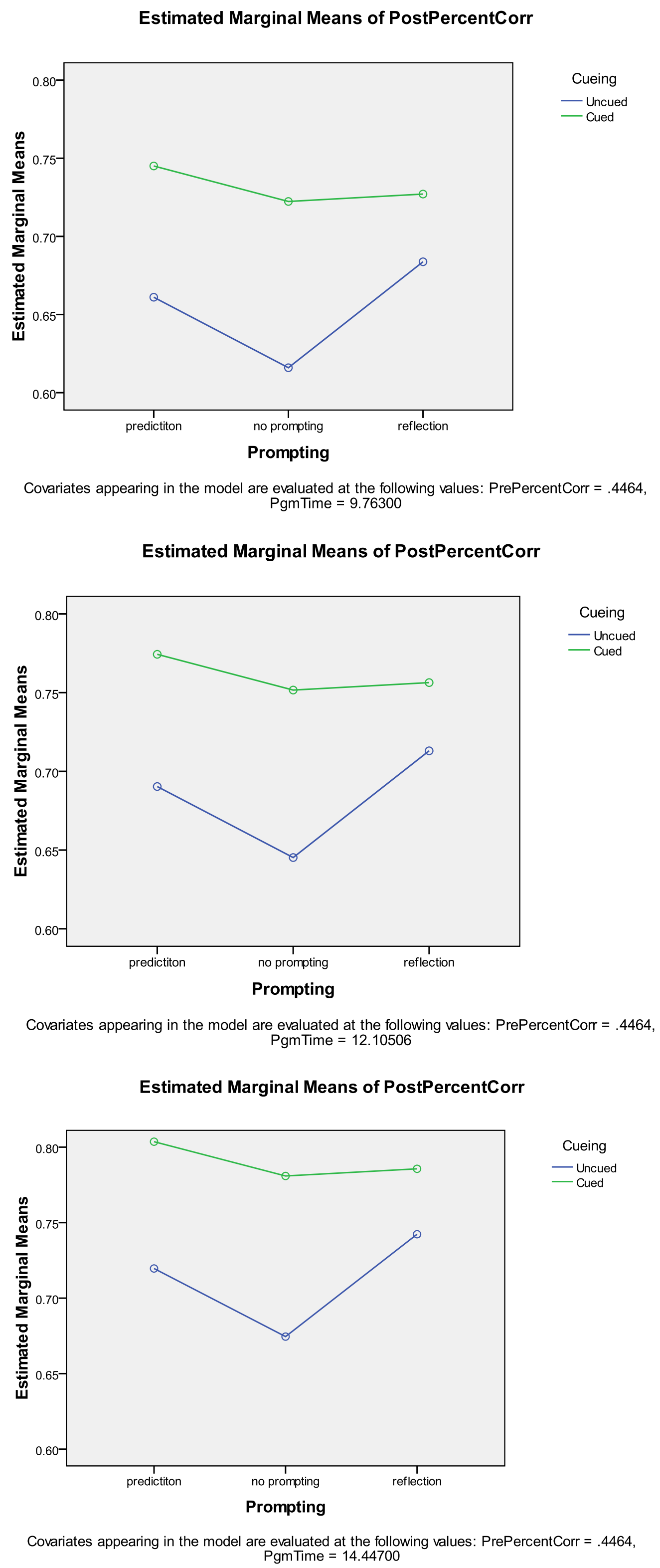

Figure 5. Plots of Adjusted Means of Posttest Percentage Scores at the Mean, One SD above and below the Mean of Learning Time

Construct Validation

Confirmatory factor analyses (CFA) were conducted on the five cognitive load measures and 21 intrinsic motivation measures respectively to validate the structure of the two core constructs in multimedia learning—cognitive load and intrinsic motivation. Mplus 6.1 was the software package used for testing the fit of the models. Robust maximum likelihood was used as the estimation technique to overcome the potential non-normality due to the Likert-type data. The fit of the hypothesized models was assessed based on global fit indices—the chi-square statistic (and *p* value), the robust comparative fit index (CFI), and the robust root mean-square error of approximation (RMSEA). According to Hu and Bentler (1999), an RMSEA of less than 0.05 and a CFI of greater than 0.95 were considered as indications of good fit of a specified model.

Cognitive load.

According to cognitive load theory, intrinsic, extraneous, and germane cognitive load are the three subcomponents of cognitive load. Practically, however, a CFA model with three latent factors and five observed items cannot be identified[1]. Therefore, a one-factor CFA model with five observed variables (task demand, effort, navigational demand, perceived success, and stress) was tested for model fit (see Figure 6). The theoretical assumption of the one-factor model was that a general factor—the overall cognitive load—existed.

[1]In an identified CFA model, "the number of free parameters is less than or equal to the number of observations" (Kline, 2005, 169-170).

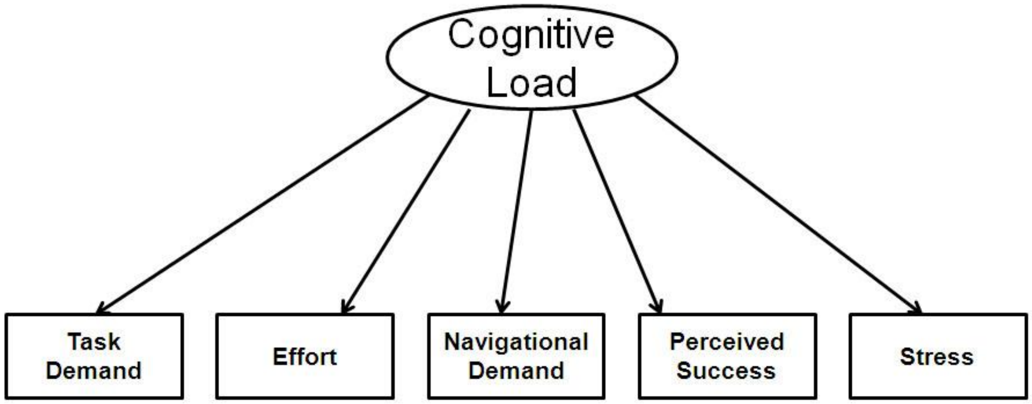

Figure 6. One-factor Model of Cognitive Load

The results showed that the one-factor model was acceptable in terms of model fit, $\chi^2(5) = 11.94$, $p = .04$, CFI = .95, RMSEA = .11 with 90% confidence interval [.03, .18]. This empirical evidence supported the hypothesized structure of an overall cognitive load. Correlations between the five subjective cognitive load measures were presented in Table 6.

Intrinsic motivation.

Four CFA models were hypothesized as the structure of intrinsic motivation. Model 1 (see Figure 7) was a single–factor model to address the question “Is intrinsic motivation uni-dimensional?” Model 2 (see Figure 8) was a six-factor model based on the existing six subscales of the 21 measures (i.e., interest, competence, value, effort, pressure and choice). Model 3 (see Figure 9) was a bifactor model with a general factor to account for the commonality of all measures, and six specific factors to account for the unique influence above and beyond the general factor. Model 4 (see Figure 10) was a higher-order model with a single second-order factor and six first-order factors.

