Interactive Learning Environments

ISSN: (Print) (Online) Journal homepage: https://www.tandfonline.com/loi/nile20

Relationship between objective and subjective cognitive load measurements in multimedia learning

Duygu Mutlu-Bayraktar , Pinar Ozel , Fatih Altindis & Bulent Yilmaz

INTERACTIVE LEARNING ENVIRONMENTS
https://doi.org/10.1080/10494820.2020.1833042

Relationship between objective and subjective cognitive load measurements in multimedia learning

Duygu Mutlu-Bayraktar [a], Pinar Ozel [b], Fatih Altindis [c] and Bulent Yilmaz [d]

[a]Istanbul University-Cerrahpasa, Buyukcekmece Yerleskesi Alkent, Buyukcekmece, Istanbul, Turkey; [b]Department of Biomedical Engineering, Nevsehir Haci Bektas Veli Universitesi, Nevsehir, Turkey; [c]Department of Electrical and Electronics Engineering, Abdullah Gul University, Kayseri, Turkey; [d]Department of Electrical and Electronics Engineering, Abdullah Gul University, Kayseri, Turkey

ABSTRACT

The aim of this study is to compare subjective and objective cognitive load measurements in a multimedia learning environment. For this purpose, 20 university students studied in multimedia environments designed by researchers during which eye movements and multichannel electroencephalography (EEG) signals were recorded. Self-report ratings were obtained at the end of the experiment, and retention performances of the students were measured. After the data were collected, Pearson Correlation analysis was applied. According to the results, significant relationship between the number of fixations and EEG frequency band powers was found. In addition, there was a negative relationship between retention performance and number of fixations. Moreover, a negative relationship was found between retention performance and self-reported measurements.

ARTICLE HISTORY
Received 6 April 2020
Accepted 28 September 2020

KEYWORDS
Cognitive load; multimedia learning; eye-tracking; EEG; mental effort

1. Introduction

Multimedia learning, the effect of which has been demonstrated many years ago, has been frequently preferred as a learning environment. Many multimedia environment designers are interested in analyzing learning processes to determine multimedia's contribution to learning. Recent studies examine students' learning performance in conjunction with the cognitive load as an indicator of their mental efforts.

Cognitive load refers to the resources used by working memory in a specific time and is a multidimensional structure that affects the student while performing a task (Paas et al., 1994). In the information processing model, working memory is assumed to have a limited capacity, and long-term memory has an unlimited capacity (Miller, 1994). Cognitive Load Theory is based on the cognitive architecture that includes working memory consisting of two independent channels that enable the processing of visual and audio information that interacts with long-term memory. The theory, which aims to ensure that the capacity of the working memory is used effectively, has focused on the working memory and its limitations in the instructional design process.

According to the cognitive theory of multimedia learning, effective learning is realized by providing the connection between verbal and visual elements that are compatible with each other. The main focus is on the structuring of information obtained from verbal and visual elements. The use of related text and images together makes it easier for users to establish cognitive connections of

CONTACT Duygu Mutlu-Bayraktar dmutlu@istanbul.edu.tr Istanbul Universitesi, Computer Education and Instructional Technology, Besim Omer Pasa Caddesi Istanbul University Kongre Kultur Merkezi yani, B Blok Oda no:103 Beyazit, Fatih, 34452 Turkey

the content presented with these items. This facilitates the understanding process and increases success in performance tests.

The cognitive theory of multimedia learning is based on three underlying assumptions: dual-channel assumption, limited capacity assumption, and active processing assumption. According to the dual-channel assumption, people have separate channels for processing verbal and visual information (Mayer, 2014a). The background of the theory is dual coding theory (Clark & Paivio, 1991) and working memory model (Baddeley, 1992). The amount of information that can be processed at once on each channel is limited. In the final assumption, people integrate the information chosen in the active learning process according to consistent mental structures and combine it with other information.

Many studies have focused on the benefits of multimedia learning based on “Cognitive Theory of Multimedia Learning” (Mayer, 2014b; Sorden, 2012) and “Cognitive Load Theory” (Sweller et al., 1998) in the last two decades (Chen & Kalyuga, 2020; Plass & Kalyuga, 2019; Sweller & Paas, 2017). Split attention, disorientation, and excessive cognitive load is some of the limitations that reduce the efficiency and effectiveness of multimedia applications. Mayer (2001) stated that for the design of multimedia, the cognitive structure of the learner and the characteristics of the working memory should be known. According to Leppink et al. (2014), it is necessary to take into account the information storage limitation of the individuals in working memory and permanence of information. Knowing how the limitations of working memory affect learning helps instructional designers in preparing multimedia environments (Schüler et al., 2011). The cognitive load theory explains this situation.

1.1. Evaluation of cognitive load

Brunken et al. (2003) discuss cognitive load measurement in two dimensions: objectivity (subjective / objective) and causal relationship (direct / indirect). Objectivity refers to whether the assessment method is subjective or based on objective criteria such as behavior, physiological status, or performance. The causal relationship, on the other hand, includes classifications on whether there is a direct relationship between the features that are measured and the measurement (Brunken et al., 2003). In this classification, it is possible to encounter both a subjective and indirect evaluation method.

