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Evaluation of redundancy effect in multimedia learning environment using EEG signals and eye-tracking

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Abstract

In the multimedia learning environment, presenting texts in different formats at the same time revealed the redundancy effect. This study aimed to evaluate cognitive load by recording brain signals and eye movements while texts were presented in different formats. For this purpose, two different multimedia learning environments in which printed text and narration were presented together and solo narration were designed, respectively. An experimental study was conducted by dividing 20 of 40 participants into two different multimedia environments. This study ensured the main perspectives of building up a learning profile structure depending on learners' cognitive profile by providing two different multimedia designs for redundancy effect via participants' brain topographies and eye movements. The findings suggested that the redundancy group demonstrated elevated cognitive load, especially in the frontal and parietal regions, as seen by heightened theta, beta, and gamma wave activity. Conversely, the non-redundancy group exhibited enhanced processing efficiency with less cognitive strain.

Introduction

Multimedia learning environments involve more than one multimedia material such as animations, videos, verbal instructions, and written texts. These materials are generally used in the same scene simultaneously. An array of cognitive procedures is required for learners to process this simultaneously presented information. First of all, learners with limited working memory capacity need to focus on the information provided (Paas, et al., 2010). Working memory that processes knowledge and builds new knowledge is highly limited in terms of capacity and duration when dealing with new knowledge (Baddeley, 1992). Making instructional designs that will ensure the most effective use of this limited capacity forms the basis of Cognitive Load Theory (Chen & Kalyuga, 2020).

Multimedia helps learners learn better, but different resource forms can affect learners' cognitive load differently. Having to process different forms of the same information inflicts a cognitive load that hinders learning (Sweller, 2010). The management of cognitive resources is critical to designing multimedia, where verbal information is presented in simultaneous and different formats. It should be designed considering the limited capacity (Paas et al., 2003; Trykpe et al., 2023).

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The redundant information may induce a redundancy effect, which is another potential obstacle to schema acquisition and occurs when the learner is required to process nonessential information. The processing of unnecessary information leads to cognitive overload. In general, the redundancy effect emerges in cases when the same information is presented in different forms and with unnecessary additional information in a way to cause learners to have difficulty and experience (Mayer & Johnson, 2008; Pastore et al., 2018). While (Mayer, 2017) reports that presenting visuals with narration together with the texts in written form might cause a negative effect in multimedia learning environments, many study results indicate that giving texts only through narration is more effective in reducing this effect (Mutlu Bayraktar & Altun, 2014; Schüler et al., 2013). The effect is explained as people learn better from graphics or illustrations and narration than graphics, narration, and redundant on-screen text (Mayer, 2014).

In recent studies where redundancy effect, learning (e.g., retention), and cognitive load (CL) were measured, the situations that should be considered in multimedia design were reported (Jung et al., 2016; Lee & Mayer, 2015; Albers et al., 2023; Baceviciute et al., 2022). This study emphasized that the research used printed text and narration to explain the redundancy effect more effectively. In a study where CL was measured with the eye-tracking method, it was seen that presenting short texts as keywords on the scene eliminated the redundancy effect. It is concluded that the learner can filter these texts and focus on the visual with narration (Liu & Chuang, 2011). In our study, all these types of verbal modalities were presented in different scenes and were examined thoroughly.

Cognitive Load Assessment through EEG Signals

EEG is a traditional brain imaging approach that measures the electrical activity in the brain generated by many neurons firing in the meantime, yielding enough electrical potential that can be quantified along the scalp. The use of EEG provides a novel and promising way of dealing with neuroscience in education. EEG is identified as a physiological measure that can fill in a continuous and real-time evaluation of CL, detecting subtle instantaneous load changes that can help explain the effects of educational interposition (Antonenko et al., 2010; Mutlu Bayraktar et al., 2023; Camnalbur et al., 2013).

On the other hand, EEG has a potential value for assessing CL during multimedia learning because it has several advantages over subjective measurements. Moreover, the physiological signal measure is prone to change over time and can be collected while learning occurs, rather than depending on CL measurement after learning is accomplished. EEG has a high spatial resolution that enables it to estimate millisecond-scale changes in CL. The model allows for externalization into various spatial load forms, such as instantaneous, peak, average, accumulated with the overall load. Despite these preferences, the use of the EEG measurement of CL remains unclear to a certain extent.