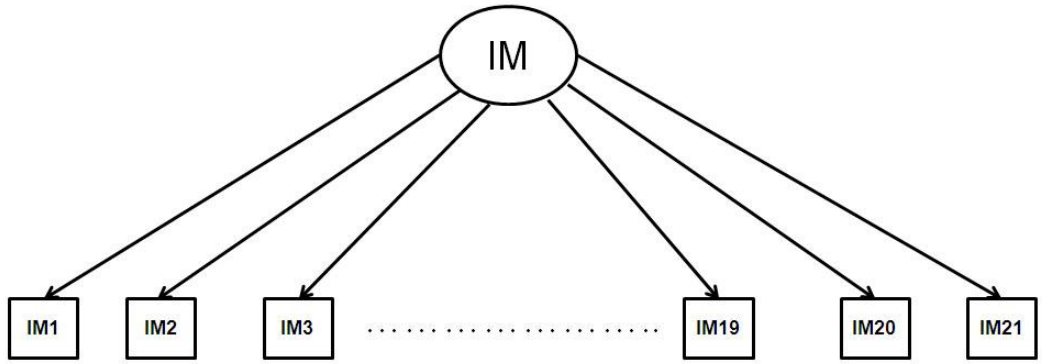

Figure 7. One-factor Model of Intrinsic Motivation

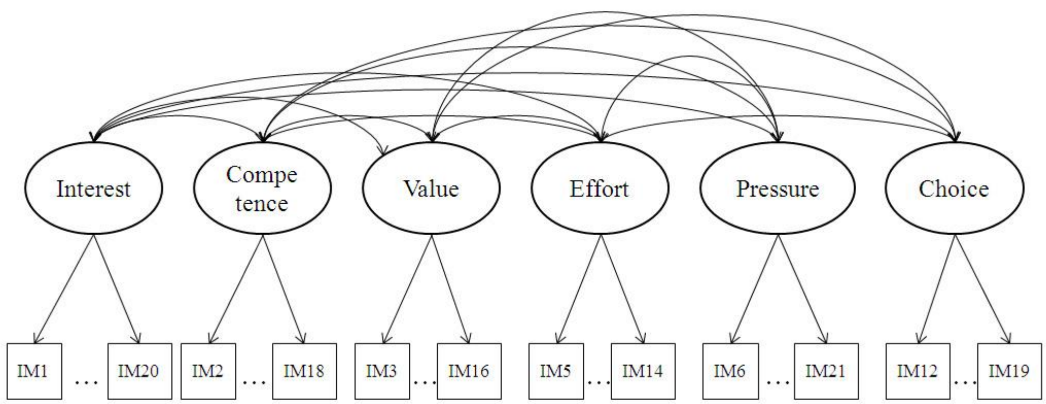

Figure 8. Six-factor Model of Intrinsic Motivation

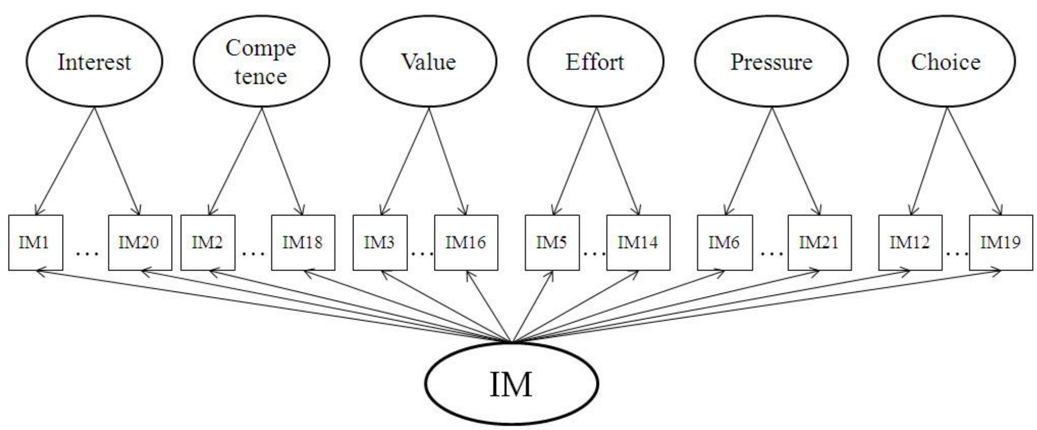

Figure 9. Bifactor Model of Intrinsic Motivation

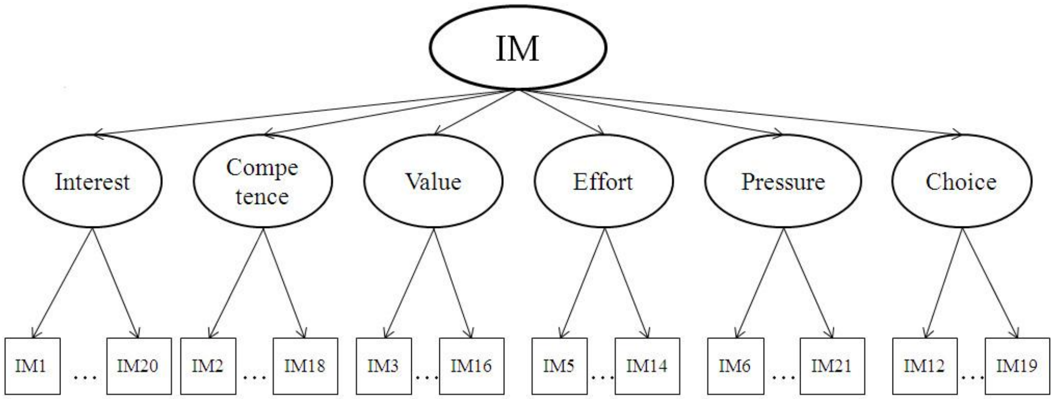

Figure 10. Higher-order Model of Intrinsic Motivation

The results estimated by the robust maximum likelihood estimation showed that the single-factor model, the six-factor model, and the higher-order model had poor fits: for the single-factor model, $\chi^2(189) = 767.07$, $p < .001$, CFI = .63, RMSEA = .16 with 90% confidence interval [.14, .17]; for the six-factor model, $\chi^2(174) = 314.77$, $p < .001$, CFI = .91, RMSEA = .08 with 90% confidence interval [.07, .09]; for the higher-order model, $\chi^2(183) = 366.64$, $p < .001$, CFI = .88, RMSEA = .09 with 90% confidence interval [.08, .10]. The fit of the bifactor model was acceptable, $\chi^2(153) = 220.85$, $p < .001$, CFI = .96, RMSEA = .06 with 90% confidence interval [.04, .08].

Three pairs of nested models—Model 1 (the single-factor model) nested within Model 3 (the bifactor model), Model 2 (the six-factor model) nested within Model 3, and Model 4 (the higher-order model) nested within Model 3—were compared. Correspondingly, three nested model tests were conducted to evaluate whether the bifactor model had a significantly improved model fit. The results revealed that the bifactor model had a better fit than (a) the single-factor model,

$\chi^2(36) = 643.62$, $p < .001$; (b) the six-factor model, $\chi^2(21) = 110.67$, $p < .001$; and (c) the higher-order model, $\chi^2(30) = 170.61$, $p < .001$.

In sum, the empirical data supported the bifactor structure of intrinsic motivation, in which a general factor explains the common variability underlying all measures, and six specific factors explain the unique variability underlying the measures.

Bivariate correlations between the 21 intrinsic motivation measures were presented in Table 7.

Cognitive Load

A two-way multivariate analysis of covariance (MANCOVA) was conducted to determine the potential effects of prompting and visual cueing on the five cognitive load measures—task demand, effort, navigational demand, perceived success, and stress; using the pretest percentage scores and learning time as the covariates. The homogeneity-of-slope assumption was not violated (all Fs< 1.00 and all ps > .50). The results showed that neither of the two main effects was significant; for the prompting main effect, Wilks' lambda = .92, F (10, 228) = 1.00, $p = .45$, $f = .21$, for the visual cueing main effect, Wilks' lambda = .97, F (5, 114) = .75, $p = .59$, $f = .18$. In addition, there was a non-significant interaction, Wilks' lambda = .88, F (10, 228) = 1.48, $p = .15$, $f = .25$. Based on the results of CFA on the cognitive load measures, the one-factor model was acceptable. Therefore, means of the five cognitive load measures were computed for all participants to represent the overall cognitive load. A two-way ANCOVA was conducted to evaluate the potential impacts of cueing and prompting on the overall cognitive load, using the pretest percentage scores and learning time as the covariates. No significant difference was found in the main effect of cueing, $F < 1.00$, $p > .90$, the main effect of prompting, $F < 1.00$, $p > .62$, or the interaction, $F(2, 118) = 1.13$, $p = .33$, $f = .14$. Means and SDs were presented in Table 8.

Intrinsic Motivation

Based on the results of CFA that supported the bifactor structure of intrinsic motivation, both the general aspect and the specific aspect of intrinsic motivation were considered. Means of the 21 intrinsic motivation items were computed for all participants to represent the general intrinsic motivation. A two-way ANCOVA was conducted to evaluate the potential impacts of cueing and prompting on intrinsic motivation, using the pretest percentage scores and learning time as the covariates. No significant difference was found in terms of the cueing main effect, $F(1, 118) = 1.63$, $p = .20$, $f = .12$, the prompting main effect, $F(2, 118) = 2.24$, $p = .11$, $f = .20$, or the interaction, $F(2, 118) < 1.00$, $p > .39$. Means of the six subscales of the intrinsic motivation measures—interest, competence, value, effort, pressure and choice—were also computed to represent the specific aspects of intrinsic motivation. A two-way MANCOVA was then conducted to determine the potential effects of prompting and visual cueing on these six intrinsic motivation subscales, using the pretest percentage scores and learning time as the covariates. The homogeneity-of-slope assumption was not violated (all Fs < 1.45 and all ps $> .15$). The results showed that neither of the two main effects was significant; for the prompting main effect, Wilks' lambda = .91, $F(12, 113) = .92$, $p = .52$, $f = .22$, for the visual cueing main effect, Wilks' lambda = .96, F (12, 113) = .76, p = .60, f = .20. In addition, there was a non-significant interaction, Wilks' lambda = .89, F (12, 226) = 1.15, p = .32, f = .25. Descriptive statistics were presented in Table 9.

Relationships Among Learning, Cognitive Load & Intrinsic Motivation

A hybrid structural equation model (SEM) was hypothesized to explore the relationships among learning, cognitive load, and intrinsic motivation in the multimedia environment. In order to control for the potential effects of learning time and prior knowledge, two observed variables—learning time and the pretest percentage scores—were included in the model as the control variables. Mplus 6.1 was software used for the analysis. The maximum likelihood estimation was used for the parameter estimation.

