Modeling Online Learning Performance with Biometrics: Current Study and Future Directions

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Abstract

As the number of students and faculty involved in online learning in recent decades has increased, we recognize that there is a limited understanding of how learners react, interact, behave, and are served by the various components in the information delivery processes. When learning online without an instructor present in real-time, we need to understand the role of the learners' cognitive load, emotions, and visual attention. This paper describes an experiment examining how engagement, cognitive load and visual attention mediate the effect of data representations and highlighting on learning performance. The results showed that in addition to tabular representations, highlighting significantly increased visual attention and decreased cognitive load, which was related to better learning performance.

Background

Higher education has witnessed a growing number of students and faculty involved in online learning in recent decades, as well as a larger number of courses offered via the Internet. Since the onset of the COVID-19 pandemic, online learning has become a common means of teaching and learning. Several theoretical models have been proposed and experiments conducted to understand the cognitive process during online learning (Mayer, 2005a; Moreno, 2005; Moreno & Mayer, 2007; Sweller, 1988). As a result, online courses have improved and become more user-friendly. However, we recognize that current instruction is based on limited understandings of how learners react, interact, behave, as well as how learners are served by the various components in the information delivery processes. For example, current online learning research has focused on the relationship between on-screen representations (e.g., text, pictures, and animation) and performance or cognitive biometrics (e.g., subjective cognitive load, subjective emotions, visual attention) (Park, Knörzer, Plass, & Brünken, 2015), but ignored the role of cognitive biometrics in mediating the effect of representations on performance. Continued research is needed to understand leaners' cognitive load, emotions, and visual attention, most acutely while learning via a computer screen when an instructor is not present in real-time. A systematic understanding of the effects of different representations on cognitive load, emotions and visual attention provides design insights for building more effective online learning systems. In the following sections, we briefly review the literature on cognitive load, emotions and visual attention, followed by how these mediators play important roles in online learning systems. We then describe an experiment examining how engagement, cognitive load and visual attention mediates the effect of data representations and highlighting (use of color to make text visually salient) on learning performances.

Cognitive Load, Emotions, and Online Learning

Cognitive Load. Cognitive load is defined as the amount of mental load that working memory applies to a specific information processing task (Sweller, Van Merrienboer, & Paas, 1998). Obtaining an optimal cognitive load is essential for successful practices in various fields (Paas, Tuovinen, Tabbers, & Van Gerven, 2003). From *Cognitive Load Theory* (CLT), cognitive load consists of three additive components: intrinsic, extraneous and germane load (Sweller, 1988). Intrinsic load refers to the cognitive load that is directly connected to the difficulty of the learning elements, the total number of elements to be learned, the interactivity between the elements, and the prior knowledge of the individual. Intrinsic load is independent of the instructional design, and can only be reduced by breaking learning materials into smaller pieces or reducing the difficulty of the learning content. Extraneous load is influenced by the format and design of the instruction. The goal of an effective design of instruction is to minimize the extraneous load. Germane load is defined as the mental effort exerted in the process of knowledge acquisition.

This load is determined by how much attention the learner pays to the learning content and is directly related to the learning performance. Thus, maintaining a certain amount of germane load is optimal for learning. The sum of these three loads is constrained by the working memory capacity of the individual (Paas, Renkl, & Sweller, 2003), which is the capacity to store information in mind temporarily. Among these three components, extraneous load is the only one that can be altered by instructional design (Sweller, 1988; Van Merrienboer & Sweller, 2005). Given that cognitive load is restricted by working memory capacity, reducing the extraneous load could benefit learning by allocating more working memory to the content needing attention. Thus, instructional design should aim to reduce the extraneous load by leaving out redundant information.

To measure cognitive load quantitively, considerable research has been conducted to understand the relationship between EEG (electroencephalogram) -detected brainwaves and cognitive load (Gevins, Smith, McEvoy, & Yu, 1997; Sterman, Mann, Kaiser, & Suyenobu, 1994). Stipacek et al. (2003) demonstrated the important role of the alpha band brainwaves in understanding the cognitive process. In their research, an increased alpha band event-related desynchronization (ERD) was observed with increasing cognitive load, which indicates that alpha ERD can be used to estimate the cognitive load one experiences. Gevins et al. (1997) also found that the alpha band power detected by EEG was lower when the participant was working on difficult spatial and verbal working memory tasks, compared to easier ones, suggesting that alpha band power is negatively associated with cognitive load and researchers can estimate cognitive load using alpha band power. Taken together, these findings indicate that alpha band power and ERD has been well studied in the literature and is proven to be effective for the estimation of cognitive load.