Also, three different types of measuring method classifications are made to measure the cognitive load: subjective, physiological, and dual-task methodology (Anmarkrud et al., 2019). Subjective measurements are based on the individual’s indication of how much effort they made in the learning process, considering their cognitive processes. The 9-point Subjective Rating Scale, developed by Paas (1992), is the most frequently used cognitive load measurement tool. It is stated that this scale is sensitive to relatively small changes in cognitive load, and the data to be obtained with this scale are valuable and reliable (Paas et al., 2003). Within the scope of the study, this scale was used to measure cognitive load.

Dual-task based measurements are made by giving two different tasks at the same time and by revealing the changes in the learner’s performance. Although this technique is stated to be highly reliable and sensitive, it was rarely used by researchers because it is difficult to apply (Paas et al., 2003).

In physiological measurements, it is based on the assumption that the change in cognitive functions will be reflected by physical variables. The reactions of the brain, heart, and pupil are considered in the cognitive load measured by these methods. These measurements are based on heart rate and changes, analysis of brain activities and eye (fixation, blink rate, changes in the pupil, etc.) activities (Anmarkrud et al., 2019; Brunken et al., 2003; Paas et al., 1994). In this study, eye-tracking and EEG methods, which are among the physiological measurements, were used.

1.2. Evaluation of cognitive load using eye-tracking

Eye-tracking data gives information about eye movements, areas where people focus their attention, the information they ignore, and objects they are disturbed (Koć-Januchta et al., 2017). Eye-tracking indicators determined for cognitive activity related to cognitive load are based on fixations. However, it provides information about cognitive activity and mental effort, along with learning performance measures (Mayer, 2010). As noted in various studies, there is evidence of a strong positive correlation between eye movement measurements (such as total fixation time) and cognitive load. For instance, a long fixation time indicates a high cognitive load (Holmqvist et al., 2011).

Eye-tracking provides information about cognitive processing by evaluating perceptual processing and learning. It can be thought that the fixation and saccades on the screen are the basis of the measurements obtained from the eye-tracking technique (Mayer, 2010). New information is acquired only during focusing. Because, during saccades, the eyes move very quickly on the visual stimulus, and an unclear perception can be obtained. Fixations are also seen as an indicator of cognitive activity. In other words, focusing on an area on the scene is considered as an indication that the individual performs a cognitive action about the information transmitted from that area (Pellicer-Sánchez & Conklin, 2020).

In the classification of content analysis by Lai et al. (2013) and Alemdag and Cagiltay (2018) on the use of eye-tracking in multimedia learning, "information processing patterns" and "the effect of instructional design" themes were the most common. Besides, the effects of the use of multimedia learning principles in design were mostly examined through eye-tracking.

Through eye tracking, a user's physical response to a task and a system is examined, and the instructional interface can be adapted accordingly. However, eye-tracking data is not descriptive. There may be several reasons why a participant looks somewhere at a particular time or order (e.g. task instructions). Consequently, eye-tracking data should be used in conjunction with other cognitive load measurements (Anmarkrud et al., 2019; van Gog & Jarodzka, 2013).

1.3. Evaluation of cognitive load using EEG

Cognitive load measurement strategies are customarily geared up into different domains as subjective measurements: performance measurements, and psychophysiological measurements (Cain, 2007). Nevertheless, the situation, setting, and context can frequently have an effect on the rating as much as the real assignment difficulty. Individual variations also have a considerable role in the accurate evaluation of cognitive load. Subjective questionnaires have a constrained sensitivity to adjustments in cognitive load levels; perceived cognitive load may additionally go up as well as down, while overall performance stays the same, mainly when assignments exist a low cognitive load solely. Additionally, there is a lack of consistency between overall performance rankings and subjective rankings of cognitive load, effort, and difficulty. And performance measurements have a tendency to be assignment-specific, differ within assignments, and not be effortlessly replicated across unrelated assignments. So, the demand to estimate cognitive load objectively has stimulated the development of alternative strategies. Physiological indices count on that cognitive load can be calculated utilizing the degree of physiological activation. These responses are physical indicators that make it viable to find out human psychological processes by tracking bodily alterations (Dan & Reiner, 2017).

The fundamental advantages of the psychophysiological measures of cognitive load are the unobtrusive procedures, the objectivity of the measurements, the sensitivity to the special cognitive processes, and their implicitness and continuity. Implicitness and continuity of EEG measurements permit near real-time evaluation of the cognitive load for the duration of learning. Hence, monitoring psychophysiological variations once they arise in response to the learning session course allows them to make modifications in the learning session depending on the skill of the individual learner (Dirican & Göktürk, 2011).

Electroencephalography (EEG) is a proficient device helping to obtain brain signals that correspond to different states from the scalp surface. In this sense, EEG measurement is capable of indicating cognitive load. The evaluation of EEG oscillations, and their decomposition into specific frequency bands, has frequently been utilized in the assessment of the alteration of the cognitive state of subjects for the duration of the execution of sensory-motor jobs, cognitive tasks, or while learning. The most beneficial evaluation of the EEG is power spectral analysis, which helps one to decide the degree of which the neurons producing the EEG output are synchronously oscillating at distinct frequencies. The variations of specific frequency bands, for different experimental tasks or different time epochs of the same experimental task, can also point to the relationships among the mean divergence of neuron groups and cognitive processes. The development of low-cost wearable EEG headsets now enables considerable usage and marketing and has, therefore, been incorporated into research (Das et al., 2014). The utilization of EEG estimations in educational settings is increasing rapidly and establishing real-time applications (Dan & Reiner, 2017).