Background of Empirical Mode Decomposition for Biophysiological Signals

Recently, a data-driven decomposition strategy known as the empirical mode decomposition (EMD) has been intended to address the issue of nonstationary signals. This strategy depends on the signal's decomposition into amplitude and frequency modulated components (called Intrinsic Mode Functions, IMFs). Additionally, it gives a great structure for catching the local phase and the signal's local amplitude variations. EMD strategy has been effectively utilized in biomedical signal processing problems like feature extraction, noise filtering, and time series modeling. In this regard, representation of analytic signals of IMFs has been proposed to depict the localized frequency information at various time scales. It is acquired from Hilbert Transform of IMFs. In the examination of IMFs for physiological signals, a few feature extraction methods have been suggested. For instance, Fu et al. (Fu et al., 2015) have utilized the Hilbert marginal spectrum analysis for automatic seizure diagnosis via EEG signals. The consequences of this case have demonstrated that the proficiency of this method was superior to Fourier analysis. The parameters estimated from the analytic IMFs have been recognized as an important feature for epileptic seizure categorization. The amplitude and frequency number of analytic IMFs have also demonstrated an encouraging outcome for the differences between ordinary and diabetic RRI signals representing the time intervals between successive heart R-waves. Furthermore, a few features obtained from the Hilbert energy spectrum have been effectively utilized to separate sleep stages (Ghaderyan & Abbasi, 2017). Zhuang et al. (2017) proposed a process of feature extraction and emotion recognition based on EMD utilizing EEG signals. Similarly, through EEG signals, Akshaya et al. (Akshaya et al., 2015), Gupta et al. (Gupta et al.,2017) and Rahman and Fattah evaluated EMD algorithms for mental task classification (Rahman & Fattah, 2017).

Cognitive Load Assessment through Empirical Mode Decomposition Strategy

In a few studies, EMD was used to determine the CL. Hossain and Yeasin (Hossain & Yeasin, 2014) proposed CL's effects on cognitive states (such as dissonance and overload) from pupillary responses with a Hilbert transform-based method to calculate temporal patterns. Ghaderyan and Abbasi proposed the dynamic Hilbert Warping method for RR-interval signals assessed in CL estimation (Ghaderyan & Abbasi, 2017). Secerbegovic et al. (Secerbegovic et al., 2017) have used EMD technique for evaluating CL vs. stress differentiation using single-channel EEG signals. Malaholi et al. proposed an approach that combines different methods: from signal processing by EMD to advanced statistical analysis in a unique process to categorize CL based on both self-evaluated measures and psycho-physiological parameters as electrodermal activity, ocular activity, cardiovascular measures, respiration rate (Malagoli et al., 2017). Gavas et al. intend to isolate different parts of the pupillary response to evaluate CL and the certainty with which the mission is accomplished. In their study, ensemble empirical mode decomposition (EEMD) followed by independent component analysis (ICA) was utilized to reconstruct the original signal (Gavas et al., 2018). As one of the commonly used cognitive tasks that can evaluate individual working memory capacity, to research the complex span tasks' electrophysiological data, Chuang et al. applied EEMD (Chuang et al., 2019; Dinçer, 2016). Dutta et al. (Dutta et al., 2018) proposed a classification method for non-motor cognitive tasks in EEG-based brain-computer interface utilizing phase space features in a multivariate empirical mode decomposition (MEMD) domain. Dutta et al. suggested another feature extraction approach based on the multivariate autoregressive model (MVAR) model of the sensitive IMF sets in MEMD domain for classifying three different non-motor cognitive tasks in EEG-based brain-computer interface (BCI) system (Dutta et al., 2018). Noshadi et al. outlined EMD and actualized this model for time-frequency domain features in evaluating cognitive assignments (Noshadi et al., 2014).

Cognitive Load Assessment through Eye-Tracking Methods

The eye-tracking method, while learners study the content on the screen, provides eye movement data about the areas they pay attention to, the items they ignore, and the things they are disturbed (Russell, 2005). With the eye-tracking method, scan path of the eyes, time spent looking at various elements, focus areas of visual attention, saccades, fixation - duration are obtained. Eye-tracking measurements are valuable in supporting and verifying the results obtained as subjective measurements in multimedia studies. Besides, eye movements provide in-depth qualitative and quantitative data about the user's information process. Eye movements are associated with cognitive processes, giving information about the brain's process, observing and interpreting data (Biedert et al., 2010; Mutlu Bayraktar etal., 2022).

Eye-tracking technology can be utilized to determine the cognitive process in multimedia learning to overcome the restriction of self-reported measurements. This technique provides reporting the perceived mental effort with eye movements in the environment presented with verbal and visual information (Biedert et al., 2010). The focusing on the scene is considered an indication that the people perform a cognitive activity about the information transmitted through that area. Studies provide evidence that there is a close relationship between total fixation time and cognitive activity; the longer duration is considered indicative of high cognitive activity (Park et al., 2015). Similarly, it has been suggested that the fixation numbers on the images in a multimedia learning environment can be seen as high cognitive performance (Russell, 2005). Additionally, eye tracking provides a way to establish a relationship between cognitive processes and learning outcome (Bayram & Bayraktar, 2012; Lai, et al., 2013).

The heat map and area of interest obtained by analyzing fixation numbers are visuals that allow easy interpretation of eye movements. The scenes are graded according to duration and fixation numbers in heat maps. In our study, heat maps were used to determine the fixation related to presenting the text on the screen and interpret it in terms of CL.