Emotions and Engagement. Emotion is defined as the feeling of bodily changes evoked by the interaction with a specific stimulus (James, 1884; Park et al., 2015). The emotions of a learner affect his or her learning by determining the attitude of an individual toward a given subject or classroom session (Tan, Mao ,Jiang, & Gao, 2021). Emotions can be categorized according to two dimensions that influence learning performance: valence, whether the emotion is positive or negative, and activation, whether the emotion activates or deactivates the cerebral cortex into a state of general wakefulness, or attention. (Pekrun, 1992; Russell, 2003; Encyclopedia Britannica, 2018). Emotions can influence performance by affecting motivation, self-regulation, learning strategies and attention to the learning material (Pekrun, Goetz, Titz, & Perry, 2002). Students with positive emotions will be good and attentive listeners in the classroom, as opposed to students with negative or confused emotions whose minds may stray away from ongoing learning activities in the classroom (Kalyuga, 2009). The reason for this assertion is that positive attitudes boost the eagerness of a student to acquire new skills, knowledge, and expertise from the instructor. Some of the essential emotions that support the learning process include motivation, interest, excitement and engagement (Conrad, 2002; LePine, LePine, & Jackson, 2004; O'regan, 2003; Zembylas, Theodorou, & Pavlakis, 2008).

Engagement refers to the active involvement in learning, or 'energy in action', which is recognized as one of the key factors that can enhance students' learning performance (Appleton, Christenson, Kim, & Reschly, 2006; Blasco-Arcas, Buil, Hernández-Ortega, & Sese, 2013; Newmann, 1992; Taylor & Statler, 2014). It is believed that engagement leads to higher academic achievement and prevents students from dropping classes (Caldwell, 2007; Ing et al., 2015; Lambert & Sugita, 2016). A study conducted by Chen and Wang (2011) examined whether and how three different multimedia learning materials (static-text based, video-based and animation-interaction based) influenced student engagement and performance. The study revealed that video-based materials elicit the most positive emotions and thus benefit learning performance (Chen & Wang, 2011). However, only the overall percentages of positive and negative emotion were calculated, which cannot account for the changes in various emotions across an entire learning process. Another study conducted by Um, Plass, Hayward, and Homer (2012) noted that learning materials designed with bright colors (vs. gray-scale) and round (vs. square) and face-like (vs. neutral) shapes are beneficial to learning and were considered to be positive emotional design. In their study, a Positive Affect Scale (PAS) was introduced as a subjective way to quantify the positive emotion. Given the limitation of subjective measurement, our research used an EEG to estimate objective measures of emotions to avoid introducing significant biases.

Attention and Signaling. The positive effect of signaling on learning and multimedia learning performance has been examined repeatedly in the literature (Chi, Gumbrecht, & Hong, 2007; Van Gog, 2014). The signaling principle in multimedia learning, also known as cuing principle, refers to the fact the learners form a deeper understanding of the message presented in a multimedia setting when a cue of essential content or highlight of crucial structure of the content is given (De Koning, Tabbers, Rikers, & Paas, 2007; Mayer, 2005b). The signaling principle is particularly essential for the first step, selecting information, in the comprehension of multimedia learning, according to the cognitive load theory of multimedia learning. The multimedia content needs to be attended by the learner before it can be processed in working memory (Van Gog, 2014). Visually salient content tends to attract more attention sooner from novice learners (Lowe, 1999).

In multimedia learning, the allocation of attention largely depends on the design of the stimulus material for novices who do not have prior knowledge. Processing information that is relevant to learning induces higher extraneous cognitive load and might hamper learning (Paas & Sweller, 2014). Thus, having salient features in the stimulus can guide the learner to attend to relevant information for deeper acquisition of the material. Van Gog (2014) also argued that signaling/cuing principle is not only crucial for reducing extraneous load in the information selecting stage, but it might also induce higher germane cognitive load through facilitating the understanding of the organization or integration of the learning content.

Signaling can be incorporated into different forms of the learning content, including text, pictures, or both. Text-based signaling has three major categories: (1) sentence precedes the learning content and highlight the structure (Mautone & Mayer, 2001), (2) sentence that guide attention to the picture (Hayes & Reinking, 1991), and (3) colored text that draws attention to a specific term or details in the learning content (Moreno & Abercrombie, 2010). Picture-based signaling generally relies on the use of arrows, flashing elements, change of colors, or inverted contrast. These methods make the peripheral content invisible and instead highlight the relevant information (Amadieu, Mariné, & Laimay, 2011; Boucheix & Lowe, 2010; Jamet, Gavota, & Quaireau, 2008; Jeung, Chandler, & Sweller, 1997).