In this study, it is aimed to analyze the relationship between fixation numbers obtained by eye-tracking and the cognitive load values measured by EEG and rating scale.

Hence, the research questions in this paper are;

RQ1. Is there a significant relationship between subjective and objective cognitive load measurements?

RQ1.1. Is there a significant correlation between the self-reporting measurements and fixation numbers?

RQ1.2. Is there a significant correlation between the self-reporting measurements and EEG frequency bands?

RQ2. Is there a significant relationship between themselves in the objective cognitive load measurements (fixation numbers and EEG frequency bands)?

RQ3. Is there a significant relationship between retention performance and cognitive load measurements?

RQ3.1. Is there a significant correlation between the retention performance and fixation numbers?

RQ3.2. Is there a significant correlation between the retention performance and EEG frequency bands?

RQ3.3. Is there a significant correlation between retention performance and self-reporting measurements?

2. Method

In this study, the correlational method was used to analyze the relationship among cognitive load measurements measured by EEG, eye-tracking, and rating scale. Correlational research is a method in which the relationships between two or more variables are examined in any way without interfering with these variables (Manning & Dubois, 1962).

The multimedia learning environment has been designed in such a way that it may cause attention to distraction. Eye movements and brain activities were recorded while participants were studying on multimedia. After this process, the rating scale and retention test were applied.

2.1. Study group

Twenty-two undergraduate students attended the research from a public university. Their mean age was 20.5 ($SD = 3.45$), with a range of 19–34. There were ten women and twelve men. The two participants were excluded from the study due to the problem in EEG data analysis. Twenty participants' data were analyzed.

2.2. Procedure

The experiment process of the study was carried out in the EEG laboratory of a public university. Participants were taken to experiment one by one. While studying multimedia, EEG signals and eye-tracking data were recorded (See Figure 1). Then they answered the paper and pencil tests (cognitive load rating scale & retention test).

Figure 1. Experiment process and devices.

2.3. Materials

2.3.1. Instructional material

The researchers used a multimedia learning environment for the experiment. The environment has been designed using image, video, text, and narration related to the car engine and its parts (Mutlu-Bayraktar & Bayram, 2018). In this multimedia, some scenes have been created in contravention of multimedia learning principles to examine changes caused by cognitive load. For example, the texts are given separately without being integrated into the images. Both pictures and videos were used; in addition, text and narration with different contents were presented at the same scene (see Figure 2).

2.4. Data collection materials

2.4.1. EEG recording device

In this study, the G.TEC brand G.Nautilus wireless EEG amplifier (Schiedlberg, Austria) with dry electrodes was used to record EEG signals. According to the international 10–20 system, EEG signals were

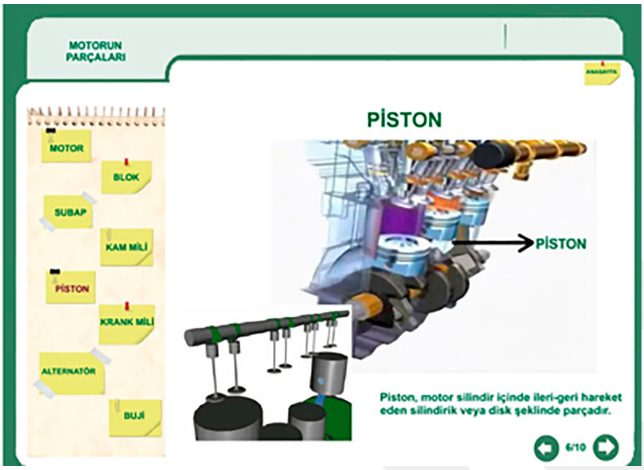

Figure 2. Scenes from the multimedia learning environment.

recorded from 16 channels (FP1, FP2, Fz, F3, F4, Cz, C3, C4, T7, T8, Pz, P4, P3, PO7, PO8, Oz). The sampling frequency was 250 samples/s, and 48–52 Hz notch filter was applied in order to prevent interference of power line noise.

2.4.2. Eye tracking device

In this study, SensoMotoric Instruments (SMI) eye-tracking glasses, which give data concerning the eye movements of the user in a mobile test device, were utilized to obtain eye-tracking data. The gadget is connected to a spectator computer or a portable phone. The central focuses being looked at with the glasses were followed and recorded. iView X, Explore Center, BeGaze are utilized as the computer programs with these gadgets.

2.4.3. Retention test

The retention test was comprised of five questions in which the parts of the engine were depicted to all students to assess the retention performance of the learners. The participants were asked to compose the definition of the concept presented and were expected to recall the names of outwardly shown parts of the engine on the picture. Each correct answer was worth 20 points.

2.4.4. Cognitive load rating scale

Cognitive Load Rating Scale is based on the individual's indication of how much effort they put in the learning process, considering their cognitive processes. The 9-point Subjective Rating Scale Likert scale that ranges from 1 (low) to 9 (high) developed by Paas (1992) is the most frequently used cognitive load measurement tool. The scale is presented to the participants as follows:

This survey measures the mental effort you put during the learning task. How much mental effort did you put while performing this task?

Please mark below the value that expresses your situation. Participants were asked to choose from the range "1: Too Little to 9: Too Much" below the statement.