Therefore, as stated, there is not yet a study in which CL analysis in multimedia learning utilizing EEG signals has been analyzed via EMD method in the literature. Furthermore, self-report studies on CL detection are highly focused; however, new interpretations for novel methods and multimedia learning principles are needed to be investigated. In this study, we aimed to explore the redundancy effect on CL. We evaluated CL via eye-tracking and EEG techniques via multimedia materials, where different verbal information formats are presented together. For this purpose, participants' heat maps and brain topographies were analyzed and interpreted using eye-tracking and M-EMD outcomes, respectively. The results were reported to make recommendations for instructional designers to develop effective multimedia materials.

Method

Participants and Experimental Design

The participants whose mean age was 20.6 (SD=3.62) consisted of 40 undergraduate students from a public university. This research was based on a quantitative research method with an experimental research design. The groups' brain signals and eye movements studying two multimedia materials were recorded, and two different text formats (written & narration vs. narration) were compared. In the experimental design, randomly, 20 students served in the non-redundancy group (N-RE), which received a narration presentation, and 20 served in the redundancy group (RE), which received a narration and written text presentation. Before the experiment, participants received oral and written details about the research before attending the experiment.

Procedure

Forty participants were taken separately into the experiment laboratory. The participants were separated randomly into two groups. The participants were allocated to groups according to the category (N-RE & RE) of multimedia learning environments. After the eyeglasses and EEG headset were put on the participants, they were ready to study the multimedia environment. The experiment began after the eyes were calibrated. While the students were studying redundancy and non-redundancy materials, their eye movements and brain signals were recorded.

Instructional Materials

The materials designed in the study included a redundancy version of multimedia (i.e., narration & written text presentation) and a non-redundancy version of multimedia (i.e., narration presentation). The two-multimedia consisted of six scenes. The parts of the car engine were selected as learning content. Different verbal information formats were used in each scene. The text formats used in the scenes are presented in Table 1. As can be stated in Table 1, all of the scenes are shortened as S1, S2, …, respectively.

Table 1.

The text formats used in the scenes.

Scenes	Non-redundancy Multimedia (N-RE)	Redundancy Multimedia (RE)
Scene 1(S1)	Animation + Narration	Animation + Image + Narration + Written text + Music (text and narration were different)
Scene 2 (S2)	Animation + Narration + Keywords on the scene	Animation + Image + Narration + Written text + Music (text and narration were different)
Scene 3 (S3)	Animation + Narration + Keywords on the scene	Animation+ Image + Narration + Written text (text and narration were different)
Scene 4 (S4)	Before Animation + After Video + Narration + Keywords on the scene	Animation+ Image + Narration + Written text (text and narration were different)
Scene 5 (S5)	Before Image + After Animation + Narration	Animation + Image + Narration + Written text (text and narration were different)
Scene 6 (S6)	Image + Narration + Keywords on the scene	Image +Image + Narration + Keywords on the scene (text and narration were different)

Data Collection Materials

Electroencephalography

In this research, G.tec brand g.Nautilus wireless EEG amplifier (Schiedlberg, Austria) was used to record EEG measurements. The frequency of sampling was adapted to 250 sample/s. The international 10-20 system included 16 dry electrodes (FP1, FP2, Fz, F3, F4, Cz, C3, C4, T7, T8, Pz, P4, P3, PO7, PO8, Oz) were localized onto the scalp.

The method generally includes the following headings.

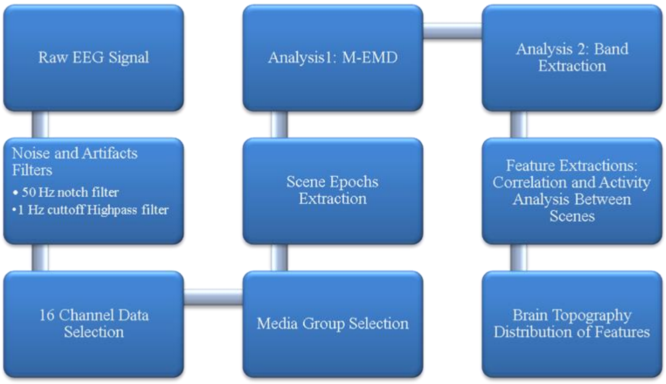

Figure 1. Magnetization as a function of applied field. Note that "Fig." is abbreviated. There is a period after the figure number, followed by two spaces. It is good practice to explain the significance of the figure in the caption.

Eye-tracking

During this research, mobile eye-tracking glasses (SensoMotoric Instruments) were utilized to identify eye movement data. They were wirelessly placed on a smartphone. A software named BeGaze (version 2.4) was operated for the evaluation of eye-tracking observations. Fixation numbers referring to the items or places on the screen where the participant looked at a two-degree distribution level and a minimum time of 100-200 ms were monitored and captured. As a consequence of an interpretation of the fixation point, heat maps displaying colors from red to blue on the screen as per the period and the number of gazes were acquired (Jacob & Karn, 2003).

