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Using a BCI to Assess Attention During an Online Lecture

Ethan Hanner
Winthrop University, hannerm2@winthrop.edu

Marguerite Doman
domanm@winthrop.edu

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Ethan Hanner
Marguerite Doman, Ph.D. (Mentor)

ABSTRACT

Brain computer interfaces (BCI) use neural signals as input into computer applications. In this study, we demonstrate the use of a low-cost, commercially available BCI to directly measure participants' attention levels while using WUtopia, and online learning platform developed at Winthrop University. Previous research demonstrated that students using this platform performed better on a post-lecture quiz than those who only viewed the lecture (Grossoehme et al.). We hypothesize that the increase in performance is due to an increase in attentiveness when using the WUtopia platform. We divided participants into the intervention (n = 7) and non-intervention (n = 12) groups. Both groups viewed the chosen lecture video, completed a survey on their experience and attentiveness during the video, and took a quiz on the content of the video while wearing the BCI. Preliminary results corroborate the finding that WUtopia users perform better on post-lecture quizzes. However, readings from the BCI indicate that the non-intervention group had greater attentiveness during the video, while participants in the intervention group rated themselves higher on the attention survey. This suggests that either a) the BCI chosen is not effective at gauging attentiveness or b) there is a disconnect between actual and self-perceived attentiveness.

KEYWORDS: Online Education, Attention, Brain-Computer Interface, NeuroSky

1. INTRODUCTION

In an increasingly technological world, educators are seeking alternatives to the traditional classroom lecture format that can engage digital natives and, in some cases, reserve valuable classroom time for discussion, experimentation, and questions. Creating online video lectures is just one way to accomplish this. However, simply posting a video lecture online is often not enough; educators must find a way to engage learners in an online setting and ensure understanding and retention of the material.

Researchers at Winthrop University have developed an online learning platform called WUtopia! for delivering video lectures and other instructional material. Alongside lecture in WUtopia!, students are presented with questions linked to specific timestamps in the video and resources such as FAQs and third-party websites. The questions are intended to reinforce important concepts and increase student engagement with the material. In their study, the researchers divided participants into two groups: the intervention group had access to the questions and resources during the video, while the non-intervention group watched the stand-alone video. After the video lecture, both groups were given a quiz on the lecture's content. The results showed that those in the intervention group not only performed better on the quiz, but completed it in less time than the non-intervention group [1]. In this study, we seek to further these findings by investigating a possible reason for the difference in performance between groups.

2. MOTIVATION AND ATTENTION

There has been much research published on the motivation to learn, what influences it, and how it affects learning outcomes. One researcher, Bruinsma, examined the relationship between motivation and academic achievement. Based on the literature and the results of his study, he states that there is a positive correlation between motivation and academic achievement; students who are more motivated tend to perform better than their peers [2]. Thus, when designing instructional content either to be delivered in a traditional classroom setting or through a multimedia platform, it is important to consider strategies for fostering the motivation to learn. If learners are not motivated, they may be less likely to retain information and more likely to quit or give up when encountering obstacles.

The ARCS Model of Instructional Design by Keller specifies four major conditions for motivation: Attention, Relevance, Confidence, and Satisfaction [3]. The model provides a systematic approach to designing instructional content that motivates learners by meeting these conditions. In particular, attention may be thought of as the precursor to learning – if a student is not paying attention to the material being presented, learning cannot take place. Keller points out that the most difficult aspect of attention is not initially getting the learner's attention, but rather sustaining that attention over an interval of time. A raised voice, sudden noise, or dramatic line are all effective ways of grabbing attention – but if the information following is dull or unappealing, that attention will quickly be lost.

Existing research attempting to quantify attention in the context of motivation largely relies on participants' self-reported measures of how attentive they perceived themselves to be during a task. There is a degree of unreliability and uncertainty with this approach, as it is impossible to say whether the participants' perceptions match reality. A more reliable, objective measure would enable researchers to compare the effectiveness of different approaches to instruction at engaging learners. We are proposing the use of a brain-computer interface (BCI) to measure participants' brain activity as an indicator of their level of attention while viewing a WUtopia! lecture. We hypothesize that recordings from the BCI will indicate a higher level of attention in the intervention group, which may be a possible explanation for their increased performance on a post-lecture quiz. More generally, we hope to demonstrate the appropriateness of BCI devices as tools to gauge the effectiveness of different pedagogical approaches by utilizing information about the learner's cognitive state.