Among all the techniques that have been used for signaling, highlighting refers to the use of color to make text visually salient. This approach has been increasingly used to guide the attention of students towards a specific area of textual contents. Mautone and Mayer (2001) examined several signaling techniques and observed that performance on a transfer test presented in written text improved with signaling while learning. During the learning phase, participants heard a low tone when a corresponding word was highlighted in the signaled group, and their performance in answering transfer test questions was significantly higher than those in the non-signaled group. This finding suggests that the pairing of audio and visual forms of signaling can enhance transfer test performance. Ozcelik, Arslan-Ari, and Cagiltay (2010) studied the effect of red-colored narration on both visual behavior and learning performance during a task that involved both text and spoken narration. The text was presented in a red color during the narration of the sentence. Participants who studied the signaled version of the text outperformed those studied the non-signaled version in two different measures of learning performance. Like the study conducted by Mautone and Mayer (2001), the results of this study further indicate that a number of signaling methods (sound, color, and highlighting) can positively impact learning and learning performance.

Learning and Eye Tracking. Another useful technique that has been recognized to explore cognitive performance in information processing is eye-tracking (Duchowski, 2007). Eye movements have been shown to explain information processing and are related to attention in learning (Rayner, 2009; Underwood, 1998). Earlier research has revealed that variables in eye-tracking are linked with the learning process. For instance, the number of fixations is related to the efficiency of searching, the duration of fixation is correlated with the level of difficulty of the content to the viewer, and the pupil size has long been used to determine the viewer's cognitive workload (Beatty, 1982; Hyönä, Tommola, & Alaja, 1995; Rayner, 1998).

Multiple eye movement variables can detect the participant's cognitive states and provide information about cognitive activities. The eye activities can be categorized into two main classes: voluntary eye movements that are controlled by the participant, including fixation and saccade; and involuntary eye movements that accompany the voluntary eye-movements, for instance, pupil dilation and blinking. Fixation refers to the focused state of eyes on information over a considerable amount of time, larger than 200-300 milliseconds. Another voluntary eye movement is saccade which is the shift of the eyes between two locations with a time range between 30-80 milliseconds. Pupil dilation is a pupillary change that can range from 1.5mm to more than 8mm. Pupil dilation is a pupillary response that accompanies effortful cognitive processing, and it has long been used as an index of cognitive load. Kramer (1991) pointed out that task-evoked pupillary response has been found to be related to the amount of information processed in short-term memory (working memory). Blinking refers to the rapid closing of the eyelid and is recognized as another critical eye-tracking metric to reflect the individual cognitive load.

Wang, Yang, Liu, Cao, & Ma (2014) confirmed the strong correlation between fixation and cognitive load. Both fixation count and duration are significantly positively related to the cognitive demand. Pomplun & Sunkara (2003) investigated changes in pupil dilation as task difficulty increases. The computer-based task was to eliminate a growing size blue circle before it reached the maximal size. The blue circle appeared with other three elements: blue squares, red squares, and red circles. In two instances the items would grow in size, and the participant had to look at the blue circle and press a designated button to eliminate the item. The difficulty level of the task was determined by the time interval between two emergences of the blue circle. For the easy level, the blue circle appeared every two seconds, dropping to 200 and 75 milliseconds, respectively for medium and hard levels. Results of this study indicate that the pupil size is a function of both cognitive load and environmental brightness. In other words, when the brightness is constant across experiments, the cognitive load can be computed directly through the pupil size. This assertion was further confirmed by Porta et al. (2012).

A study conducted by Chen, Epps, Ruiz, & Chen (2011) further addressed the usage of eye-tracking parameters to measure cognitive load. In their research, the participant was required to learn basketball strategies to identify defenders and attackers, as well as recall the position of players through a computer-based training application. The tasks were preset to three complexities by adjusting the total number of positions to be memorized and the number of defenders/attackers. The required cognitive load was assumed to be higher for more complex tasks. All four kinds of eye movement (fixation, saccades, blinking, and pupil dilation) were significantly correlated with cognitive load. The duration and rate of fixation indicated that higher effort was allocated to more complex tasks. Saccade speed and size were also reliable discriminatory parameters for the cognitive workload. Finally, blink latency, blink rate and pupil size were significantly correlated with cognitive load variations. In sum, all these parameters are positively associated with the cognitive load.

Summary. Based on the extant literature, emotions and visual attention might compete with cognitive load while participants are learning, thus necessitating a balance between the competing mediators in instructional design. Therefore, positive emotion arousal is necessary in learning, but it should be maintained at a reasonable level to minimally increase extraneous load and allow spaces for germane load to achieve meaningful and active learning. Even though the role of the cognitive load, emotions and visual attention have been addressed in the literature, the trade-off and systematic relationship of these three biometrics during an online learning session remains opaque. Furthermore, cognitive load and emotion have mostly been measured by subject instruments (questionnaires, self-reports, etc.) rather than object measurements (EEG, eye-tracking), which might introduce a considerable amount of bias into the data. Thus, the joint role of emotions and cognitive load is an important area that needs to be investigated objectively to better understand the relationship between instructional design, emotions, cognitive load and learning performance. To better contribute to the overarching goal of optimally designing online learning systems, our study addressed this gap in the literature. We examined the relationship between instructional design, biometrics, and learning performance by determining whether biometrics measured using EEG and eye-tracking are mediators in the relationship between instructional design and learning outcomes.