Signal Processing Method

Multiresolution empirical mode decomposition

EMD works by breaking a signal into an oscillating function named an intrinsic mode function (IMF). The fragmentation of the signal into several IMFs is comparable to the transformation in Fourier and Wavelet transforms. Like those methods, EMD is not based on mathematics. IMF can, therefore, give insight into the different signals found in the data. In general, the approach is valuable for studying natural signals, mostly nonlinear and nonstationary. Since the signal's noise is prevalent in high-frequency components, EMD is used to achieve comparatively low-frequency components. Let x(t) be pointed to as a signal, and for each IMF, these two requirements must be fulfilled:

- The total number of peak values and zero crossings roughly corresponds to or varies by only one.
- Therefore, the average envelope described by local minima and local maxima must be zero at any point presented in the signal.

EMD may analyze any signal to IMFs. EMD has a sifting procedure with the purpose of disintegrating the signal into narrowband signals. The sifting phase can be described in the following:

I. Determine both the local minima and maxima.

II. Link all local maxima and minima to shape the upper / lower boundary with a cubic spline.

III. Compute the arithmetic mean of these envelopes m1 and subtract them from the signal h1= x(t) - m1.

IV. Test whether h1 fulfills the two IMF conditions. Unless h1 satisfies these two criteria, replicate these processes from 1 to 3 until h achieves the IMF's requirements.

In general, EEG is defined based on its frequency band. The amplitude of EEG demonstrates the changeability of both the external stimulation and the internal mental state. Brainwaves are categorized as slow, medium, and fast frequency bands; these brainwaves like delta, theta, alpha, beta, and gamma comprise useful info that is taken into consideration by researchers as they encompass certain roles that cannot be detected explicitly from the total wavebands (Young-Min Park, Hee-Jae Che , Chang-Hwan Imc, Hyung-Tae Jung, S.-M. B. S., 2008). All those frequency bands shift with physical and psychological exertion. The analysis of these rhythms is, therefore, necessary to research the numerous alterations. Frequency analysis or filtering is a well-established and traditional approach to treat a single-channel signal. When concerning in a certain frequency band, time-invariant bandpass filtering or Fourier Transform (FT) would be derived from the selected frequency parameter. EEG may be processed using IIR digital filters to separate specific frequency levels: Butterworth filter and Chebyshev type 1 and 2 filters. In our study, we utilized the first one. Butterworth filter generally alluded to as a maximum flat magnitude filter. The Butterworth filter's frequency response is at maximum flat, i.e., it has no ripples in the passband, and rolls-off toward zero in the stopband is utilized. A set of four bandpass filters was included, each of which is utilized to isolate one of the rhythms.

The first bandpass filter is based on processing theta waves in the frequency range of 4-7 Hz with a sampling frequency of 25 Hz. The second bandpass filter is utilized for detecting alpha rhythms in a frequency range of 7-12 Hz with a sampling frequency of 30 Hz. The third bandpass filter is filtered the delta frequency band in the range of 0.5-3 Hz with a sampling frequency of 10 Hz. The fourth bandpass processing is carried out, filtering the beta band in the range of 14-30 Hz with a sampling frequency of 75 Hz (Suresh et al., 2014). So, the signals were bandpass filtered using Butterworth filters according to the cut-off frequencies of each band one by one, and then the samples from the filtered signals were squared and summed to obtain each band power value. Therefore, a Multiresolutioned Empirical Mode Decomposition (M-EMD) was obtained. At this point, the most important question mark that comes to mind is why we prefer a filter based multiresolution algorithm instead of a wavelet-based multiresolution algorithm because the filter based multiresolution algorithm has given more successful results in signals that are divided into intrinsic components such as IMF.

Data Analysis

The learners' eye movements were analyzed via the BeGaze program, and heat maps were obtained for each scene. And then, to comment on students' brain signals about CL, their EEG signals were registered when participants were evaluating the redundancy and non-redundancy items. As a second step, all these signals were filtered via noise and artifact filters. After deciding which group (N-RE & RE) was examined for the redundancy effect, scene epochs were extracted. And M-EMD process was applied. After this point, the related IMF components were decomposed into their frequency bands of each subject EEG data for each scene (six scenes) and the group (N-RE & RE). Then, we have mapped the correlation degree between the same groups' subjects for each scene to show the activity change of the brain-regions between the two groups. After calculating the cross-correlation between all the same group subjects at each sense-band pair, we have obtained results as in Figures 2 and 3.

Results

When we examined the brain topographies obtained from EEG measurements according to N-RE and RE groups, we could state the following outcomes according to Figures 2 and 3.

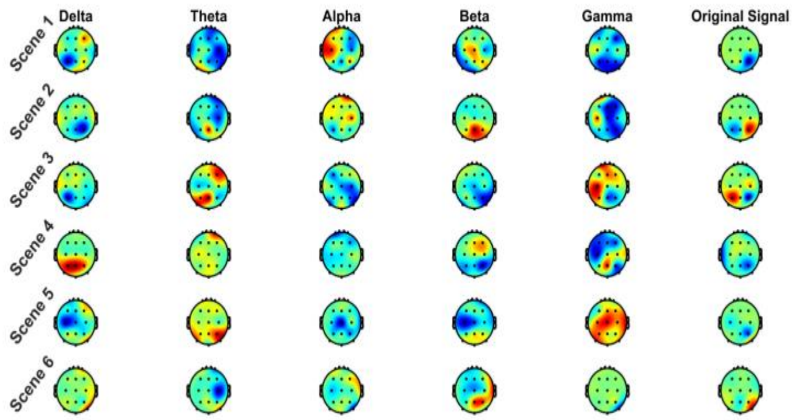

Figure 2. The brain topographies of N-RE group for each scene.