3. BRAIN COMPUTER INTERFACES AND NEUROSKY

A new frontier is emerging for computing technology: interfacing with the brain. A brain-computer interface (BCI) collects information about a user's brain activity to be used as input into applications. There are many different methods of obtaining this information, including electroencephalography (EEG) and functional near-infrared spectroscopy (fNIRS), each with their own advantages and disadvantages. Some potential uses of BCI which are already being researched are enabling direct control of a device such as a prosthetic limb or computer interface by motor-impaired users. Other research applications include MindLogger, an application that allows users to build words and sentences by selecting individual letters based on readings from a BCI device, and NeuroPhone, which utilizes the P300 brain signal to select the correct contact to call from a list [4][5]. These are all categorized as "active" BCI. By contrast, "passive" BCI uses information about a user's brain activity to respond in some way, such as by adjusting elements of an interface or providing feedback to the user. For example, Rebolledo-Mendez et al. developed an artificial intelligence (AI) avatar in the game Second Life that utilized data about a participant's attention level to give feedback intended to increase or maintain the participant's attention as they completed a series of multiple choice questions [6]. Some possible responses of the AI included proposing a different activity if the attention level was low or suggesting supporting resources and material to further engage the participant with the subject matter. Verkijika et al. also showed that a BCI can be used to assess students' levels of math anxiety and track changes over time [7].

As an alternative to medical-grade EEG devices that can be prohibitively expensive, the company NeuroSky has developed a low-cost, commercially available EEG device consisting of one dry electrode placed directly onto the user's forehead. This device, the NeuroSky

MindWave Mobile, reads the electrical signals generated by the brain as it performs tasks. Using a proprietary algorithm, the MindWave processes these signals and reports the user's attention level at a frequency of 1 Hz. Attention is output as a number in the range of 0 to 100; the meaning of each possible value is shown in Table 1. Previous research has demonstrated the ability of NeuroSky's EEG devices to accurately detect a user's mental state and use it as input into novel applications [8][4][6].

4. METHODS

For this study, a TED talk on microbial communities by Rob Knight was chosen as the lecture video. The lecture was between seventeen and eighteen minutes in length. The researchers devised questions from the content for the quiz and to display alongside the video.

Participants in the study were randomly assigned to either the intervention or non-intervention group. While watching the lecture video, the intervention group was presented with a series of questions linked to particular timestamps in the video. The questions would automatically update as the video progressed.

Table 1. The meanings of each of the possible ranges of attention values output by the MindWave Mobile according to the documentation on NeuroSky's website

Value	Meaning
0	Special value indicating that the attention level cannot be calculated with a reasonable amount of reliability, usually due to excessive noise
1 – 20	Attention is "strongly lowered"
20 – 40	Attention is "reduced"
40 – 60	Attention is "neutral" – baseline
60 – 80	Attention is "slightly elevated"
80 – 100	Attention is "elevated"

These questions were intended to reinforce the material and increase engagement with the lecture content. The control group viewed the same video but without any supplemental questions.

After watching the video, both groups were asked to complete a survey asking them to provide demographic information and reflect on their experience during the lecture. Participants were asked whether they paused, rewound, or fast forwarded the video and whether they took notes on the content. For the intervention group, a question on the survey asked them to rate how beneficial they felt the questions were in aiding them with learning the material in the video. The bulk of the survey was a self-reported measure of attention and mind wandering. The survey asked participants to report the frequency of their mind wandering during the video, rate their level of attention on a scale of 1 (low) to 7 (high), and report the degree to which they felt their behavior during the study matched selected criteria for ADHD from the DSM-V. The latter portion of the survey was adapted from Rebolledo-Mendez et al. [6]. Responses from the survey were compared against actual attention levels recorded by the MindWave to determine the effectiveness of the device, and responses were also compared between groups as another measure of the difference in attention for the two groups.

After completing the survey, both groups were given a quiz on the material presented in the lecture. The quiz questions were identical for both groups to avoid differences in performance based on subject matter or question style. The quiz was worth fourteen points; one point for each correct answer, and an additional point each for answering the two questions with multiple answers correctly with no incorrect answers chosen. Participants were given a final score out of 100%.

Because the MindWave reports an attention value once per second, we elected to examine the average value reported in fifteen-second samples once every two minutes. Based on a previous study on video production and student engagement, a video lecture should ideally be presented in chunks of six minutes or less [10]. Therefore, we chose to examine attention during the first eight minutes and fifteen seconds of watching the video; the extra two minutes was intended to determine how attention changed after the six minute mark, and the fifteen seconds was needed to get a full sample at eight minutes. This led to the creation of exclusion criteria – in order to be considered in the final sample, the participant must have watched the video for at least eight minutes and fifteen seconds. Additionally, participants must have completed the survey and quiz (blank answers were permitted) and must have answered I agree to the prompt on the survey "Do you agree to be as honest as possible and accurate to the best of your ability while participating in this survey?"