We hypothesized that: (1) data presented in tabular form would significantly decrease the cognitive load as well as the engagement a learner experiences compared to a graph, and consequently yield better performance; and (2) text highlighting would significantly increase the visual attention towards the Area of Interest (the area highlighted that has relevant and important information) and decrease the cognitive load, thereby fostering learning through selecting, integrating and organizing the information.

Methodology and Results

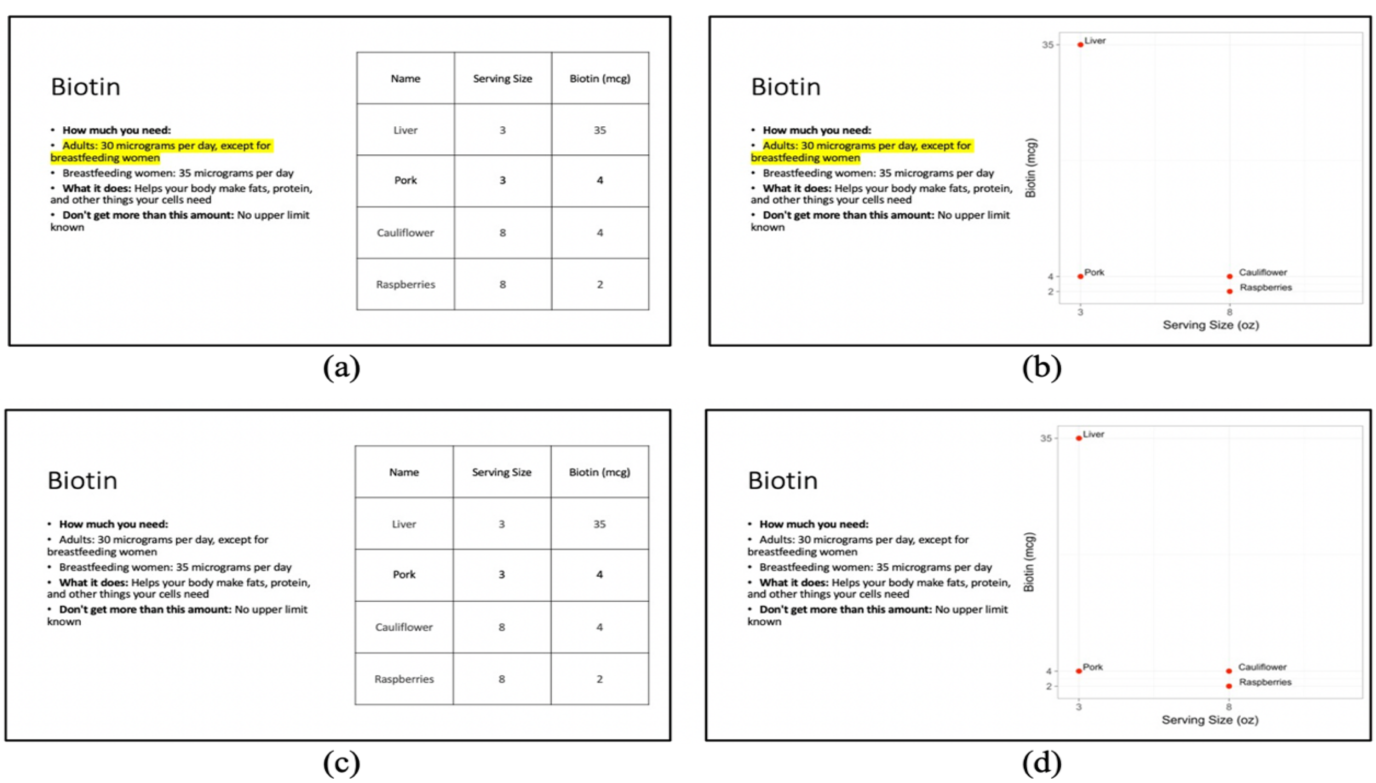
We conducted a two-by-two Latin square designed experiment to investigate specifically how cognitive load and engagement is influenced by: (1) highlighting (highlighting relevant information vs. no highlighting) and (2) different data representation (table or graph) to capture information about visual attention as measured by an eye-tracker. We used alpha band event-related desynchronization (ERD) and theta band event-related synchronization (ERS) as two estimates of cognitive load. Engagement was quantified based on the engagement index introduced by Pope, Bogart, and Bartolome (1995). An engagement index was calculated as the ratio of alpha band power over the sum of alpha and beta band power. This ratio represents the general arousal level in the brain based on alpha band power.