* In N-RE group, for S1, only alpha frequency band was more active in the left frontal and temporal region, while in RE group, theta, beta, and gamma frequency bands were more active in the frontal and parietal region.

* In N-RE group, there was high activity in the beta frequency band depicted as occipital lobe in Figure 4 in S2, while in RE, almost all frequency bands were more activity in the frontal and parietal region except beta frequency band.

* If we take a look at S3, it could be realized that there was high activity in the frontal, right frontal, and left-parietal region of the brain for theta and gamma wavebands in N-RE group, there was high activity in RE for the beta band in the frontal region and gamma-band for the left frontal and parietal region.

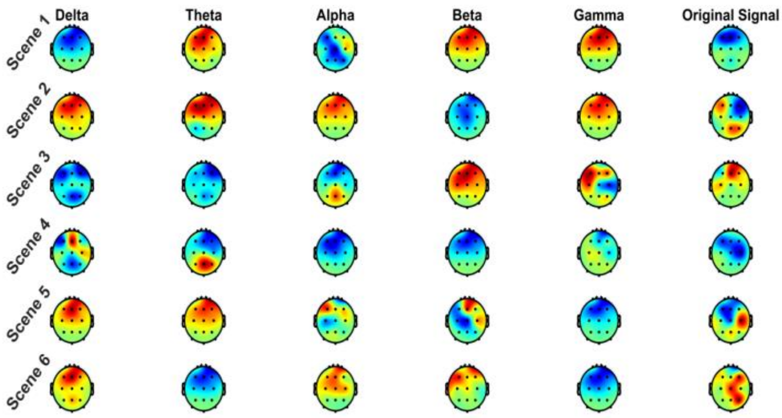

Figure 3. The brain topographies of RE group for each scene.

- As for S4, while it could be realized an activity in the brain's occipital for delta frequency and parietal lobe of beta frequencies in N-RE group, there were a few activities in the frontal region for the theta band and in the occipital of the brain for gamma band. In the RE group for S4, there were a few activities in the frontal region for the delta band and the brain's occipital for theta band.
- In S5, high activity was seen in the theta frequency band in the occipital lobe and the gamma frequency band in almost all brain regions in the N-RE group. However, in S5, RE showed high activity in the frontal and parietal region in theta and delta frequency band, left frontal in the alpha frequency band, and right frontal in the beta frequency band.
- Lastly, it could be recognized that there was a noticeable activity in the brain's occipital lobe in the beta waveband in S6 for N-RE group. And there were high activities in the delta, alpha, and beta frequency bands in the RE group's frontal and parietal regions.
- When we examined the brain topographies, which we mentioned as the original signal in Figures 4 and 5, there were differences between the scenes and between the groups.
- According to these topographies, for S1, no region stood out as high activity when we looked at N-RE and RE groups.
- In S2, high activity appeared in the right occipital lobe of the signal in N-RE; however, the brain's left frontal and right occipital lobe region seemed active in RE.
- For S3, N-RE topologies showed high activity in the left occipital region, while RE topologies showed high activity in the left frontal region.
- As another step, in S4, no noticeable activity was detected in all brain regions within the two groups.
- In S5 for N-RE, no noticeable high activity was observed. However, it seemed that there was a high activity right temporal lobe.
- And finally, while a few activities were realized in the brain's left-back, there was high activity in the right parietal and temporal regions. We discussed these results in the discussion section.

Simultaneously, the eye movements recorded with the Experiment 2.4 program were analyzed using BeGaze 2.4 software. As a result of the analyzes, heatmaps were obtained.

S1; Narration with animation was given in N-RE-S1. The focus was on video. Attention was distracted in RE-S1 because participants should focus on both animation, image, and text simultaneously. The written text and narration caused extra fixation duration and CL (See Figures 4 and 5). Music was also given at the same time.

S2; Narration along with animation in N-RE-S2 and the name of the engine part described were given as keywords. The focus was on video and keywords. Attention was distracted in RE-S2 because it should focus on both animation, image, and text. The written text given in addition to narration caused extra fixation duration and CL (See Figures 6 and 7). Music was also given at the same time.

S3; Narration along with animation in N-RE-S3 and the name of the engine part described were given as keywords. In this scene, similarly, only narration was given to reduce the redundancy effect. The focus was on video and keywords. Attention was distracted in RE-S3 because it should focus on both animation, image, and text. The written text given in addition to narration caused extra fixation duration and CL (See Figures 8 and 9).