A series of preliminary analyses were conducted to find the appropriate structure to represent intrinsic motivation in this hybrid SEM model. Taking into account the identification issue, multicollinearity, and the overall model fit, the final model included all six measures in the interest subscale to represent the (latent) intrinsic motivation, as well as all five measures to represent the (latent) overall cognitive load (see Figure 11).

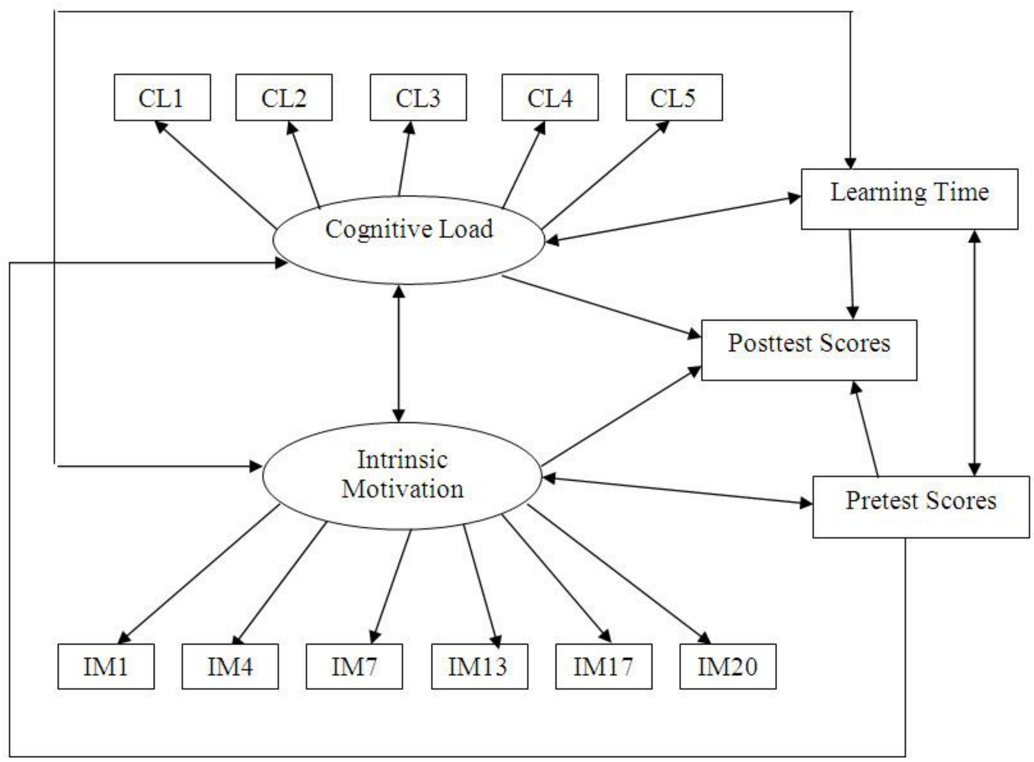

Figure 11. Relationships Among Learning, Cognitive Load & Intrinsic Motivation

First, the hybrid SEM model was fit to the entire sample in the study, which included 126 participants. The overall model fit was acceptable taking into account the moderate sample size, $\chi^2(70) = 162.05$, $p < .001$, CFI = .92, RMSEA = .10 with 90% confidence interval [.08, .12]. The results showed that latent overall cognitive load predicted the posttest scores in a negative direction, $z = -2.29$, $p = .02$; whereas latent intrinsic motivation was not a strong predictor, $z = 1.41$, $p = .16$. The latent overall cognitive load and intrinsic motivation were not substantially correlated, $r = -.15$, $p = .14$. In addition, the observed pretest scores and learning time significantly predicted the posttest scores in a positive direction.

As the participants in the cueing conditions were qualitatively different from their peers in no-cueing conditions, a multiple-group model (based on the hybrid model) using cueing as the grouping variable (cueing and no-cueing) was tested to see if visual cueing had any moderation effect on the relationships among learning, cognitive load, and intrinsic motivation. The multiple-group model had an acceptable fit, χ^2 (158) = 255.99, p < .001, CFI = .92, RMSEA = .10 with 90% confidence interval [.08, .12]. In the no-cueing group, the results revealed that the latent overall cognitive load significantly predicted the posttest scores in a negative direction, z = -2.05, p = .04, whereas the latent intrinsic motivation didn't, z = -.76, p = .45. The size of correlation between the latent overall cognitive load and intrinsic motivation was small, r = -.20, p = .13. In the cueing group, the latent overall cognitive load was not a strong predictor, z = -1.65, p = .10, whereas the latent intrinsic motivation was, z = 2.21, p = .03. The size of correlation between the latent overall cognitive load and intrinsic motivation within the cued group was small, r = -.08, p = .56. In sum, cognitive load and intrinsic motivation had different impacts on learning in multimedia due to the moderation effect of visual cueing.

Parameter estimates for these two-step model tests were presented in Table 10.

Due to the relatively small sample size (N = 42) within each prompting condition (prediction prompts, reflection prompts and none) and the large set of estimated parameters, the multiple-group model, which was based on the hybrid model and used prompting as the grouping variable, produced biased standard errors for the model parameters. Therefore, the results of this model were not trustworthy and not reported.

Eye Tracking Measures

Three areas of interest (AOIs) were defined (see Figure 12). Eye movement parameters—the total fixation duration (in seconds) and the total fixation count (in frequencies)—were computed for these three AOIs separately by utilizing Tobii Studio. Preliminary data screening revealed that the total fixation duration and the total fixation count in AOI2 and AOI3 were identical for each participant. Therefore, only eye movement data from AOI1 and AOI2 were used in the analysis.

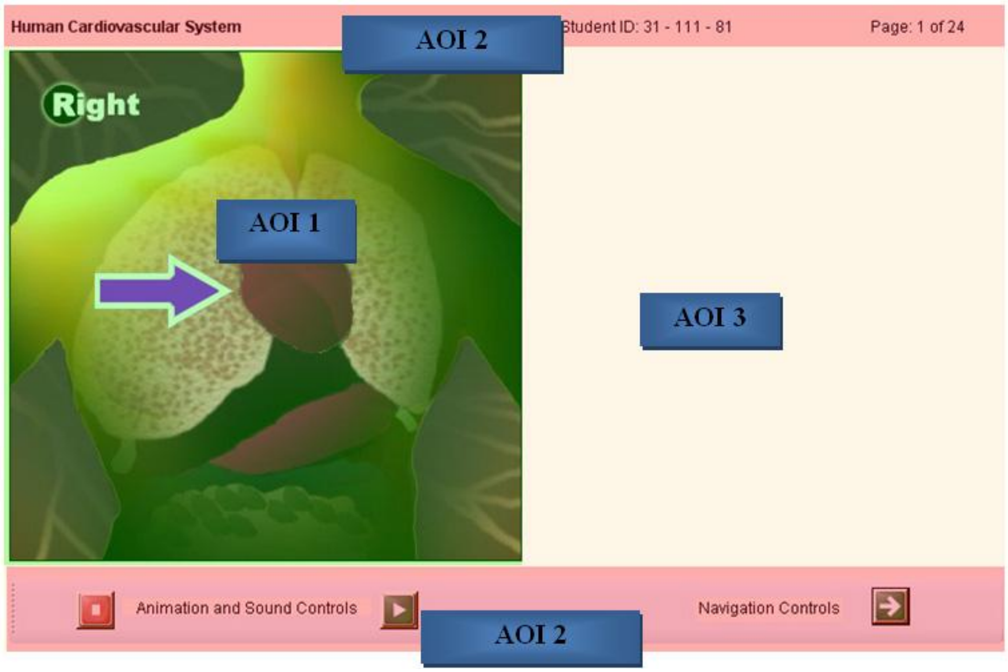

Figure 12. Areas of Interest

A subsample (49 out of 126) of participants' eye movements were successfully recorded by the eye tracker. The remaining 77 participants' eye movement data were missing, and resulted in a 61% missing data rate. The missing data mechanism in this situation was considered as missing completely at random (Rubin, 1976), i.e., the cause of missing the eye movement data were neither related to the eye movement data themselves, nor related to any other variables collected from the present study. Therefore, the maximum likelihood estimation, one of the state-of-the-art techniques for handling missing data (Enders, 2010; Schafer & Graham, 2002), was used to analyze these eye movement data.

Preliminary analyses found that the posttest scores, learning time, intrinsic motivation subscales (interest, competence, value, pressure, choice), and the five cognitive load measures were correlated with the eye-movement variables, which had missing data. Taking into account the correlations between the variables, a subset of these variables—the posttest scores, learning time, choice from the intrinsic motivation scale and stress from the cognitive load measures—were incorporated in the missing data analysis as auxiliary variables[2] to increase power and reduce standard error (Collins, Schafer, & Kam, 2001).