Forty-eight students (25 males, 23 females, age ranging between 19 to 40) at Oregon State University (OSU) participated in this study. All participants were recruited via lists of OSU departments and Ecampus, the university’s daily online newsletter and flyers distributed around the campus. Students enrolled in majors that required nutrition courses and students with prior knowledge regarding the nutrition course used in the study were excluded. Students came to the Human Analytic Laboratory to participate in the study. Participation was voluntary, and each participant received $30 compensation in cash upon the completion of the experiment. Using a within-subjects design, 48 participants experienced all four treatments from an asynchronous general human nutrition (Nutrition 225) online course.

All participants were tested in experimental sessions in the same day. Upon arrival, participants were informed about the study by the experimenter and provided a written consent form. They were asked to express any concern or questions about the experiment before starting the example session. After the consent form was signed, participants were seated in front of the monitor within a sound-proof experimental booth. The participants were first asked to progress with the example slides to become familiar with the representations and the pattern of questions. The calibration of emotiv EEG headset was performed after participants had finished learning the example slides and all questions were answered. Baseline raw EEG for eye-closed and eye-open relax status was recorded after the calibration was done. As the EEG baseline recording was finished, a calibration of the Tobii X2-30 eye-tracker was performed with the Tobii pro studio. The participants were then asked to progress with the experimental sessions until all sessions were completed.

All experimental slides consisted of both a text and a data representation, with the text on the left illustrating the function and recommended intake of a specific nutrient, and the data representation showing the foods that have that nutrient and the amount of the nutrient. We implemented a table and a dot graph as two forms of data representation to show four kinds of foods with a specific nutrient, the standard serving size and the amount of nutrients in one serving size. Figure 1 illustrates the four representations presented in the experiment.

Figure 1. An example of learning materials for four different representations, with different levels of highlighting and data visualization: (a) highlighting, table (b) highlighting, graph (c) no highlighting, table (d) no highlighting, graph



Participants were asked to progress through four sessions of slides with six slides in each session. All slides were presented on-screen via Tobii Studio in the form of a downloaded PowerPoint provided in an online module in a learning management system. The task was system-paced with each slide appearing once for 60 seconds. There was a three-question retention test following each slide, wherein the questions were related exactly to the one corresponding slide. One question was to examine the learning outcomes (retention) of memorizing content in the text, and the other two questions were related to learning on the data representation. Learning performance was measured using the sum of correct responses to three questions for all 24 slides tested (score ranges between 0 and 3 for a single slide).

We first performed a Fast Fourier Transform(FFT) with the original raw EEG data and then calculated two frequency domain EEG measures, alpha ERD and theta ERS through Matlab, as estimates for cognitive load in our model. We extracted data between 8-13Hz for the alpha band and 4-7Hz for the theta band. ERD and ERS were calculated using the following equation: *(test band power – baseline band power)/baseline band power* for each slide. We also estimated the engagement participants experienced while learning via various learning representations. Pope et al. (1995) introduced an engagement index and reported that *beta/(alpha + beta)* reflects task engagement best in terms of the strength in producing expected feedback (better performance). The *engagement index = beta/(alpha + beta)* has been used effectively by a number of researchers and was therefore adopted for this study. The EEG frequency bands were set as follows: alpha(8-13Hz), beta(14-22Hz) and theta(4-7Hz). The 60-second EEG recording for each slide was truncated to 20 segments of 20-seconds with a 2-second moving window. The engagement index for a specific slide was determined by averaging the index of the corresponding segments. As mentioned above, eye-tracking has been used to explore cognitive performance in information processing (Duchowski, 2007). We used the number of fixations and total visit duration in the Areas of Interest (AOIs) to quantify the visual attention. In our study, the AOIs were defined as the area that contains information that was tested in the retention task.

To examine the effect of highlighting and data representation on learning performance and the mediating effects of cognitive load, engagement, and visual attention, we examined several structural equation models with the results shown below in Figures 2 and 3.