S4; Narration along with animation in N-RE-S4 and the name of the engine part described were given as keywords... In this scene, the same pictures were used in both media. As the narration continues in N-RE, the pictures were shown sequentially. The focus was on video and keywords. Concerning RE, all pictures were presented simultaneously with narration and written text. Attention was distracted in RE-S4 because it should focus on both animation, image, and text. The written text given in addition to narration caused extra fixation duration and CL (See Figures 10 and 11).

S5; To test the redundancy effect in this scene, narration and animation were presented in N-RE-S5, and the name of the engine part described was given as keywords. Attention was distracted in RE-S5 because it should focus on both animation, image, and text. The written text given in addition to narration caused extra fixation duration and CL (See Figures 12 and 13).

S6; Narration along with animation in N-RE-S6 and the name of the engine part described were given as keywords. The focus was on video and keywords. Attention was distracted in RE-S6 because it should focus on both animation, image, and text. Written text and keywords given in addition to narration caused extra fixation duration and CL (See Figures 14 and 15).

Figure 4. Heat map of N-RE-S1

Figure 5. Heat map of RE-S1.

Figure 6. Heat map of N-RE-S2.

Figure 7. Heat map of RE-S2.

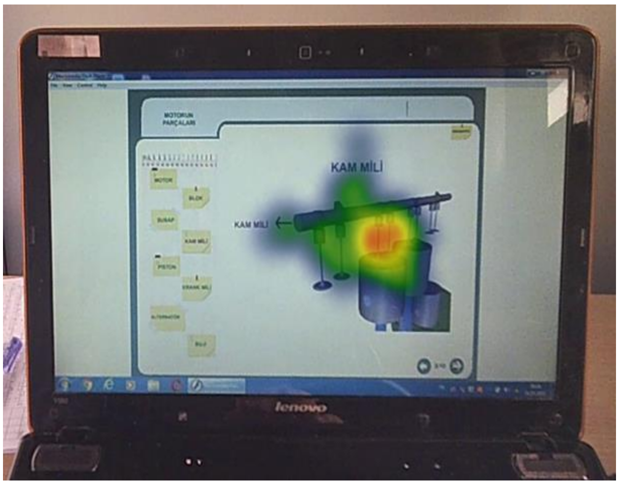

Figure 8. Heat map of N-RE-S3.

Figure 9. Heat map of RE-S3.

Figure 10. Heat map of N-RE-S4.

Figure 11. Heat map of RE-S4.

Figure 12. Heat map of N-RE-S5.

Figure 13. Heat map of RE-S5

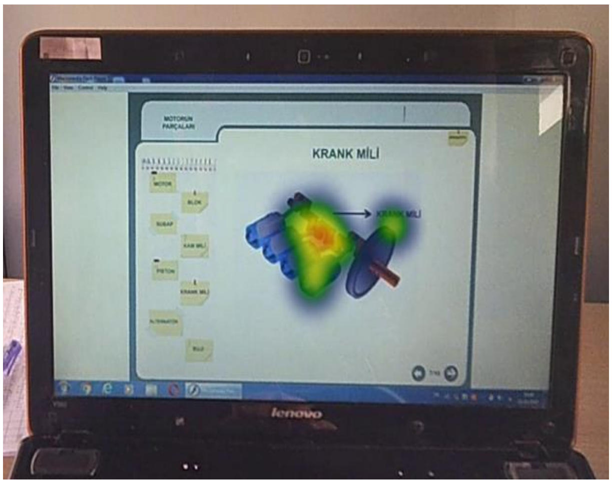

Figure 14. Heat map of N-RE-S6.

Figure 15. Heat map of RE-S6

Discussion

Our focus as the redundancy effect indicated that people learn better only in multimedia environments where the narration was given, compared to environments where text is given along with narration. There were extensive study examples of how EEG could be used to provide a meaningful understanding of the learning process, including multimedia studies utilizing subjective measures and EEG signals to research hypertext learning (Antonenko & Niederhauser, 2010). They determined that alpha, beta, and theta frequency bands from EEG signals were significantly smaller when using hypertext and that hypertext led CLs to decrease using EEG measurements prone to CL. In an alternative study (Makransky et al., 2019), EEG was used to assess CL in a multimedia learning three-dimensional version versus a virtual reality simulation (VR) desktop version. They stated that the simulation's three-dimensional VR version tends to cause lower learning outcomes, but it had created a greater self-reported presence. They discovered a cognitive overload among learners late in the learning phase in the three-dimensional VR variant of simulation. These studies were examples of how EEG's temporal resolution could give a substantial understanding of the learning process. While there appeared to be useful for learning to use EEG signals as a cognitive process metric, more thorough study evidence is needed. In the study of Makransky et al. (2019) CL was measured via EEG in a virtual reality environment, which used text and narration. In the results of this research, it was reported that in the environment where the printed text was used, there was a higher CL than the environment in which text and narration were used.