Five dummy coded variables were used to represent the six experimental conditions. Specifically, using the no-prompts condition as the reference group, the three prompting conditions were dummy coded into two variables, representing the prediction-prompts/no-prompts comparison and reflection-prompts/no-prompts comparison, respectively. Visual cueing was also dummy

[2] Auxiliary variables are variables that are included in the analysis "because they are either correlates of missingness or correlates of an incomplete variable" (Enders, 2010, p.17).

coded, and then multiplied by each of the two prompting dummy coded variables to create two variables to represent the interaction terms.

The substantive analysis models were four regression models with the total fixation duration from AOI1 and AOI2 and the total fixation count from AOI1 and AOI2 as dependent variables, respectively (for an example model, see Figure 13). The five dummy coded variables were included in the regression models as the independent variables. The quality of eye tracking recording, represented by a percentage of valid eye tracking samples, was also included in the models as a control variable. Alpha was set at .013 (.05/4) for each regression model to control for the type I error. It is of note that, rather than the ordinal least squares estimation, maximum likelihood was used to estimate the regression coefficients. The four auxiliary variables, which were not of substantive interest, were not included in the regression model but were programmed into the analysis to increase power and reduce standard errors. Mplus 6.1 was used for these analyses. Estimated model parameters were presented in Table 11.

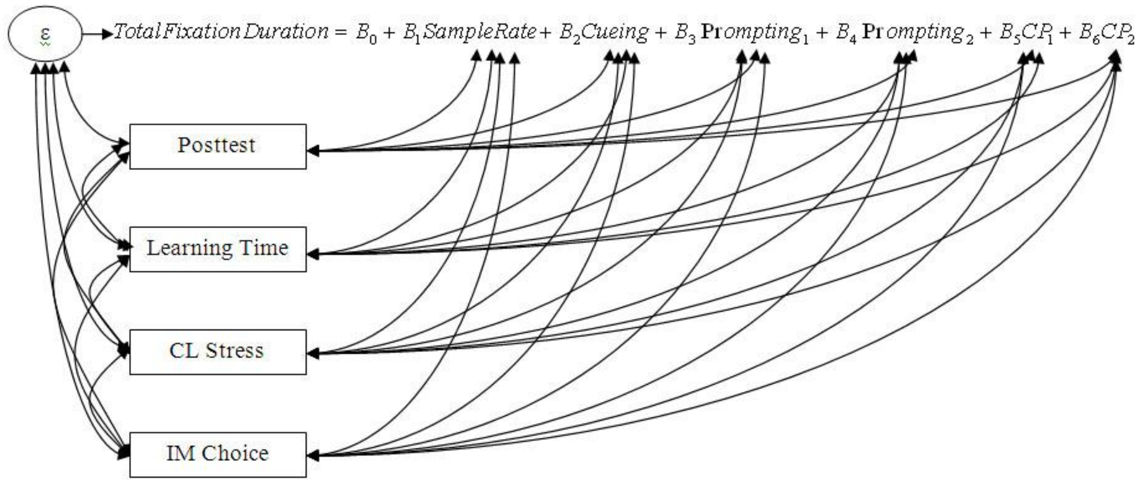

Figure 13. A Missing Data Analysis Model Including a Substantive Regression Model and Auxiliary Variables

In the first regression model where the total fixation duration in AOI1 regressed on the sample rate and the experimental conditions, the model was non-significant, $R^2 = .18$, $z = 1.30$, $p = .19$. None of the predictors were significant, all *z*s in the range of [-1.04, 1.91], all *p*s > .06. The regression model in which the total fixation duration in AOI2 regressed on the same predictors were also non-significant, $R^2 = .26$, $z = 1.60$, $p = .11$. Although the sample rate negatively predicted the total fixation duration in AOI2, $z = -2.13$, $p = .03$, other predictors of interest were not significant, all *z*s in the range of [-1.10, 1.23], all *p*s > .22. The third and fourth model, in which the total fixation count in AOI1 and AOI2 regressed on the sample rate and the experimental conditions, were not significant either, for AOI1, $R^2 = .15$, $z = 1.41$, $p = .16$; for AOI2, $R^2 = .25$, $z = 1.88$, $p = .06$. The estimated regression coefficients of the five dummy coded variables, which represented the six conditions, were non-significant in the two models, all *z*s in the range of [-2.03, 1.24], all *p*s > .04. Based on these results, neither visual cueing nor self-explanation prompting had any effect on learners' eye movement.

Chapter 4

DISCUSSION

Discussion of the Main Purpose

The purpose of the current study was to investigate the impacts of visual cueing and different types of self-explanation prompts on learning, cognitive load, and intrinsic motivation—as well as the potential interaction between the two instructional aids—in a multimedia environment that delivered instruction about the human cardiovascular system via a series of animations accompanied by human narrations. The results revealed two significant findings: (a) participants presented with visually cued animations had significantly higher learning outcome scores than their peers who viewed uncued animations; and (b) cognitive load and intrinsic motivation had different impacts on learning in multimedia due to the moderation effect of visual cueing. There were no other significant findings in terms of learning outcomes, cognitive load, intrinsic motivation, and eye movements. Limitations, implications, and future directions are discussed within the framework of cognitive load theory, cognitive theory of multimedia learning and cognitive-affective theory of learning with media.

Is visual cueing effective to enhance learning? One of the significant findings of the study was that using visual cueing device enhanced knowledge acquisition in the domain. This is consistent with a number of empirical studies in the current literature (e.g., de Koning et al., 2007, 2010b; Jeung et al., 1997; Kalyuga, Chandler & Sweller, 1999; Lin & Atkinson, 2011). In contrast to recent findings (Boucheix & Lowe, 2010), the unique contribution of this medium-to-large cueing effect is that the arrow cues utilized in the current study are not a suboptimal visual cueing device. Specially designed arrow cues are effective to enhance learning, even in the specific conditions that provide self-explanation prompts. In the current study, there was only one arrow pointing to the important visual part for each segment of the animations. Consequently, learners may be able to easily focus their attention on the arrow-pointed visualizations. Therefore, visual search activity may be reduced, which leads to the enhanced learning. On the other hand, too many arrows applied in a single animation, like in Boucheix and Lowe's study, may not be effective to reduce learners' visual search. They may add more complexity to the animation and result in the possibility that learners don't know where they should pay special attention. Therefore, the implication for instructional design based on the findings is that arrow cues have great potential to enhance learning in a multimedia environment on the condition that they are used sparingly.

Is visual cueing an effective technique to direct learners' attention in a multimedia environment? It is of note that, similar to the results revealed by Lowe and Boucheix (2011), the analysis conducted on the learners' eye movement data did not provide the evidence to support the visual cues' attention-directing effect. The finding of this non-significant effect is not surprising, considering the weak effect and the lack of empirical evidence reported in the current literature. One possible explanation is that some unknown factors, such as the salience of visual representations, the time of studying the animation, and learners' interest, may moderate or mediate the attention-directing effect of visual cueing. For instance, visual cues, like arrows and color codes, may compete with the multiple dynamic elements or diverse colors included in an animation to attract learners' attention. Also, this competition may depend upon the time that learners view the animations—cueing is effective to direct learners' attention for the initial presentation of cued animation, but the cueing effect wanes after multiple exposures (de Koning et al., 2010; Lower & Boucheix, 2011). Or visual cues may influence learners' interest, which mediates their attention. Future research should identify these moderators and mediators. On the other hand, the non-significant results may be due to the relatively low power caused by the high missingness of the eye tracking data (i.e., 61% missingness). Future empirical studies are recommended to collect as many participants' eye movement data as possible to overcome the limitation of the current study.

What are the relationships among learning, cognitive load, and intrinsic motivation in the multimedia environment? In the literature related to multimedia learning, the impacts of visual cueing, self-explanation prompts, or other instructional aids were investigated separately on learning, cognitive load, and motivation. The relationships among these constructs in the multimedia learning are unknown. The current study directly addressed this issue to make contributions to the literature. The results revealed that cognitive load and potentially intrinsic motivation were significant predictors of learning, taking into account learners' prior knowledge and learning time. In addition, visual cueing moderated the relationships among the three outcome variables—when visual cues were provided in the multimedia environment, intrinsic motivation significantly impacted learning; whereas cognitive load had a significant impact on learning when visual cues were not present in the environment. The findings with regard to the visual cueing' moderation effect imply that visual cueing may impact learning, cognitive load, and intrinsic motivation in an indirect way, even though its direct impacts on cognitive load and intrinsic motivation are not obvious (i.e., statistically non-significant). Therefore, motivational and cognitive constructs, in addition to learning, should be considered and measured in the multimedia research and cognitive load research, as they each contribute differently to learning by being significant predictors. Theoretically, the cognitive-affective framework of multimedia learning (*cognitive-affective theory of learning with media*, cf. Brünken et al., 2010; Moreno, 2009; Moreno & Mayer, 2007) incorporates all three variables, which provide theoretical underpinning for the findings of the current study. Due to the relatively small sample size in contrast to the complex estimation model, the current study did not investigate the potential moderation effect of self-explanation prompts. Nevertheless, it is worthwhile to address this issue in future research when more participants are recruited. It is important to note in the findings that cognitive load was not substantially correlated with intrinsic motivation. Consequently, mediation effects are not applicable (Baron & Kenny, 1986). Thus, the two factors—cognitive load and intrinsic motivation—make unique contribution to learning in the multimedia context. Since Moreno and Mayer (2007) pointed out that motivation mediated learning in multimedia, a future research direction can be to clarify whether motivation and cognitive load uniquely contribute to learning or mediate learning.