5. RESULTS

5.1 Demographics

A total of 19 participants completed the survey and met the criteria for inclusion. They were divided into the intervention (n = 7) and non-intervention (n = 12) groups. The sample was comprised primarily of college students at Winthrop University – approximately 74% (n = 14) reported their education level as "some college." Participants were approximately 74% female (n = 14) and 26% male (n = 5).

5.2 MindWave Recordings

We found the opposite effect of what was expected in recordings from the BCI. For each of the 15 second intervals, the average attention rating was higher for the non-intervention group than for the intervention group. Further, the overall average attention rating (taken from 0:00 to 8:14) for the non-intervention group was 52.75 versus 47.93 for the non-intervention group. For both groups, the average attention rating at each interval and overall remained within the baseline range – 40 to 60 – although some individuals peaked as high as 73.6 and dipped as low as 20.81. The averages for both groups are given in Table 2.

Table 2. Average attention rating from both groups at each sample interval.

Sample	Intervention Group	Non-Intervention Group
Sample 1 (0:00 – 0:14)	53.1	57.99
Sample 2 (2:00 – 2:14)	47.15	52.86
Sample 3 (4:00 – 4:14)	46.52	50.76
Sample 4 (6:00 – 6:14)	41.64	45.84
Sample 5 (8:00 – 8:14)	42.98	53.01
Overall (0:00 – 8:14)	47.93	52.75

As seen in Table 2, the average attention value for both groups tended to decrease at each successive interval, although for the final sample it increased for both. This increase was more pronounced for the non-intervention group.

5.3 Frequency of Mind Wandering and ADHD Criteria

Both groups were asked during the survey to report approximately how many times their mind wandered during the video lecture. The choices were 0 – 1 times, 2 – 3 times, 4 – 5 times, or 5+ times. For both groups, the most frequent response was 2 – 3 times – with approximately 57% (n = 4) for the intervention group and approximately 42% (n = 5) for the non-intervention group. Only about 14% (n = 1) in the intervention group reported 4 -5 times, while about 33% (n = 4) reported 4 – 5 times in the non-intervention group.

Each participant was asked to rate their attention on a scale of 1 (low) to 7 (high) and also the frequency with which they experienced selected criteria for ADHD from the DSM-V during the lecture, from 1 (all the time) to 7 (never). Some of these criteria included "Difficulty staying in one position," "Difficulty following through on instructions," and "Difficulty listening to what is being said by others." The responses to each of these prompts were averaged for each participant to arrive at a self-perceived attention rating. For these ratings, we found the opposite of what was indicated by the MindWave recordings; the intervention group rated themselves at 5.88 on average (sd = 0.70) while the non-intervention group rated themselves at 5.64 on average (sd = 1.36).

5.4 Quiz Performance

As in the previous WUtopia! study, participants in the intervention group performed better on the post-lecture quiz than those in the non-intervention group. The average score for the intervention group was 76.53% (sd = 6.29%). For the non-intervention group, that average was 73.22% (sd = 12.75%). For the three questions that were repeated from alongside the video, 100% of the intervention group answered correctly on the quiz. The non-intervention group, which did not see these questions alongside the video, did not answer all three correctly.

6. DISCUSSION

It is important to note that these results are preliminary, as after applying the exclusion criteria we did not meet the minimum number of participants required to perform a full statistical analysis. Of particular interest at this point, however, is that the MindWave recordings, where the non-intervention group fared better, seem to be in conflict with the self-reported attention rating, where the intervention group scored higher. The two scores were not clearly correlated in individual participants, either; in the intervention group, the participant with the highest overall attention rating from the MindWave (60.61) had the lowest self-reported attention rating (4.5) and in the non-intervention group, the participant with the highest self-reported attention rating (6.88) had the third lowest overall attention rating from the MindWave. This suggests that either a) the BCI chosen is not effective at gauging attentiveness or b) there is a disconnect between actual and self-perceived attentiveness. More data is needed to reach a conclusion on this matter.

The preliminary results indicate a limit on the length of video that can be effectively used in the WUtopia! setting. It appears that for the intervention group, the presence of questions alongside the video and the ability to move forward in the video led to participants quickly scrolling through the questions without watching the full video. Indeed, the average time spend watching the video for the intervention group was 15 minutes and 52 seconds, versus 19 minutes and 57 seconds for the non-intervention group. This effect was not observed in the previous WUtopia! study, where the lecture video was much shorter.

While this study corroborates the finding that the use of the full WUtopia! platform leads to better performance on the post-lecture quiz, the difference in scores were not as pronounced as in the previous study. The researcher who devised the questions notes that this may be due to the choice of relatively easy questions that were pulled directly from the video, rather than questions which required full understanding and application of the material presented.

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