The model in Figure 2 on page 9 examines the effects of data representation on learning performance and how cognitive load and engagement mediates this relationship. We modeled cognitive load as a latent variable, estimated through alpha ERS and theta ERD. We estimated engagement directly from the engagement index defined above. We selected the two electrodes located in the prefrontal lobe to test this model because the prefrontal area has been recognized in the literature as an important region of the brain that is sensitive to emotional arousal (Robbins, 2000). This model, based on electrode AF3, shows that the use of tables (rather than figures) increases the cognitive load and also increases engagement, and both ultimately yield higher scores. This model represented the experimental data well with a good Comparative Fit Index (CFI) of 0.931 (where CFI $>$ 0.9 is recommended; Hu & Bentler, 1999); and RMSEA of 0.059 (where RMSEA $<$ 0.08 is recommended; Hu & Bentler, 1999). We also examined the model above with data from electrode AF4, which was consistent overall with the model in Figure 1 and showed a similar relationship between the independent, mediating and dependent variables. However, the AF4 based model failed the indices of good model fit (CFI and RMSEA).

Figure 2. The effect of table/graph on learning performance, cognitive load and engagement

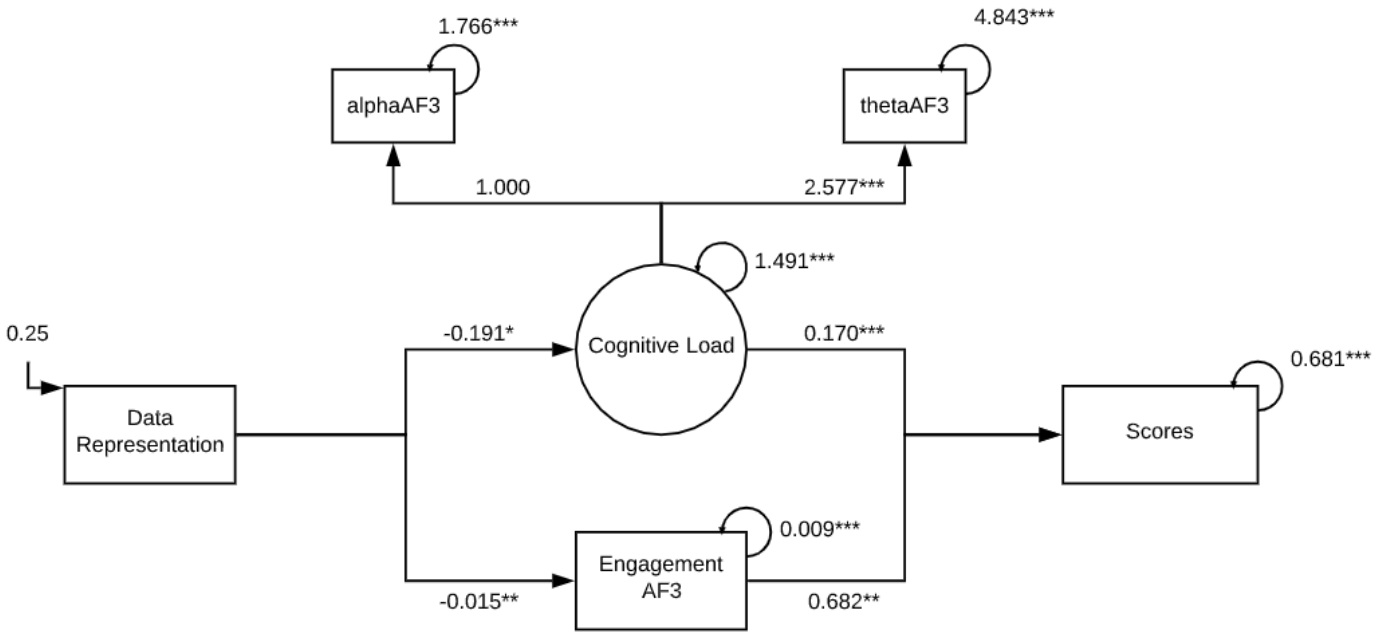


Figure 3. The effect of highlighting on learning performance, cognitive load and visual attention