2.5. Experiment process

At the EEG laboratory, the participants were measured separately in one session. Firstly, all participants were given a performance test to assess the students' previous knowledge for the parts of a car engine. The test consisted of two open-ended questions, which helped to determine the level of prior knowledge. Three students showing disparities on prior-knowledge were excluded from the analysis. The students were asked to study at the notebook on the multimedia. After the calibration of the eye-tracking device, the experiment was ready to begin. Hence, the record started in 0th second, and the multimedia learning environment screen was engaged in 15th second. All scenes were set to 10 s approximately. So, 9 scenes passed at self-paced, and the experiment ended. In this way, participants' eye movements and brain electrical activity were observed and registered with eye-tracking and EEG signal acquisition equipment while studying in multimedia learning environments

2.6. Data analysis

In this study, data analysis was performed with retention performance, EEG frequency band (theta, alpha, beta, gamma) powers, and fixation numbers. The Kolmogorov–Smirnov normality test was performed on the data; the EEG frequency band powers, retention performance, self-reported cognitive load, fixation numbers exhibited a normal distribution ($p > 0.05$).

EEG recordings were analyzed after the experiment on MATLAB. First, EEG signals were filtered using a filterbank that consists of four different digital filters (4–8 Hz, 8–15 Hz, 15–32 Hz, 32–48 Hz), which were 8th order bandpass filters (Butterworth). Filtered signals were squared in the time domain, and corresponding band powers (theta, alpha, beta, gamma) were calculated. Hence, for each channel, the power values of the 4 bands were calculated. EEG recordings of two participants have been removed from the study due to the data recording problem, and those of 20 participants' data were analyzed.

The fixation numbers were analyzed from eye movements via BeGaze 2.4. Fixation is defined as gazing at objects or areas usually with a distribution level of 2 degrees and a minimum of 100–200 ms duration.

In order to make a relational analysis, Pearson Correlation Analysis was performed with SPSS 21.0 program, and the results were evaluated.

3. Results

RQ1. Is there a significant relationship between subjective and objective cognitive load measurements?

Pearson Moments Product Correlation Coefficient analysis was performed to determine the relationship between objective and subjective cognitive load measurements.

RQ1.1. Is there a significant correlation between the self-reporting measurements and fixation numbers?

According to the research finding analyzing the correlation between self-reporting measurements and fixation numbers, no significant relationship was found between self-reporting measurements and fixation numbers ($p > 0.05$, See Table 1).

RQ1.2. Is there a significant correlation between the self-reporting measurements and EEG frequency bands?

As another finding, no significant relationship was found between self-reporting measurements and EEG frequency bands ($p > 0.05$, See Table 1).

RQ2. Is there a significant relationship between themselves in the objective cognitive load measurements (fixation numbers and EEG frequency bands)?

The results revealed that a statistically significant, weak, and positive relationship was found between fixation numbers and EEG frequency bands ($p < 0.05$; $r = 0.130$, See Table 1). It has been observed that as the fixation numbers increase, brain signals increase.

RQ3.1. Is there a significant correlation between the retention performance and fixation numbers?

As a result of the analysis, a statistically significant and negative correlation was noted between retention performance and fixation numbers ($p < 0.05$, $r = -0.370$, See Table 1). According to the results, retention scores decreased as the fixation numbers increased.

Table 1. Results of Pearson Moment Product Correlation Coefficient.

Variables	*N*	*r*	*p*
Mental Effort & Fixation Numbers	20	0.134	0.283
Mental Effort & Frequency Bands	20	0.072	0.439
Fixation Numbers & Frequency Bands	20	0.130	0.03
Retention Performance & Fixation Numbers	20	−0.370	0.044
Retention Performance & Frequency Bands	20	0.072	0.133
Retention Performance & Metal Effort	20	−0.510	0.030

RQ3.2. Is there a significant correlation between the retention performance and EEG frequency bands?

No significant relationship was found between retention performance and frequency bands ($p >$ 0.05, See Table 1).

RQ3.3. Is there a significant correlation between retention performance and self-reporting measurements?

The results revealed that a statistically significant and negative relationship was found between retention performance and self-reporting measurements ($p < 0.05$; $r = -0.510$, See Table 1). It has been observed that as the retention performance increased, mental effort self-reported decreased.

4. Conclusion

Cognitive Load Theory assumes that when processing information, people have limited working memory and unlimited capacity long-term memory. Considering this limitation in working memory, it focuses on using the working memory capacity most effectively in instructional design processes (Koć-Januchta et al., 2017). Thus, the theory advocates that learning will be more accessible because the correct use of design principles will ensure that cognitive resources are directed correctly. Based on the assumptions, it can be said that if the limited capacity of the working memory is overloaded, it will decrease the efficiency of learning and be affected by the processes of remembering and transferring information (Paas et al., 2003).

When we look at the studies on Cognitive Load Theory, the efficiency of design principles is generally examined. In these studies, it is seen that subjective measurements were mostly used (Mutlu-Bayraktar et al., 2019). In recent years, the researches, especially on cognitive load measurements, have started to be supported with objective measures like eye-tracking, EEG, fNIRS techniques. In this study, it is aimed to analyze the relationship between objective and subjective measurements with each other. For this purpose, eye movements and brain signals were recorded while the participants were studying in multimedia learning environments. As a result of the measurements, the relationship among fixation numbers, frequency bands, and self-reporting measures was analyzed.