Do different types of self-explanation prompts have any impact on learning, cognitive load, and intrinsic motivation? The purpose of the current study to introduce self-explanation prompts was to engage learners in active and deep cognitive processes and to investigate the potential interaction between self-explanation prompting and visual cueing. The results did not reveal any learning, cognitive, or motivational benefits of self-explanation prompts, regardless of whether they were administered right before the delivery of the related instruction to prompt learners to predict what was to be learned or right after the related instruction to let learners reflect on what they had learned. Similarly, some empirical studies also revealed the non-significant results (de Koning, et al., 2010b; Große & Renkl, 2006; Experiment 1 & 2, Moreno & Mayer, 2005) of self-explanation prompting. Gerjets, et al (2006) even found a small preventative effect on learning reported in the literature. Therefore, the non-significant prompting effect found in the current study is consistent with what has been revealed in some previous studies. One could argue that the study might find the prompting effect, if learners were asked to self-explain via think-aloud or typing methods. However, this may not be the fundamental mechanism that contributes to the results in the study, as some studies found the prompting effect without asking learners to engage in written or spoken self-explanations (Atkinson, et al., 2003; Hegarty, et al., 2003; Mayer, et al., 2003, Experiment 3; Moreno, Reisslein, & Ozogul; 2009, Experiment 3; Moreno, 2009). In the future, researchers should focus on specific factors that influence the self-explanation activities in multimedia learning.

Do learners in the uncued-animations/no-prompts condition need visual cues or self-explanation prompts to support learning? Specific group comparisons revealed that learners' posttest scores in the uncued-animations/no-prompts condition were the lowest among the six experimental conditions and were significantly lower than the scores in the three cueing conditions (with large effect sizes). This finding, along with Berthold and Renkl's findings (2009), provide some evidence that learners indeed need some instructional aids, especially visual cueing, in multimedia learning. What differs between the current study and the Berthold and Renkl study is that the current study found no benefits of self-explanation prompts, whereas Berthold and Renkl found self-explanation prompts fostered both conceptual understanding and misconceptions. The implication for instructional design is that techniques to direct learners' attention are important in multimedia learning. However, taking into account the findings with regard to the relationships among learning, cognitive load, and intrinsic motivation, instructional designers and educational researchers could also consider other instructional aids that have the potential to impact learners' interests, motivation, and ultimately, their learning.

Discussion of the Supplemental Research Questions

The current study also addressed two supplemental research questions about the structure of two constructs in multimedia research—cognitive load and intrinsic motivation. Recent theory development in cognitive load pointed out the central role of element interactivity in intrinsic, extraneous, and germane load (Sweller, 2010). Thus, the assumption that an overall cognitive load exists was tested. The related findings in the current study supported this assumption. The recommendations for researchers are that it is theoretically and empirically reasonable to (a) measure the overall cognitive load or (b) compute this load based on multiple cognitive load measures. The bare fact is that how to measure cognitive load is still an open question. Consequently, the cognitive load structure in the current study was limited to a single-factor model. Future research should provide more measures so that more cognitive load structures (models) could be hypothesized and tested to explain the relationships among intrinsic, extraneous, germane, and overall cognitive load, as well as the relationships between learning and motivation.

With respect to intrinsic motivation, the results preferred the bifactor model to the single-factor model, the six-factor model, and the second-order factor model. Methodologically, a bifactor model, in which a general factor explains the commonality within the measures and six specific factors explain the unique variations, has some advantages for substantive research and interpretation (Chen, West, & Sousa, 2006; Reise, Morizot & Hays, 2007). Substantively, the implication is that intrinsic motivation is multi-faceted. The investigation of the impacts of the instructional techniques on intrinsic motivation should not only consider the general factor interpretation, but also look into the variations in the level of specific domains/factors.

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Table 1

Cognitive Load Measures

Item	**Measure**
1. How much mental and physical activity was required to accomplish the learning task, e.g., thinking, deciding, calculating, remembering, looking, searching, etc.?	Task Demands
2. How hard did you have to work in your attempt to understand the contents of the learning environment?	Effort
3. How much effort did you have to invest to navigate the learning environment?	Navigational Demands
4. How successful did you feel in understanding the contents?	Perceived Success
5. How insecure, discouraged, irritated, stressed, and annoyed did you feel during the learning task?	Stress

Note. Questions were adapted from the NASA-TLX (Hart & Staveland, 1988).

Table 2

Intrinsic Motivation Measures

Item	Subscale
1. I thought it was a boring activity.	Interest
2. I think I was pretty good at this activity.	Competence
3. I think that doing this activity could be useful.	Value
4. I thought this activity was quite enjoyable.	Interest
5. I didn't try very hard to do well at this activity.	Effort
6. I did not feel nervous at all while doing this.	Pressure
7. This activity did not hold my attention at all.	Interest
8. I believe I had some choice about doing this activity.	Choice
9. It was important to me to do well at this task.	Effort
10. I believe doing this activity could be beneficial to me.	Value
11. I felt very tense while doing this activity.	Pressure
12. I did this activity because I had no choice.	Choice
13. This activity was fun to do.	Interest
14. I put a lot of effort into this.	Effort
15. This was an activity that I couldn't do very well.	Competence
16. I believe this activity could be of some value to me.	Value
17. I would describe this activity as very interesting.	Interest
18. I am satisfied with my performance at this task.	Competence
19. I did this activity because I wanted to.	Choice
20. I enjoyed doing this activity very much.	Interest
21. I felt pressured while ding these.	Pressure

Note. Measures were adapted from Ryan (Ryan, 1982) and McAuley, Duncan, and Tammen (1989).

Table 3

Self-Explanation Prompts

Item
1. Could you explain the function of blood in your own words?
2. Could you explain how the blood vessels work?
3. Could you explain pulmonary circulation and systemic circulation in your own words?
4. Could you explain the process of material exchange in your own words?

Table 4

Number of Participants Who Had Eye Movement Data

Visual Cues	Types of Self-explanation Prompts	Sample Size within Each Condition
Present	No Prompts	9
	Prediction Prompts	8
	Reflection Prompts	8
Not Present	No Prompts	8
	Prediction Prompts	8
	Reflection Prompts	8

Table 5

Descriptive Statistics of Pretest & Posttest

			Pretest Percentage		Posttest Percentage		
		N[a]	M	SD	M	SD	Adj. M
Cues	NP	21	.42	.14	.73	.15	.74
	PP	21	.39	.12	.73	.15	.77
	RP	21	.49	.18	.79	.16	.77
No Cues	NP	21	.48	.19	.67	.15	.66
	PP	21	.47	.12	.70	.16	.70
	RP	21	.44	.14	.70	.19	.70

Note. M = Mean. SD = Standard Deviation. Adj. = adjusted. NP = No Prompts. PP = Prediction Prompts. RP = Reflection Prompts.
[a]Sample size within conditions.

Table 6

Bivariate Correlations Between Cognitive Load Measures

	TD	ET	ND	PS
ET	.73			
ND	.41	.49		
PS	-.40	-.49	-.39	
SS	.38	.49	.37	-.48

Note. All bivariate correlations were significant at .01 level. TD = Task Demands. ET = Effort. ND = Navigational Demands. PS = Perceived Success. SS = Stress.

Table 7

Bivariate Correlations Between Intrinsic Motivation Measures

	IM1	IM2	IM3	IM4	IM5	IM6	IM7	IM8	IM9	IM10	IM11	IM12	IM13	IM14	IM15	IM16	IM17	IM18	IM19	IM20
2	.35																			
3	.32	.41																		
4	.73	.56	.49																	
5	.26	.15	.27	.27																
6	-.22	-.29	-.23	-.19	.06															
7	.68	.49	.42	.68	.32	-.19														
8	.35	.41	.27	.39	.22	-.24	.37													
9	.49	.31	.35	.60	.41	-.05	.46	.42												
10	.31	.32	.63	.49	.25	-.10	.39	.32	.49											
11	-.20	-.34	-.23	-.26	.09	.49	-.23	-.21	-.02	-.16										
12	.34	.29	.19	.34	.33	-.11	.37	.69	.38	.18	-.13									
13	.77	.50	.44	.89	.26	-.22	.71	.43	.62	.48	-.25	.34								
14	.34	.10	.34	.33	.63	.14	.34	.17	.60	.41	.22	.15	.41							
15	.19	.44	.10	.32	-.07	-.35	.25	.31	.09	.06	-.52	.18	.28	-.16						
16	.43	.36	.61	.51	.27	-.20	.44	.36	.55	.88	-.15	.23	.56	.44	.04					
17	.71	.49	.49	.78	.31	-.09	.62	.44	.54	.53	-.23	.35	.81	.36	.16	.63				
18	.35	.60	.31	.46	.10	-.33	.44	.46	.44	.30	-.27	.42	.47	.20	.43	.37	.41			
19	.51	.40	.28	.54	.32	-.20	.44	.67	.55	.38	-.11	.65	.62	.32	.16	.45	.56	.52		
20	.69	.50	.39	.84	.28	-.16	.70	.42	.63	.48	-.20	.34	.88	.39	.26	.54	.78	.52	.61	
21	-.12	-.43	-.11	-.24	.05	.49	-.19	-.25	-.03	-.08	.61	-.13	-.19	.22	-.55	-.06	-.09	-.32	-.12	-.11

Note. IM = Intrinsic Motivation.