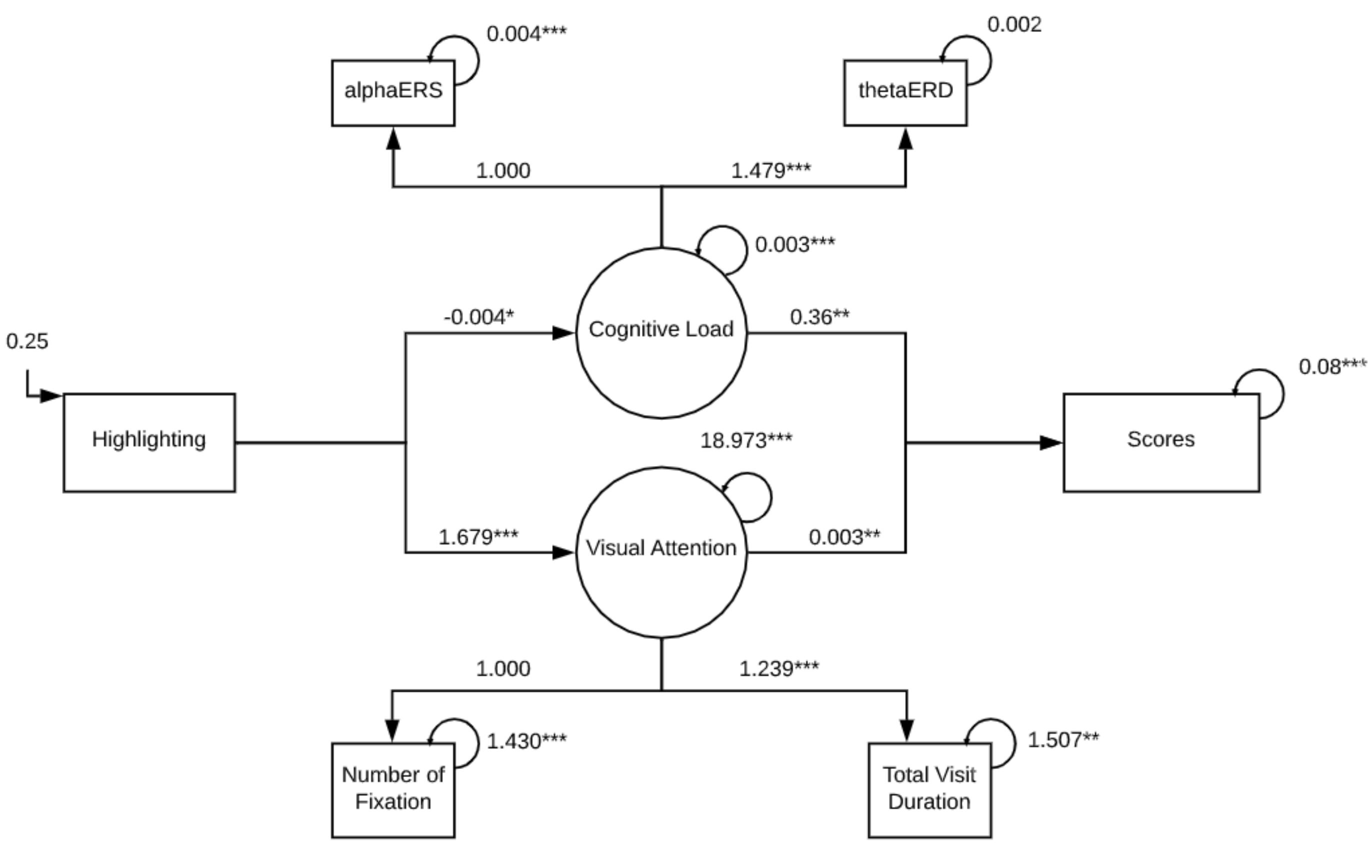


Figure 3 on page 9 shows the effect of highlighting on learning performance, and how visual attention and cognitive load mediates this relationship. We modeled cognitive load and visual attention as two latent variables, with cognitive load estimated using alpha ERS and theta ERD, and visual attention estimated using the number of fixations and total visit duration on each slide. This model yielded a good Comparative Fit Index (CFI) of 0.998 and a good RMSEA of 0.037. It shows that highlighting significantly increased the visual attention and decreased the cognitive load. Further, having both lower cognitive load and higher visual attention yielded significantly better learning performance.

Conclusion and Discussion

As some researchers have posited, eliciting positive emotions usually promotes learning by making the instructional material more appealing (Um et al., 2012). Heidig, Müller, and Reichelt (2015) proposed a concept called Emotional Design which advocates the use of visual attraction in the design of instructional media to elicit positive learning and facilitate learning as a consequence. However, emotion is also a potential source of extraneous load, and adding components that are emotionally attractive but irrelevant or unnecessary may hinder learning (Sweller, 1988; Sweller et al., 1998). Mayer, Heiser, and Lonn (2001) also found that components that elicit positive emotions cause the *coherence effect*, wherein learners allocate more cognitive load to priming inappropriate schemas as they try hard to locate the key points of the learning task. Our results align with the coherence effect. From Figure 2, we note that presenting data in tables creates higher levels of engagement with the learner than a corresponding graphic representation, as estimated through EEG engagement index. Nonetheless, the tables were associated with greater cognitive load and participants *outperformed* those learning via the graphical representation. That is, increasing the engagement of participants increases the cognitive load, which at the same time occupies more germane load, which together may lead to better performance. An increase in the representational complexity increases the engagement level of the participants, which might benefit learning instead of hindering it. When diagrammatic elements are not simplified and must be processed interactively, rather than shown serially or in isolation, the extraneous load increases and has the potential to lessen learning performance.