In recent years, many different studies have been presented to demonstrate a corresponding connection among eye-tracking, EEG frequency bands, and self-reports. Measures that directly indicate the cognitive process are required to support self-reporting cognitive load measurements while learners are studying in multimedia (Mayer, 2017). As a result of our study, which analyzes the correlation between self-reporting measurements and fixation numbers, there was no significant relationship between self-reporting measurements and fixation numbers. Rayner (1998) stated that a longer fixation duration may be an indicator of deep processing. It is stated that measuring longer fixation numbers on an item may indicate processing difficulty (Kruger & Doherty, 2016). However, it is an expected result that longer fixation does not give results related to self-reporting measurements, considering that it may be affected by other factors such as changes and brightness (van Gog & Jarodzka, 2013).

According to another study finding that the relationship between objective and subjective measurements was analyzed, no significant relationship was found between self-reporting measurements and EEG frequency bands. Similarly, according to the results of (Örün & Akbulut, 2019), none of the EEG waves were correlated with either self-reported cognitive load. Lee (2014) examined a solid and substantial strategy for estimating cognitive load during learning by comparing different sorts of cognitive load measurements: self-reporting, EEG, and learning outcome. EEG was calculated while watching a documentary delivered in English or in Korean, and the subjective rating load was recorded immediately following watching. Perception has been checked for achievements in learning. The findings showed a significant relationship between self-report difficulty rating and beta frequency in the T3 area via EEG. Difficulty rating and learning performance are negatively correlated (Rayner, 2009). Beal and Galan (2012) intended to assess whether EEG measurement of cognitive load and attention obtained as students solved mathematics problems could be utilized to estimate the success or failure in solving problems. Students resolved a set of SAT mathematical problems while EEG signals, which produced measurements of sustained attention and cognitive workload every second, were recorded. Students also commented on their level of dissatisfaction and each problem's perceived complexity. Outcomes from a Support Vector Machine (SVM) training showed that the problem consequences could be estimated properly from the incorporation of the workload signals and attention at a better level than unmeasured conditions. EEG results were also correlated with self-report of problem difficulty by students themselves.

On the other hand, when we examine the studies in which EEG and self-reporting measurements were hand-in-hand, the following comments were obtained. In the study presented by Lee, the findings had conceptual consequences in terms of a negative relationship between difficulty rating and learning performance (Lee, 2014). In the research examined by Chang et al. (2016), there were no substantial findings in terms of the preliminary correlation between the theta/alpha ratio on the EEG and the cognitive load observed.

Future studies need more EEG-based data analysis, such as non-linear approaches with a high enough sample size. Results demonstrate that relatively non-intrusive EEG techniques may be used to boost the tutoring systems' effectiveness. In our study, however, no significant correlation was observed between self-reporting measurements and EEG frequency bands even though each frequency band was evaluated separately. In EEG and cognitive load studies, alpha and beta wave band powers from the frontal lobe were found to be valid (Lee, 2014; Makransky et al., 2019; Örün & Akbulut, 2019). In our study, the averages of alpha and beta wave band powers were analyzed. It was seen that there was no significant relationship in the analysis of other band powers. Some studies indicated that subjective and objective cognitive load assessments could provide any information to test the theoretical mechanisms involved in multimedia learning (Makransky et al., 2019). Yet, self-reporting measurements and EEG results are thought to be better in separate evaluation in our study.

According to our study, the findings showed that between fixation numbers and EEG frequency bands, a statistically significant, weak, and positive correlation was noticed. It was found that as the number of fixations rose, EEG band powers also rose. That means EEG and eye-tracking correlation may help to interpret cognitive load results. In another study that reached results in parallel with the results, we obtained in our study, Soussou et al. (2012) outlined a project whose aim was to assess the feasibility of using unobtrusive cognitive evaluation strategies to maximize training efficiency and expediency. The project team showed a correlation between performance assessment, cognitive workload, and subject expertise X-ray screening tasks based on EEG and eye-tracking. Findings suggested a strong correlation between EEG and eye-tracking metrics based cognitive workload measurement obtained during a simulated baggage screening task, as well as subject expertise and error rates in the same process. These findings indicate that cognitive monitoring may be beneficial in enhancing training efficiency by allowing training paradigms to adapt to increased expertise.

As another result of the study, a negative correlation was found between retention performance and fixation numbers. According to Holmqvist et al. (2011), during the multimedia learning, as the fixation numbers of learners increased, demands on working memory increased. This required more cognitive load, and this was expected to affect retention performance negatively.

The goal of the study presented by Wang et al. (2016) was to investigate the relationships between the visual behaviors and learning outcomes of students, and between visual behaviors and prior cooking interest in multimedia recipe learning. An eye-tracking analysis was performed with a group of 29 volunteer hospitality majors in Taiwan, including the pretest, recall test, and retention test. A static page displaying the ingredients in a text and picture depiction and a dynamic page displaying the knife skills in a text and picture depiction was part of the multimedia recipe. Total fixation duration, number of fixations, whole reading time, and inter-scanning count were used to examine the visual attention distributions of the students among the different components of representation and their visual strategies to learn the recipe. The findings indicate that for the static recipe, every student paid more visual attention to the text than to the picture information, and paid more visual attention to the video than to the text on the dynamic page. The visual attention paid to the text on the dynamic page was also negatively correlated with the retention of the episodic knowledge of knife skills. As a result, the best indicator to negatively predict the learning retention of students was the inter-scanning count between text and video on the dynamic page. Similarly, the best indicator to positively predict students' prior cooking interest was total fixation duration on the text information on the static page.