Table 8

Descriptive Statistics of Cognitive Load Measures

			Task Demands		Effort		Navigational Demands		Perceived Success		Stress		Overall CL	
		N[a]	M (SD)	Adj. M	M (SD)	Adj. M	M (SD)	Adj. M	M (SD)	Adj. M	M (SD)	Adj. M	M (SD)	Adj. M
Cues	NP	21	4.95 (2.03)	4.91	4.67 (2.00)	4.60	3.95 (2.36)	3.84	5.95 (1.77)	6.07	2.86 (1.78)	2.81	4.48 (1.14)	4.53
	PP	21	5.43 (1.66)	5.22	5.05 (1.75)	4.83	4.19 (2.40)	3.91	5.90 (1.41)	6.14	2.62 (1.69)	2.41	4.64 (1.09)	4.50
	RP	21	5.05 (2.29)	5.12	4.67 (1.88)	4.78	3.95 (2.38)	4.13	6.10 (1.58)	5.92	3.10 (1.84)	3.18	4.57 (1.12)	4.21
No Cues	NP	21	4.57 (1.69)	4.60	4.38 (1.77)	4.45	4.67 (2.06)	4.79	6.33 (1.11)	6.19	2.57 (1.43)	2.61	4.50 (1.01)	4.53
	PP	21	5.29 (2.15)	5.39	5.05 (1.91)	5.15	3.67 (2.35)	3.79	5.81 (1.21)	5.72	3.71 (2.08)	3.82	4.70 (1.22)	4.77
	RP	21	4.38 (2.29)	4.42	4.71 (2.28)	4.73	3.57 (2.60)	3.55	5.38 (1.60)	5.43	2.90 (1.67)	2.94	4.19 (1.19)	4.21

Note. M = Mean. SD = Standard Deviation. NP = No Prompts. PP = Prediction Prompts. RP = Reflection Prompts.
[a]Sample size within conditions.

Table 9

Descriptive Statistics of Intrinsic Motivation Measures

			Interest		Competence		Value		Effort		Pressure		Choice		IM	
		N[a]	M (SD)	Adj. M	M (SD)	Adj. M	M (SD)	Adj. M	M (SD)	Adj. M	M (SD)	Adj. M	M (SD)	Adj. M	M (SD)	Adj. M
Cues	NP	21	5.62 (1.46)	5.70	5.76 (1.52)	5.85	6.57 (1.32)	6.61	4.48 (1.07)	4.50	2.33 (1.23)	2.31	5.50 (1.77)	5.58	5.32 (.87)	5.37
	PP	21	5.61 (1.66)	5.72	5.74 (1.28)	5.89	6.48 (1.32)	6.53	4.38 (.89)	4.41	2.60 (1.43)	2.43	5.81 (1.82)	5.94	5.35 (1.04)	5.41
	RP	21	5.30 (1.97)	5.19	5.79 (1.61)	5.67	6.11 (1.64)	6.06	4.89 (.74)	4.86	2.60 (1.68)	2.66	5.81 (1.67)	5.70	5.28 (1.02)	5.20
No Cues	NP	21	5.98 (1.21)	5.88	6.13 (.96)	6.02	6.60 (1.08)	6.55	4.75 (.86)	4.71	2.11 (1.42)	2.12	6.25 (1.52)	6.16	5.56 (.76)	5.48
	PP	21	5.61 (1.69)	5.27	5.27 (1.57)	5.22	6.25 (1.38)	6.24	4.89 (.96)	4.88	2.95 (1.83)	3.04	4.97 (2.03)	4.92	5.10 (1.05)	5.08
	RP	21	4.69 (1.85)	4.75	5.02 (1.62)	5.07	6.09 (1.74)	6.13	4.41 (1.14)	4.43	2.50 (1.54)	2.48	4.75 (2.14)	4.79	4.69 (1.29)	4.73

Note. M = Mean. SD = standard deviation. NP = No Prompts. PP = Prediction Prompts. RP = Reflection Prompts. IM = Intrinsic Motivation.

[a]Sample size within conditions.

Table 10

Estimated Parameters in the Hybrid SEM Model

	Predictor	Unstandardized	Standardized	z	*p*	R^2
Entire Sample	CL	-.02	-.21	-.229	.02	.44
	IM	.01	.10	1.41	.16	
	LT	.01	.19	2.69	.01	
	Pre	.57	.53	6.87	.00	
Cued Group	CL	-.02	-.21	-1.65	.10	.46
	IM	.02	.21	2.21	.03	
	LT	.01	.22	2.29	.02	
	Pre	.51	.50	4.77	.00	
Uncued Group	CL	-.02	-.23	-2.05	.04	.53
	IM	-.01	-.07	-.76	.45	
	LT	.02	.21	2.25	.03	
	Pre	.72	.66	6.30	.00	

Note. CL = Cognitive Load. IM = Intrinsic Motivation. LT = Learning Time. Pre = Pretest Score.

Table 11

Estimated Parameters in the Regression Models Involving Eye Movement Data

	Predictor	Unstandardized	Standardized	Z	*p*	R^2
Total Fixation Duration in AOI1	Intercept	277.56		2.92	.00	.19
	Sample Rate	221.47	.31	1.91	.05	
	Cueing	-28.09	-.16	-.93	.35	
	Prediction	-8.82	-.05	-.30	.77	
	Reflection	-30.43	-.16	-1.04	.30	
	Interaction 1	28.11	.12	.65	.52	
	Interaction 2	72.55	.30	1.71	.09	
Total Fixation Duration in AOI2	Intercept	154.89		4.73	.00	.11
	Sample Rate	-81.46	-.29	-2.13	.03	
	Cueing	17.32	.24	1.23	.22	
	Prediction	-13.08	-.17	-.90	.37	
	Reflection	-13.02	-.17	-.92	.36	
	Interaction 1	-22.57	-.23	-1.10	.27	
	Interaction 2	-10.32	-.11	-.52	.61	
Total Fixation Count in AOI1	Intercept	1413.89		4.57	.00	.16
	Sample Rate	-430.53	-.18	-1.17	.24	
	Cueing	10.19	.02	.09	.93	
	Prediction	-240.95	-.39	-2.03	.04	
	Reflection	-102.431	-.16	-.88	.38	
	Interaction 1	209.47	.26	1.24	.22	
	Interaction 2	175.80	.22	1.07	.29	
Total Fixation Count in AOI2	Intercept	632.37		5.53	.00	.25
	Sample Rate	-404.40	-.41	-3.02	.00	
	Cueing	40.54	.16	.83	.41	
	Prediction	-51.36	-.19	-1.02	.31	
	Reflection	-38.83	-.15	-.79	.43	
	Interaction 1	-43.30	-.13	-.60	.55	
	Interaction 2	7.56	.02	.11	.91	

APPENDIX A

IRB APPROVAL

ARIZONA STATE UNIVERSITY

Research Compliance Office
Office for Research & Sponsored Projects Administration
P.O. Box 873503
Tempe, AZ 85287-3503

Phone
(480) 965-6788
Facsimile
(480) 965-7772

To:	Robert Atkinson EDB
From:	Mark Roosa, Chair Institutional Review Board
Date:	09/14/2007
Committee Action:	**Exemption Granted**
IRB Action Date:	09/14/2007
IRB Protocol #:	0508000145R002
Study Title:	Exploring the Efficacy of Pedagogical Agents: Do They Primarily Trigger Socio-Motivational or Cogr

The above-referenced protocol is considered exempt after review by the Institutional Review Board pursuant to Federal regulations, 45 CFR Part 46.101(b)(1) .

This part of the federal regulations requires that the information be recorded by investigators in such a manner that subjects cannot be identified, directly or through identifiers linked to the subjects. It is necessary that the information obtained not be such that if disclosed outside the research, it could reasonably place the subjects at risk of criminal or civil liability, or be damaging to the subjects' financial standing, employability, or reputation.

You should retain a copy of this letter for your records.

APPENDIX B

PRETEST

1. The valves in the heart are like
A. gates.
B. windows.
C. walls.
D. chambers.

2. The right ventricle pumps blood to
A. the left atrium.
B. the right atrium.
C. the left ventricle.
D. the lungs.

3. What is a difference between your heart muscle and the muscles in your legs and arms?
A. The heart can contract (flex) while your legs and arms cannot.
B. The heart muscle never relaxes, but your legs and arms do.
C. The heart muscle never relaxes, but your legs and arms do.
D. Your arms and legs need exercise, but your heart does not.