On the other hand, there had been very few studies in recent years to measure the redundancy effect using EEG. A study that belonged to Makransky et al. (2019) had attracted considerable attention. In their study, the whole analysis's primary goals were to evaluate the implications of incorporating immersive virtual reality (VR) to virtual learning simulations and explore whether multimedia learning concepts are applied to immersive VRs. Hence, similarly to ours, simulations that included text on-screen or narrated text on-screen were utilized. In both text forms, participants indicated being more active in the VR situation; nevertheless, they learned but less and have slightly higher cognitive loads dependent on the EEG measurement. Despite the motivational properties, learning science in VR might be overwhelmed and confused the learner resulting in fewer chances for learning outcomes. According to this study, we agree that EEG is an effective CL measurement tool. However, in their study, learners even had higher CLs dependent on EEG in the immersive VR environment. Importantly, we may interpret more cognitive load measurements in different frequency bands and different brain regions thanks to both the brain topologies we suggest and the different multimedia environments we use. Accordingly, we encounter less CL formation in environments where the narration is used in our measurements.

Previous groups have shown that EEG-estimated oscillatory in brain activity typically varies based on changes in cognitive stimulus concentrations. Several experimental trials have explored a relationship between CL and energy in distinct EEG spectral frequency bands, which have different frequency ranges (Baceviciute et al., 2022; Makransky et al., 2019; Mazher et al., 2017). According to these examinations, (van Gog et al., 2006) study CL measurements, showing that alpha and theta waves play an important role in CL estimation. Delta waves' characteristics can be used to distinguish cognitive states. Another research examined various feature-extraction approaches to estimate CL and consider brainwaves throughout cognitive assignment (Sweller, 2010). Alpha wave power spectral densities are usually used as EEG signals separating CL in different mental states. Theta and alpha frequency bands of EEG metrics in frontal and parietal brain areas have shown a correlation with CL. Different studies have demonstrated that frontal theta rises with a higher CL, and alpha comes down with a higher CL (Grimes et al., 2008; Zarjamet al., 2017; Chik, 2013; Holm et al., 2009). However, in our study, as the least effective alpha frequency band, almost all brain waves play an important role in CL measurements.

On the other hand, Liu & Chuang (2011) conduct a study in the multimedia learning environment in which the redundancy effect is evaluated using the eye-tracking method. This study shows that redundant text on-screen expanded CL when voice-over narratives describing the same knowledge are given in a multimedia learning environment. The eye-movement analysis also shows that participants may isolate redundant details while verbal content is presented in two separate platforms. Participants tend to have lower CL grades and follow a more global view for pictorial content as the text on the screen is substituted with a voice-over explanation. This situation triggers the split-attention effect. (Majooni et al., 2016) use eye-tracking techniques in their study to suggest strategies for reducing redundancy effects. Although it is claimed that the multi-mode format should be used in designs, the importance of these elements being applied properly is emphasized in terms of redundancy effect. Contrary to these studies, because of eye movements and EEG data analysis Kruger et al. (2013) conclude that subtitling the same text as narration reduces CL.

In RE-S1, compared to N-RE-S1, theta, beta, and gamma frequency bands appear higher in the frontal and parietal regions. Throughout N-RE group, in S1, only alpha frequency band was more prominent in the left frontal and temporal areas. In the frontal and temporal lobes, it has been reported that the activity in these lobes increases with the emergence of situations in which abstract thinking, working memory, attention, and executive control (organization, focus, integration ability) are regulated (Doyle, 2006). Memory, meaning, hearing, and language falls under the temporal lobes' responsibility; they are of particular interest in emotion and learning. Temporal lobes also participate in the perception and retrieval of sensory stimuli (Lah & Smith, 2014). In our study, the moderate movements in the brain regions as in N-RE group indicate the typical course of task functioning in these lobes. As in RE group, excessive movements are also the results of the concepts selected to form redundancy effects and cause excessive CL. The striking difference between these two groups that can create a CL is that all contents are given simultaneously and text. And the written text and music tell a different format on the same topic than narration in RE, unlike N-RE. In heat maps in this scene, RE group shows more fixation duration. At the same time, the saccades of RE group are scattered over text and images. (Liu et al., 2011) tested the redundancy effect with eye-tracking, and similar results are obtained. In the eye movement results, they report that the group in which the extra written text is given together with the narration experienced more fixation durations and split attention.

Unlike N-RE-S2, delta, theta, alpha, gamma bands are higher in the frontal and parietal regions in RE-S2. As a result of this intensity in the frontal lobe responsible for attention and executive control (Doyle, 2006), it can be concluded that RE group displays more intense mental activity. In the N-RE group, there is a high activity in the beta frequency band shown as an occipital lobe in S2. Unlike N-RE, there is written text and music that tells something different from the narration in RE. However, keywords have been added as text in N-RE. When the S1 and S2 scenes are compared to other scenes, the important findings striking us are the music in these scenes and the emergence of gamma brainwaves in RE groups.