Nisiforou and Laghos (2013) reported the findings of research attempting to determine the extent of field dependence/independence (FD/FI), which is an important cognitive style dimension of individuals during the processing of visual stimulus tasks. In particular, whether there were variations among cognitive groups in terms of the time taken to accomplish the given tasks or not in addition to the correlation between eye-tracking measures and the Hidden Figure Test (HFT) scores were analyzed. Findings showed a statistically meaningful correlation between HFT scores and Eye-Tracker scores. Besides, the FD and the FI groups varied in the time-completion of tasks.

The results showed the capacity for eye-tracking to be used as a mechanism in analyzing the cognitive characteristics of users. Eventually, the concept of the additional program, as well as some theoretical underpinnings, were answered for educational designers and instructors. As for our study, a statistically meaningful and negative correlation between the retention score and fixation numbers was reported as a consequence of the study. Retention scores declined as fixation numbers increased, according to the results. We are in close agreement with Nisiforou and Laghos (2013) and Wang et al. (2016) about eye-tracking, the retention test, and the applications which are similar to retention test combinations.

In our study, no significant relationship was found between retention performance and frequency band powers. In their paper, Zarjam et al. (2012) examined the correlation dimension, Hurst exponent (different time series methods including correlation), and approximate entropy analysis of EEG signals to investigate alterations in working memory load during the operation of a cognitive task of varying degrees of complexity and difficulty. EEG signals had been recorded during an arithmetic assignment while the induced load was once varying in seven stages from very easy to extraordinarily difficult. Experimental findings exhibited that the values of the measurements taken from the delta frequency band of signals obtained from the frontal and occipital lobes of the brain differed in accordance with the task challenge degree triggered. In contrast, the Hurst exponent values and approximate entropy reduced as task challenge increased, indicating extra regularity and predictability in the signals. Hence, concerning our results, no significant correlation was observed between retention performance and frequency bands. It may indicate a hint even though the task challenge is not the same application for the retention test. Many more studies are necessary to comment on this parallelism for correlation analysis.

In our final research question result, the findings showed a significant and negative correlation between measurements of self-reporting and retention performance. It was found that self-reported mental effort reduced as the retention output grew. That is promising for the correlation interpretation using retention performance and the application, which is similar to self-reporting measurement. Örün and Akbulut (2019), in a computer-supported learning environment, examined the effect of multitasking, EEG, and physical setting on cognitive load and retention among undergraduate students. In the first trial, 129 participants were randomly allocated to three multitasking scenarios when researching a biology video: multitasking as simultaneous, multitasking as sequential, and multitasking as control. While some participants studied the content in a library room, others studied in a café. Subjective cognitive load, retention, working memory, mental perceived effort, and objective cognitive load were assessed. Results demonstrated a significant loss in retention among simultaneous multitaskers whose perceived mental effort increased in a café. The perceived mental effort was found to be correlated with frontal lobe beta band power (F7). The effect of using EEG headsets was tested in the second experiment. So, 60 new participants were exposed to a computational laboratory without EEG headsets to the same interventions. The measures of retention and cognitive load were identical to Trial 1. Retention of the content was slightly worse during online messaging. Working memory components and perceived mental effort in both trials were correlated with retention, while the subjective cognitive load was not correlated.

In studies comparing objective and subjective cognitive load measurements, it was seen that there were also results that should be evaluated separately, together with the results that they were related to each other. In this study, although there were related measurements, it was concluded that they should be evaluated separately and then analyzed.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Notes on contributors

Duygu Mutlu Bayraktar received her PhD in Computer Education and Instructional Technology Department from Marmara University in July 2014. She obtained her master degree in Computer Education and Instructional Technology Department from Hacettepe University in June 2010. Her research interests include multimedia learning, instructional design, eye-tracking, cognitive science, and human–computer interaction.

Pınar Özel received her BS degree in Electrical-Electronics Engineering from Erciyes University, Kayseri in 2007, and MS degree in Biomedical Engineering from Bogazici University, İstanbul in 2011. She obtained her Ph.D. degree in Biomedical Engineering from Istanbul University in 2019. As a professional experience, she worked as a product manager. Her research areas are signal processing and machine learning techniques to biomedical signals.

Fatih Altindis was born in Kayseri, on 1 October 1992. He graduated from Bilkent University with a Bachelor degree of Electrical and Electronics Engineering in January 2016. He has completed his Master of Science education at Electrical and Computer Engineering of Abdullah Gul University in January 2018. His main study fields in master programme were brain-computer interfaces and intra-ocular systems. He is a Ph.D. student and research assistant at Abdullah Gul University since then.

Bülent Yılmaz received his BS and MS degrees in Electrical-Electronics Engineering from the Middle East Technical University, Ankara, in 1997 and 1999. He obtained his PhD degree from the Bioengineering Department of the University of Utah, Salt Lake City, Utah. He has been working as a faculty member since 2011 in Abdullah Gül University, Department of Electrical-Electronics Engineering, Kayseri. His current research interests include biomedical signal and image processing applications on brain-computer interfaces, texture analysis on colonoscopic and PET/CT images.