4. An atrium in the heart
A. is larger than a fist.
B. is a lower chamber.
C. is an artery.
D. is an upper chamber.

5. When blood returns to the heart from the body, where does it enter?
A. The right ventricle.
B. The right atrium.
C. The left ventricle.
D. The left atrium.

6. When you breathe,
A. plasma carries oxygen to the body.
B. plasma carries carbon dioxide to the body.
C. red blood cells carry oxygen to the body.
D. red blood cells carry carbon dioxide to the body.

7. How many chambers are there in your heart?
A. One.
B. Two.
C. Three.
D. Four.

8. You probably know that you can donate blood. You can also donate just the plasma part of the blood. If you donate plasma, you are donating the part that
A. carries oxygen to the body.

B. is the liquid part of the blood that carries nutrients.
C. carries carbon dioxide away from the body.
D. is red in color.

9. Why are there valves in veins and not in arteries?
A. Blood in veins flows under high pressure and the valves prevent backward blood flow.
B. Blood in veins flows under low pressure and the valves prevent backward blood flow.
C. Walls of veins are very elastic and the valves keep them from stretching.
D. Blood in veins flows under low pressure and the valves push blood through the veins.

10. Where does blood flow under the lowest pressure?
A. Leaving the heart and sending blood to the body.
B. Leaving the heart and sending blood to the lungs.
C. Through the capillaries.
D. Returning blood to the heart from the body.

11. Why do doctors take blood from a vein and not an artery?
A. Blood in veins do not move.
B. Blood in veins is under less pressure.
C. Blood in veins is moving toward the heart.
D. Veins have thick walls.

12. What is it that you are feeling when you take your pulse?
A. A vein stretching.
B. One ventricle contracting.
C. One atrium contracting.
D. An artery stretching.

13. Which option is the correct order (highest --> lowest) for blood pressure in blood vessels? Start with the highest pressure and end with the lowest pressure.
A. Artery -> capillary -> vein
B. Artery -> vein -> capillary
C. Vein -> capillary -> artery
D. Vein -> artery -> capillary

14. What is the path that deoxygenated blood follows?
A. Lungs -> heart -> body
B. Body -> lungs -> heart
C. Body -> heart -> lungs
D. Heart -> lungs -> body

15. The diastolic phase of the heartbeat is where
A. The ventricle is relaxed and the valves open.

B. The ventricle is contracted and the valves closed
C. The atrium is relaxed.
D. The blood pressure is at maximum output.

16. Humans have two kinds of circulation in the body. What are they called?
A. Systolic and Diastolic.
B. Pulmonary and Systemic.
C. Open and Closed.
D. Artery and Vein.

17. What is the pathway of blood during pulmonary circulation?
A. Heart -> Lung -> Heart
B. Lung ->Heart -> Body
C. Body -> Lung -> Heart
D. Lung -> Body -> Lung

18. Cholesterol is found in many of the foods we eat. Some kinds of cholesterol can stick to the walls of your arteries, making them narrower or even blocking them. Why is this a serious health risk?
A. Diffusion can’t take place as easily.
B. The heart has to pump more blood than normal.
C. Carbon dioxide concentrations rise in the blood.
D. Blood pressure increases.

19. What is diffusion?
A. Molecules moving from areas of high concentration to low concentration.
B. Molecules moving from the heart to the lungs.
C. Molecules moving from areas of low concentration to high concentration.
D. Molecules moving from one cell to another cell.

20. What two things help make diffusion possible?
A. Equilibrium and oxygen-rich blood.
B. Thin capillary walls and oxygen-rich blood.
C. High blood pressure and slow blood flow.
D. Semi-permeable capillary walls and slow blood flow.

APPENDIX C

POSTTEST

1. What is the purpose of the heart?
A. Remove wastes from blood.
B. Make new blood.
C. Pump blood through the body.
D. Transfer heat to the rest of the body.

2. The ventricles in the heart
A. pump blood out to the body and lungs.
B. pump blood to the atrium.
C. prevent blood from flowing backwards.
D. receive blood from the body and lungs.

3. Which of the following is most similar to the heart?
A. A hose because blood travels in tubes.
B. A cup because it is open on the top.
C. A broom because it cleans the blood.
D. A pump because it pushes blood through the body.

4. How many chambers does the human heart have?
A. 2—one atrium, one ventricle.
B. 3—one atrium, one left and one right ventricle.
C. 4—one upper and one lower ventricle, one upper and lower atrium.
D. 4—one right and one left ventricle, one right and one left atrium.

5. When blood is sent out from the heart to the body, what part of the heart does it leave?
A. Left atrium.
B. Right ventricle.
C. Left ventricle.
D. Right atrium.

6. Why can you die if you lose too much blood?
A. You lose carbon dioxide faster than normal.
B. You lose wastes faster than they can be replenished.
C. You are not getting the carbon dioxide needed to survive.
D. You do not get the oxygen needed to survive.

7. What part of the blood carries nutrients to our body?
A. Red blood cells.
B. Plasma.
C. White blood cells.
D. Platelets.

8. After you donate blood, you shouldn't do any tiring exercise that same day. Why?
A. You have less blood to carry oxygen to your muscles.
B. You have less blood to carry carbon dioxide to your muscles.

C. Your blood can’t regulate your body temperature as well.
D. Your blood removes too much carbon dioxide and wastes.

9. Why is the blood red?
A. The red blood cells are red.
B. Red is the color of plasma.
C. Red is the color of deoxygenated blood.
D. Oxygen makes it red.

10. Blood flows into the atrium of the heart, where does it flow to next?
A. Ventricle.
B. Lungs.
C. Plasma.
D. Arteries.

11. The thick and elastic walls of the artery help to
A. lower blood pressure.
B. prevent heat loss.
C. maintain blood flow through the body.
D. pump blood under high pressure.

12. What is one reason why nutrients can pass through the walls of the capillaries?
A. Capillaries break open when they are full of nutrients.
B. There are more nutrients in the capillaries than in the other vessels.
C. Capillary walls are very strong.
D. The capillary walls are not tightly closed.

13. Which one is the correct order (highest -> lowest) for blood pressure?
A. Artery -> capillary -> vein
B. Artery -> vein -> capillary
C. Vein -> capillary -> artery
D. Vein -> artery -> capillary

14. If humans had an open circulatory system, which of the following would be TRUE?
A. Our blood vessels would leak to the outside of our bodies.
B. Our heart would only have one large chamber instead of four.
C. Blood would be pumped directly into our muscles.
D. Blood would flow through vessels, and then into open spaces in the body.

15. Which of the following is a TRUE statement about the way blood flows in the human body?
A. Blood floats freely in the body because organs in the body need blood for nutrients and oxygen.
B. Blood floats freely in the body because it is better for the muscles to get nutrients and oxygen.

C. Blood circulates in one direction through the blood vessels.
D. Oxygen-rich blood and deoxygenated blood flow in the same vessels so they can mix.

16. The systolic phase of the heartbeat is where
A. the ventricle is relaxed and the valves open.
B. the ventricle is contracted and the valves close.
C. the atrium is contracted.
D. the blood pressure is very high.

17. Blood in the left atrium is oxygen-rich and coming from the lungs. Blood in the right ventricle is
A. oxygen-rich and going towards the body.
B. oxygen-rich and coming from the lungs
C. deoxygenated and going towards the lungs.
D. deoxygenated and going towards the body.

18. What is equilibrium?
A. Your heart contracting and relaxing.
B. The amount of carbon dioxide in a cell.
C. An equal concentration of molecules spread evenly throughout a space.
D. The amount of deoxygenated blood in an artery.

19. Why does diffusion occur into the blood in the lungs?
A. The lungs have more oxygen than blood.
B. Blood has more oxygen than the lungs.
C. Equilibrium exists between the lungs and blood.
D. The lungs have less oxygen than the body.

20. Diffusion takes place in capillaries because
A. atrium is contracted.
B. capillary walls are thick.
C. capillaries contain pressure.
D. capillary walls are semi-permeable.