In RE-S3, unlike N-RE-S3, beta waves in the frontal region and gamma-band for the left frontal and parietal regions are higher. However, in N-RE-S3, theta and gamma frequency band in the frontal, right frontal, and left-parietal regions of the brain are higher. But not as marked difference as in RE-S3. In general, the frontal lobe struggles with action, feelings, organizing, parts of speech, and reason. And it also specializes in purposeful tasks such as planning, imagination, problem-solving, and judgment, along with activity control and attention skills. The parietal lobe's location is shown above the temporal lobes and below the frontal lobes. It is involved with the management of sensory-related nerve impulses such as temperature, touch, pressure, pain, and taste. It also has language-related roles. Moreover, certain parietal cortex areas are interested in perceiving objects and other visual-spatial analysis (Culham et al., 2006). In addition to these known functions of the frontal lobe and parietal lobe, the beta and gamma frequency band activity, which stands out in topography, can be interpreted that beta's brain signals dominate our ordinary aroused level of consciousness when attention is paid to cognitive tasks and the outside world. Beta waveband is a 'fast' cycle and introduces itself when we are involved in problem-solving, concentrated mental practice, decision-making, alertness, higher mental capacity, and judgment (Calomeni et al., 2017; Marzbani et al., 2016; Smith & Kosslyn, 2007). High-frequency gamma signals in the brain provide speed in thought.

Although high activity is detected in theta and gamma bands in N-RE group in this scene, intense activity is not observed as formed in RE group's beta signal. Therefore, we can talk about the beta signal in the frontal and parietal areas due to more effort in the RE group. Compared with the S1 and S2 scenes, not using music also is considered to be caused CL existence in fewer brain waves. According to the heat map analysis of S3, it is seen that there are fewer fixation numbers in the N-RE group. Presenting the texts with narration reduced the cognitive load.

There is written text in RE-S4 compared to N-RE-S4. N-RE group has keywords. The brain's occipital for delta frequency and parietal lobe of beta frequency looks high activity in N-RE. These are a few occurrences for the theta band in the frontal area and the gamma band in the occipital cortex. In RE category for S4, there are a few actions for the delta band in the frontal zone and theta band in the occipital brain. This scene is a scene where we saw movement in the occipital lobe both in N-RE group and in RE group. The occipital lobe is situated at the rear of the brain. This area is part of the brain's capacity to recognize items (Adcock & Panayiotopoulos, 2012).Those mentioned written text items and keywords may be triggered the occipital lobe activity. The parameter tried to measure here was to give the contents consecutively as in N-RE-S4 or to evaluate all the contents by giving them all simultaneously as in RE-S4. Nevertheless, it is this scene where we do not find much difference according to our measurements. In RE multimedia, simultaneous presentation of pictures, videos, and written text caused an increase in fixation numbers. The attention of the learners is split into these three items.

In RE-S5 in the frontal and parietal region in theta and delta frequency band, the left frontal in the alpha frequency band and the right frontal in the beta frequency band occurs high activity. In N-RE-S5, high activity exists in the theta frequency band in the occipital lobe and gamma frequency band in almost all regions of the brain in N-RE group. As in other scenes, in the scenes where the redundancy effect parameters are set, activity appears more in the frontal and parietal lobes, suggesting that the brain is currently too active in tasks such as attention, reasoning, and problem-solving. We determine that when we compare the S5 scene with the S4 scene, removing the keywords causes more CLs in S5. According to heat map analysis, attention is distracted in RE-S5 because it should focus on both animation, image, and written text. The written text given in addition to narration caused extra fixation duration and CL.

In RE-S6, delta, alpha, beta frequency bands have a higher value. N-RE-S6 also has a higher beta (occipital lobe) value. During peacefully moving thinking, alpha frequency bands overpower. Alpha is an interaction to the present, displays the brain's resting-state wave, and promotes calmness, mental discipline, mind/body integration, alertness, and learning. Although there are studies in the literature that present alpha brain signal as a determinant CL measurement indicator, as understood in our topography results, alpha brain signal measurement showed variability in a more stable range according to our findings. The parameter tried to evaluate here is to check whether the attention is distracted by putting more than one image. There is CL in frontal in all scenes in RE. Since this attention is focused on more than one source in RE group, it can be interpreted that the attention is divided, and the signal in the frontal increases. Similarly, in heat map analysis, it is seen that attention is distributed in the RE group, and there is more fixation duration.

As we stated in the Discussion section's first paragraph, brain regions and frequencies have many complementary functions. When we compare the N-RE and RE groups' brain topologies in general, it is observed that CL regions were seen in the frontal and parietal regions. At this point, according to the outcomes of our study, frontal and parietal area measurements seem more important than other region measurements for CL evaluation. Furthermore, we believe that brain region activation evaluation will be a more accurate assessment of CL measurement due to variations in brain frequency band measurements. In parallel with brain signals analysis, eye movements also showed more fixation duration in the RE group.

Due to the difficulty of the methods used in this study and the length of the experimental process, the number of participants was limited to 40. The brain signals were analyzed by EMD method. Topographies can be analyzed using different analysis methods.

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The authors declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

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