ORCID

Duygu Mutlu-Bayraktar http://orcid.org/0000-0002-1026-5606
Pinar Ozel http://orcid.org/0000-0002-9688-6293
Fatih Altindis http://orcid.org/0000-0002-3891-935X
Bulent Yilmaz http://orcid.org/0000-0003-2954-1217

References

Alemdag, E., & Cagiltay, K. (2018). A systematic review of eye tracking research on multimedia learning. *Computers & Education*, *125*, 413–428. https://doi.org/10.1016/j.compedu.2018.06.023

Anmarkrud, Ø, Andresen, A., & Bråten, I. (2019). Cognitive load and working memory in multimedia learning: Conceptual and measurement issues. *Educational Psychologist*, *54*(2), 61–83. https://doi.org/10.1080/00461520.2018.1554484
Baddeley, A. (1992). Working memory. *Science*, *255*(5044), 556–559. https://doi.org/10.1126/science.1736359
Beal, C. R., & Galan, F. C. (2012). EEG estimates of cognitive workload and engagement predict Math problem solving outcomes. In *Society for research on educational effectiveness*. https://eric.ed.gov/?id=ED536318
Brunken, R., Plass, J. L., & Leutner, D. (2003). Direct measurement of cognitive load in multimedia learning. *Educational Psychologist*, *38*(1), 53–61. https://doi.org/10.1207/S15326985EP3801_7
Cain, B. (2007). *A review of the mental workload literature*. Defence Research And Development Toronto (Canada). https://apps.dtic.mil/docs/citations/ADA474193
Chang, H.-C., Hung, I.-C., Chew, S. W., & Chen, N.-S. (2016). Yet another objective approach for measuring cognitive load using EEG-based workload. *2016 IEEE 16th International Conference on Advanced Learning Technologies (ICALT)* (501–502). https://doi.org/10.1109/ICALT.2016.145
Chen, O., & Kalyuga, S. (2020). *Cognitive load theory, spacing effect, and working memory resources depletion: Implications for instructional design* [Chapter]. Form, Function, and Style in Instructional Design: Emerging Research and Opportunities. https://doi.org/10.4018/978-1-5225-9833-6.ch001
Clark, J. M., & Paivio, A. (1991). Dual coding theory and education. *Educational Psychology Review*, *3*(3), 149–210. https://doi.org/10.1007/BF01320076
Dan, A., & Reiner, M. (2017). Real time EEG based measurements of cognitive load indicates mental states during learning. *JEDM| Journal of Educational Data Mining*, *9*, 31–44. https://doi.org/10.1016/j.ijpsycho.2016.08.013
Das, R., Chatterjee, D., Das, D., Sinharay, A., & Sinha, A. (2014). Cognitive load measurement—A methodology to compare low cost commercial EEG devices. *2014 International Conference on Advances in Computing, Communications and Informatics (ICACCI)* (1188–1194). https://doi.org/10.1109/ICACCI.2014.6968528
Dirican, A. C., & Göktürk, M. (2011). Psychophysiological measures of human cognitive states applied in human computer interaction. *Procedia Computer Science*, *3*, 1361–1367. https://doi.org/10.1016/j.procs.2011.01.016
Holmqvist, K., Nyström, M., Andersson, R., Dewhurst, R., Jarodzka, H., & Weijer, J. v. d. (2011). *Eye tracking: A comprehensive guide to methods and measures*. OUP Oxford.
Koć-Januchta, M., Höffler, T., Thoma, G.-B., Prechtl, H., & Leutner, D. (2017). Visualizers versus verbalizers: Effects of cognitive style on learning with texts and pictures – An eye-tracking study. *Computers in Human Behavior*, *68*, 170–179. https://doi.org/10.1016/j.chb.2016.11.028
Kruger, J.-L., & Doherty, S. (2016). Measuring cognitive load in the presence of educational video: Towards a multimodal methodology. *Australasian Journal of Educational Technology*, *32*(6), Article 6. https://doi.org/10.14742/ajet.3084
Lai, M.-L., Tsai, M.-J., Yang, F.-Y., Hsu, C.-Y., Liu, T.-C., Lee, S. W.-Y., Lee, M.-H., Chiou, G.-L., Liang, J.-C., & Tsai, C.-C. (2013). A review of using eye-tracking technology in exploring learning from 2000 to 2012. *Educational Research Review*, *10*, 90–115. https://doi.org/10.1016/j.edurev.2013.10.001
Lee, H. (2014). Measuring cognitive load with electroencephalography and self-report: Focus on the effect of English-medium learning for Korean students. *Educational Psychology*, *34*(7), 838–848. https://doi.org/10.1080/01443410.2013.860217
Leppink, J., Paas, F., van Gog, T., van der Vleuten, C. P. M., & van Merriënboer, J. J. G. (2014). Effects of pairs of problems and examples on task performance and different types of cognitive load. *Learning and Instruction*, *30*, 32–42. https://doi.org/10.1016/j.learninstruc.2013.12.001
Makransky, G., Terkildsen, T. S., & Mayer, R. E. (2019). Role of subjective and objective measures of cognitive processing during learning in explaining the spatial contiguity effect. *Learning and Instruction*, *61*, 23–34. https://doi.org/10.1016/j.learninstruc.2018.12.001
Manning, W. H., & Dubois, P. H. (1962). Correlational methods in research on human learning. *Perceptual and Motor Skills*, *15*(2), 287–321. https://doi.org/10.2466/pms.1962.15.2.287
Mayer, R. E. (2010). Unique contributions of eye-tracking research to the study of learning with graphics. *Learning and Instruction*, *20*(2), 167–171. https://doi.org/10.1016/j.learninstruc.2009.02.012
Mayer, R. E. (2014a). Multimedia Instruction. In J. M. Spector, M. D. Merrill, J. Elen, & M. J. Bishop (Eds.), *Handbook of research on educational communications and technology* (pp. 385–399). Springer. https://doi.org/10.1007/978-1-4614-3185-5_31
Mayer, R. E. (2014b). *The Cambridge handbook of multimedia learning*. Cambridge University Press.
Mayer, R. E. (2017). Using multimedia for e-learning. *Journal of Computer Assisted Learning*, *33*(5), 403–423. https://doi.org/10.1111/jcal.12197
Mayer, R. E. (2001). *Multimedia learning*. Cambridge University Press.
Miller, G. A. (1994). *The magical number seven, plus or minus two: Some limits on our capacity for processing information*. https://doi.org/doi.org/10.1037/h0043158
Mutlu-Bayraktar, D., & Bayram, S. (2018). Evaluation of situations causing split of attention in multimedia learning environments via eye-tracking method. Khosrow-PourIn, M. (Eds.), *Digital multimedia: Concepts, methodologies, tools, and applications* (pp. 348–372). IGI Global.
Mutlu-Bayraktar, D., Cosgun, V., & Altan, T. (2019). Cognitive load in multimedia learning environments: A systematic review. *Computers & Education*, *141*, 103618. https://doi.org/10.1016/j.compedu.2019.103618