APPENDIX D

MPLUS PROGRAM SYNTAX

1.

```
TITLE:  Confirmatory Factor Analysis on Cognitive Load Measures

DATA: FILE IS cl.dat;

VARIABLE: NAMES ARE
   CL1 CL2 CL3 CL4 CL5;

ANALYSIS:
     TYPE = GENERAL;
     estimator = mlr;

MODEL:
     F1 BY CL1* CL2 CL3 CL4 CL5;
     F1@1;

OUTPUT: sampstat standardized residual tech1 tech3;
```

2.

```
TITLE:
Confirmatory Factor Analysis on Intrinsic Motivation Measures
One-Factor Model

DATA: FILE IS IM.dat;

VARIABLE: NAMES ARE
   IM1 IM2 IM3 IM4
   IM5 IM6 IM7 IM8 IM9 IM10
   IM11 IM12 IM13 IM14 IM15 IM16
   IM17 IM18 IM19 IM20 IM21
    IM1Rev IM5Rev IM6Rev IM7Rev IM12Rev
    IM15Rev;

      USEVARIABLES ARE
      IM2-IM4 IM8-IM11
      IM13 IM14 IM16-IM21
      IM1Rev IM5Rev IM6Rev IM7Rev
      IM12Rev IM15Rev;

   missing are all (-99);

ANALYSIS:
   type = missing;
   estimator = mlr;
```

```
MODEL:
        F1 BY
   IM1Rev* IM4 IM7Rev IM13 IM17 IM20
   IM2 IM15Rev IM18
   IM3 IM10 IM16
   IM5Rev IM9 IM14
   IM6Rev IM11 IM21
   IM8 IM12Rev IM19;
   F1@1;

OUTPUT: sampstat standardized residual tech1 tech3;
```

3.

```
TITLE:
Confirmatory Factor Analysis on Intrinsic Motivation Measures
Six-Factor Model

DATA: FILE IS IM.dat;

VARIABLE: NAMES ARE
   IM1 IM2 IM3 IM4
   IM5 IM6 IM7 IM8 IM9 IM10
   IM11 IM12 IM13 IM14 IM15 IM16
   IM17 IM18 IM19 IM20 IM21
    IM1Rev IM5Rev IM6Rev IM7Rev IM12Rev
    IM15Rev;

     USEVARIABLES ARE
     IM2-IM4 IM8-IM11
     IM13 IM14 IM16-IM21
     IM1Rev IM5Rev IM6Rev IM7Rev
     IM12Rev IM15Rev;

   missing are all (-99);

ANALYSIS:
   type = missing;
   estimator = mlr;

MODEL:

   F1 BY IM1Rev* IM4 IM7Rev IM13 IM17 IM20;
   F2 by IM2* IM15Rev IM18;
```

```
   F3 by IM3* IM10 IM16;
   F4 by IM5Rev* IM9 IM14;
   F5 by IM6Rev* IM11 IM21;
   F6 by IM8* IM12Rev IM19;

   F1@1 F2@1 F3@1 F4@1 F5@1 F6@1;

   F1 with F2 F3 F4 F5 F6;
   F2 with F3 F4 F5 F6;
   F3 with F4 F5 F6;
   F4 with F5 F6;
   F5 with F6;

OUTPUT: sampstat standardized residual tech1 tech3;
```

4.

```
TITLE:
Confirmatory Factor Analysis on Intrinsic Motivation Measures
Bi-Factor Model

DATA: FILE IS IM.dat;

VARIABLE: NAMES ARE
   IM1 IM2 IM3 IM4
   IM5 IM6 IM7 IM8 IM9 IM10
   IM11 IM12 IM13 IM14 IM15 IM16
   IM17 IM18 IM19 IM20 IM21
   IM1Rev IM5Rev IM6Rev IM7Rev IM12Rev
   IM15Rev;

USEVARIABLES ARE
   IM1 IM2 IM3 IM4
   IM5 IM6 IM7 IM8 IM9 IM10
   IM11 IM12 IM13 IM14 IM15 IM16
   IM17 IM18 IM19 IM20 IM21
   IM1Rev IM5Rev IM6Rev IM7Rev IM12Rev
   IM15Rev;

   missing are all (-99);

ANALYSIS:
   type = missing;
   estimator = mlr;
```

```
MODEL:

   F1 BY IM1Rev IM4 IM7Rev IM13 IM17 IM20;
   F2 by IM2 IM15Rev IM18;
   F3 by IM3 IM10 IM16;
   F4 by IM5Rev IM9 IM14;
   F5 by IM6Rev IM11 IM21;
   F6 by IM8 IM12Rev IM19;

   !F1@1 F2@1 F3@1 F4@1 F5@1 F6@1;

   F7 by
   IM1Rev@0 IM4@0 IM7Rev@0 IM13@0 IM17@0 IM20@0
   IM2@0 IM15Rev@0 IM18@0
   IM3@0 IM10@0 IM16@0
   IM5Rev@0 IM9@0 IM14@0
   IM6Rev@0 IM11@0 IM21@0
   IM8@0 IM12Rev@0 IM19@0;

   F7 with F1@0;
   F7 with F2@0;
   F7 with F3@0;
   F7 with F4@0;
   F7 with F5@0;
   F7 with F6@0;

OUTPUT: sampstat standardized residual tech1 tech3;
```

5.

```
TITLE:
Confirmatory Factor Analysis on Intrinsic Motivation Measures
Higher-Order Factor Model


DATA: FILE IS IM.dat;

VARIABLE: NAMES ARE
   IM1 IM2 IM3 IM4
   IM5 IM6 IM7 IM8 IM9 IM10
   IM11 IM12 IM13 IM14 IM15 IM16
   IM17 IM18 IM19 IM20 IM21
   IM1Rev IM5Rev IM6Rev IM7Rev IM12Rev
   IM15Rev;

USEVARIABLES ARE
```

```
   IM1 IM2 IM3 IM4
   IM5 IM6 IM7 IM8 IM9 IM10
   IM11 IM12 IM13 IM14 IM15 IM16
   IM17 IM18 IM19 IM20 IM21
   IM1Rev IM5Rev IM6Rev IM7Rev IM12Rev
   IM15Rev;

   missing are all (-99);

ANALYSIS:
   type = missing;
   estimator = ml;

MODEL:

   F1 BY IM1Rev IM4 IM7Rev IM13 IM17 IM20;
   F2 by IM2  IM15Rev IM18;
   F3 by IM3  IM10 IM16;
   F4 by IM5Rev IM9 IM14;
   F5 by IM6Rev  M11 IM21;
   F6 by IM8 IM12Rev IM19;

   F7 by F1* F2 F3 F4 F5 F6;
   F7@1;

OUTPUT: sampstat standardized residual tech1 tech3;
```

6.

```
title:
Relationship Among Learning, Cognitive Load, and Motivation

data: file is LearningCLIM.dat;

variable:
   names are
   id condition prompting cueing PrePerc PostPerc
   Interest Competence
   Value Effort Pressure Choice PgmTime Male Age CL1 CL2
   Cl3 CL4 CL5 IM1 IM2 IM3 IM4 IM5 IM6 IM7 IM8 IM9 IM10 IM11 IM12
   IM13 IM14 IM15 IM16 IM17 IM18 IM19 IM20 IM21
   IM1Rev IM5Rev IM6Rev IM7Rev
   IM12Rev IM15Rev;

   grouping is cueing (1 = cued 0= uncued);
```

```
   usevariables are PrePerc PostPerc PgmTime
      CL1 CL2 Cl3 CL4 CL5
     IM4    IM13    IM17  IM20
   IM1Rev IM7Rev;

   missing are all (-99);

analysis:
  estimator = ml;

model:

   InterestLa BY IM1Rev IM4 IM7Rev IM13 IM17 IM20;

   CLLa by CL1 CL2 Cl3 CL4 CL5;
   CLLa;

   PostPerc on PrePerc PgmTime InterestLa CLLa;

   PrePerc with PgmTime InterestLa CLLa;
   PgmTime with InterestLa CLLa;
   InterestLa with CLLa;

   Model cued:

  Model uncued:

output: sampstat standardized residual;
```

7.

```
title:
Missing Data Handling for Eye Tracking Measures

data: file is ET 22.dat;

variable:
   names are
   id condition Prompting cueing P1 P2 CP1 CP2 ET
   SampleR MT1Extra MNBf1FixExtra FixDuCued FixDuExtra
   FixDuNavi FixCntCued FixCnExtra FixCntNavi NVstCnCued
   NVstCnExtra PreTotal PostTotal Interest Competence
   Value Effort Pressure Choice PgmTime Age CL1 CL2
   Cl3 CL4 CL5;
```

```
    usevariables are cueing P1 P2 CP1 CP2
    SampleR FixDuExtra;

    missing are all (-99);

    auxiliary = (m) PostTotal Choice PgmTime CL5;

analysis:

    type = missing;
    estimator = ml;

model:

    [FixDuExtra SampleR cueing];
    FixDuExtra SampleR cueing;

    FixDuExtra on SampleR cueing P1 P2 CP1 CP2;

  output: sampstat standardized residual;
```

BIOGRAPHICAL SKETCH

Lijia Lin was born in Suzhou, P. R. China. He completed his secondary education in 2003 at Suzhou Middle School in Suzhou. Thereafter, he started studying Educational Technology in Donghua University in Shanghai, China. After receiving a Bachelor's degree in education in 2007, he moved to Arizona State University (ASU) in the United States to pursue a Ph.D in the Educational Technology Program. At ASU, he received training in educational technology, instructional design and quantitative analysis. Beginning in the fall of 2011, he will be a lecturer/assistant professor in the School of Psychology and Cognitive Science at the East China Normal University in Shanghai, China.