In addition to a tabular representation, we find that highlighting also enhances the learning performance through decreases in cognitive load and helps with construct schemata (a cognitive structure that organize the information) that promotes comprehension. Past research on highlighting has noted its effectiveness towards learning. The existing literature offers several potential explanations for this, including the *isolation effect* which refers to the phenomenon that an item isolated against a homogeneous background will be more likely to be noticed and remembered (Von Restorff, 1933). Chi et al. (2007) reported a high rate of fixation on the highlighted areas of the text and validated the isolation effect. We draw a similar conclusion based on a significantly higher number of fixations and longer total visit duration in the areas-of-interest (see Figure 3 - visual attention). This isolation effect agrees with the attention-guiding hypothesis proposed by Ozcelik et al. (2010) in which highlighting increases the cognitive processing of specific elements, and these increases should be measurable through a long time of average fixation or longer total fixations. Even though researchers have hypothesized that highlighting has an important role in cognitive processes and influences cognitive load, there is no extant research that quantitatively confirms this hypothesis. We examined cognitive load and visual attention concurrently and found support for the hypothesis that highlighting influences cognitive load by isolating the appropriate schema for learners to prime, increases the visual attention and decreases the cognitive load and eventually promotes learning performance. The proper use of highlighting (text highlighting, underlines, or bolded text) is beneficial to learning by decreasing the extraneous load, which allows learners greater capacity for learning the content itself.

Future Research

Although the current study deters the use of some components that elicit higher engagement, we should not ignore the general role of engagement and other positive emotions in learning. That is, cognitive load and emotions are two aspects associated with cognitive processing that should be considered together at the instructional design stage. We propose that there is a point in which cognitive load and emotion might be balanced such that both positive emotion and a reasonable cognitive load are obtained, thereby optimizing learning performance. One might apply emotional design to promote learning while maintaining a comparatively low extraneous load in a low cognitive load condition (easier tasks; tasks that demand less effort). For specific learning content, such a tradeoff point likely varies. Since the content itself has an associated intrinsic load, a material with a lower intrinsic load would allow more space for emotional eliciting elements in the extraneous load. For instance, if we are presenting the participants with slides having only one object under a low cognitive load condition (e.g., learning the meaning of psychological terms, such as "schema"), the germane load is low for comprehending a single word, and pictures or animation that introduces higher extraneous load would have minor impact on the learning outcomes. Investigating these trade-offs between cognitive load and emotions for courses, along with complexity levels, would enhance our understanding of the relationship between emotions and cognitive load in online learning. We demonstrated how one emotion (engagement) mediates the learning process via cognitive load, but other emotions, including excitement and interest, remain to be investigated. If well designed, it is possible to engage participants with potentially more complex stimuli (e.g., video, colorful pictures) by decreasing abundant information and highlighting the key structures. This could help the learner to more quickly build a schema and maintain some working memory capacity. In this study, both data and text were processed via the visual channel; future research could take the verbal channel of background spoken narration in human information processing into consideration. Allocating some of the content onto the verbal channel will decrease the amount of information to be processed in the visual channel. This can vacate working memory of the emotion eliciting components in emotional design, if needed. An examination of this hypothesis may reveal whether such design elements are separable or fundamentally linked.

We also found that highlighting is effective for promoting learning, by itself or alongside other design elements (e.g., simplified data representations). Highlighting, seen as emotional eliciting elements by some researchers, could increase the cognitive load instead when an attractive design elicits positive emotions. Further investigations are needed determine how the effect changes when highlighting is working with other design elements.

Other Research Projects Derived from this Study

Key elements of this study have been instrumental in developing a currently funded NSF project entitled, *FW-HTF-RM: Collaborative Research: Assistive Intelligence for Cooperative Robot and Inspector Survey of Infrastructure Systems* (AI-CRISIS) D. A. Nembhard (PI), $332,000, ECCS-2128561, Sept. 2020 - Sept. 2023. The purpose of the project is to design efficient and effective training for inspectors to conduct drone-assisted bridge inspections. We are using biometric sensors including eye-tracking and EEG. The design of the training has several common aspects with more general online training, including questions related to the cognitive load requirements on the learner (i.e., inspector). Several of the broad goals of this Ecampus project and the NSF project are closely aligned, with the lessons learned from the former informing the development of the latter. It should also be noted that inspector performance on the project is quite closely tied with the efficacy of the training system, and will thus have a relatively immediate impact on practice.

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Vision

The Ecampus Research Unit strives to be leaders in the field of online higher education research through contributing new knowledge to the field, advancing research literacy, building researcher communities and guiding national conversations around actionable research in online teaching and learning.

Mission

The Ecampus Research Unit responds to and forecasts the needs and challenges of the online education field through conducting original research; fostering strategic collaborations; and creating evidence-based resources and tools that contribute to effective online teaching, learning and program administration.

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