Nisiforou, E. A., & Laghos, A. (2013). Do the eyes have it? Using eye tracking to assess students cognitive dimensions. *Educational Media International*, *50*(4), 247–265. https://doi.org/10.1080/09523987.2013.862363

Örün, Ö, & Akbulut, Y. (2019). Effect of multitasking, physical environment and electroencephalography use on cognitive load and retention. *Computers in Human Behavior*, *92*, 216–229. https://doi.org/10.1016/j.chb.2018.11.027

Paas, F. G. (1992). Training strategies for attaining transfer of problem-solving skill in statistics: A cognitive-load approach. *Journal of Educational Psychology*, *84*(4), 429–434. https://doi.org/10.1037/0022-0663.84.4.429

Paas, F., Renkl, A., & Sweller, J. (2003). Cognitive load theory and instructional design: Recent developments. *Educational Psychologist*, *38*(1), 1–4. https://doi.org/10.1207/S15326985EP3801_1

Paas, F. G. W. C., van Merriënboer, J. J. G., & Adam, J. J. (1994). Measurement of cognitive load in instructional research. *Perceptual and Motor Skills*, *79*(1), 419–430. https://doi.org/10.2466/pms.1994.79.1.419

Pellicer-Sánchez, A., & Conklin, K. (2020). Eye-tracking as a data collection method. In H. Rose and J. McKinley (Eds.), *The Routledge handbook of research methods in applied linguistics* (pp. 370–382). Routledge.

Plass, J. L., & Kalyuga, S. (2019). Four ways of considering Emotion in cognitive load theory. *Educational Psychology Review*, *31*(2), 339–359. https://doi.org/10.1007/s10648-019-09473-5

Rayner, K. (1998). Eye movements in reading and information processing: 20 years of research. *Psychological Bulletin*, *124* (3), 372–422. https://doi.org/10.1037/0033-2909.124.3.372

Rayner, K. (2009). Eye movements in reading: Models and data. *Journal of eye movement research*, *2*(5), 1.

Schüler, A., Scheiter, K., & van Genuchten, E. (2011). The role of working memory in multimedia instruction: Is working memory working during learning from text and pictures? *Educational Psychology Review*, *23*(3), 389–411. https://doi.org/10.1007/s10648-011-9168-5

Sorden, S. D. (2012). The cognitive theory of multimedia learning. B. J. Irby & R. Lara–Alecio (Eds.), *Handbook of educational theories, information age publishing* (pp. 1–31). Charlotte.

Soussou, W., Rooksby, M., Forty, C., Weatherhead, J., & Marshall, S. (2012). EEG and eye-tracking based measures for enhanced training. *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (1623–1626). https://doi.org/10.1109/EMBC.2012.6346256

Sweller, J., & Paas, F. (2017). Should self-regulated learning be integrated with cognitive load theory? A commentary. *Learning and Instruction*, *51*, 85–89. https://doi.org/10.1016/j.learninstruc.2017.05.005

Sweller, J., van Merrienboer, J. J. G., & Paas, F. G. W. C. (1998). Cognitive architecture and instructional design. *Educational Psychology Review*, *10*(3), 251–296. https://doi.org/10.1023/A:1022193728205

van Gog, T., & Jarodzka, H. (2013). Eye tracking as a tool to study and enhance cognitive and metacognitive processes in computer-based learning environments. In R. Azevedo, & V. Aleven (Eds.), *International handbook of metacognition and learning technologies* (pp. 143–156). Springer. https://doi.org/10.1007/978-1-4419-5546-3_10

Wang, C.-Y., Tsai, M.-J., & Tsai, C.-C. (2016). Multimedia recipe reading: Predicting learning outcomes and diagnosing cooking interest using eye-tracking measures. *Computers in Human Behavior*, *62*, 9–18. https://doi.org/10.1016/j.chb.2016.03.064

Zarjam, P., Epps, J., Lovell, N. H., & Chen, F. (2012). Characterization of memory load in an arithmetic task using non-linear analysis of EEG signals. *2012 Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (3519–3522). https://doi.org/10.1109/EMBC.2012.6346725