MSc Interaction Technology
Thesis

Influence of Real-Time Haptic Feedback on Sustained Attention using a BCI-based approach

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Abstract

During the COVID-19 pandemic, online learning has become increasingly popular. However, this method of learning possesses some challenges. Many students struggle to maintain focus in high-distraction environments. Research indicates that the use of brain-computer interfacing (BCI) systems to monitor engagement during online learning can keep the users engaged. These methods, however, often rely on auditory and visual feedback, which compete for the same cognitive resources needed for online learning. To address this limitation, this study investigates how haptic feedback can be used to enhance sustained attention during online learning. By integrating BCI with haptic feedback, real-time engagement monitoring and intervention can be used to potentially improve learner focus.

An experiment was conducted with ten university students who watched a 35-minute online lecture under three conditions: no feedback, vibrotactile feedback, and thermal feedback. Their sustained attention, or engagement, was measured by the EEG Engagement Index using a Electro-Encephalography (EEG) headset. While the study analyzed the mean EEG Engagement Index across feedback modalities, no significant differences were found between them. Some participants noted that the haptic feedback worked distracting, which could explain the lack of a significant difference.

Keywords: BCI, Sustained Attention, Online Learning, Haptic Feedback

Contents

Acronyms

API Application Programming Interface. 18

BCI brain-computer interfacing. 1, 5, 7–9, 12–14

CLT Central Limit Theorem. 21

EEG Electro-Encephalography. 1, 6, 8–10, 12–15, 18, 19, 24, 32

EWMA Estimated Weighted Moving Average. 16, 26

fMRI functional magnetic resonance imaging. 9

MEG magnetoencephalography. 9

PSD Power Spectral Density. 10, 15, 16

PWM Pulse-Width Modulation. 15

SDK Software Development Kit. 24

UAV Unmanned Aerial Vehicle. 12

Glossary

EEG Engagement Index A metric that quantifies the users' level of alertness based on the ratio of beta to alpha and theta brain waves. This metric is often used in brain-computer interface (BCI) systems to monitor and assess cognitive engagement. 1, 5, 6, 10, 12–14, 16, 19–34

Haptic feedback A range of feedback modalities that utilize the sense of touch, including vibrotactile, thermal, pressure, and electrotactile feedback, commonly used in devices to convey information through physical sensations. 5–7, 10, 11, 13

Chapter 1

Introduction

The presence of online learning has significantly increased, especially since the COVID-19 pandemic, and it is likely not going anywhere anytime soon [1]. This shift has made education more accessible, allowing students to view recorded lectures regardless of time or location. However, this method of learning has downsides as well. A survey done on a group of students shows that the majority of students have shown to have had some difficulty with online learning [2]. Online learning often occurs in high-distraction environments, making it even more challenging to stay focused. This is problematic since focusing, also known as active engagement, is essential for effective learning [3, 4]. Maintaining focus is especially important in the context of online learning because the students are mainly responsible for their own learning process. Automatically monitoring student attention can help identify when the focus is lost, enabling timely interventions to re-engage students, which could improve their learning experience.

Previous studies have demonstrated the potential of using BCI systems to monitor engagement during online learning [5]. These systems measure brain signals and provide automatic feedback when a user's alertness decreases. This combination has been shown to improve the engagement of the users [6]. However, these studies often rely on auditory and visual feedback, which utilize the same cognitive resources required for lectures. To address this, the present study focuses on haptic feedback, which leverages the user's sense of touch. Unlike auditory and visual feedback, Haptic feedback makes use of touch to convey information to the user. This distinction suggests that Haptic feedback might be particularly effective in improving user engagement [7]. Specifically, this research looks at vibrotactile and thermal feedback due to their practicality and ease of deployment, making them well-suited for applications beyond the scope of this study.

Based on this objective, the following research questions have been formulated:

MQ: To what extent does haptic feedback, compared to no feedback, help improve attention in university students during an online lecture, as measured by the EEG Engagement Index?

SQ 1: To what extent does vibrotactile feedback, compared to no feedback, help improve attention in university students during an online lecture, as measured by the EEG Engagement Index?

SQ 2: To what extent does thermal feedback, compared to no feedback, help improve sustained attention in university students during an online lecture, as measured by the EEG Engagement Index?

SQ 3: To what extent does vibrotactile, compared to thermal feedback, help improve sustained attention in university students during an online lecture, as measured by the EEG Engagement Index?

This project addresses the research gap concerning the effectiveness of Haptic feedback in enhancing user engagement. Rather than begin offering a definitive answer to this problem, the research findings are intended to inform and inspire further research into the role of haptic feedback in enhancing sustained attention during online learning. [8].

To address the research questions, an experiment was conducted involving ten participants who watched a 35-minute online lecture. The lecture was divided into four phases: a five-minute calibration period, a ten-minute baseline period with no feedback, and two consecutive ten-minute periods during which feedback was provided.

The experiment begins with a five-minute calibration period to determine participants' minimum and maximum engagement levels so the results can be normalised, and an average engagement to serve as a threshold to determine whether the participant is alert or not. Engagement values falling outside the calibrated minimum and maximum will be capped within a 0 to 1 range. Determining a threshold is necessary because the EEG Engagement Index lacks a standardized scale, allowing the method to adapt to participant engagement differences. Engagement levels were assessed by measuring participants' brain activity using EEG, from which the EEG Engagement Index was calculated. To minimize the potential effects of fatigue on the results, the order of the feedback modalities was switched across participants. Feedback was administered whenever the EEG Engagement Index dropped below the adaptive threshold. After the experiment, the EEG Engagement Index values were analyzed and compared across the different feedback conditions to evaluate their effectiveness.

This research aims to provide insights into how haptic feedback can be used to keep students engaged in online lectures. Because the EEG Engagement Index has no standardized scale, the proposed pipeline will initially be tested on a pre-existing dataset. This approach ensures the methods are in the same context of prior research [5].

Chapter 2 provides the necessary background information. Chapter 3 reviews related studies on this topic. Chapter 4 details the research methods. Chapter 5 presents and discusses the research findings. Chapter 6 discusses the results, confounding factors and possible future directions of this research. Chapter 7 shows the conclusions drawn from this study.

Chapter 2

Background

This chapter discusses the background information of this research. The topics engagement, BCI and Haptic feedback are covered.

2.1 Sustained Attention

Attention is not constant but fluctuates over time, alternating between focused and unfocused states [9, 10]. Over time, the intervals between the focused and unfocused state become shortened [11]. Sustained attention is the ability to maintain focus over an extended period of time. This is an important skill for monotonous or repetitive tasks like studying [10]. The term sustained attention is often used interchangeably with vigilance, alertness, and engagement [5].

Because of its important role in studying, researchers have investigated the impact of sustained attention on learning performance. One study used eye-tracking to measure participants' sustained attention during online lectures by analyzing the duration and frequency that participants were fixated on the lecture [12]. Learning performance was assessed through pretests and posttest with questions. Results revealed a significant correlation where participants with higher levels of sustained attention also had a better learning performance, indicated by the improved posttest scores in relation to their pretest scores [12]. These findings are consistent with results from other studies in the field [13, 14].

Several factors influence sustained attention, which can be broadly categorized into three groups: task parameters, environmental or situational factors, and subject characteristics [15]. These factors do not only influence sustained attention individually, but interactions between these categories influence sustained attention as well. This research will mainly focus on the task parameters as it researches the relationship between haptic feedback on sustained attention.

Given the importance of sustained attention in learning and its natural decline during prolonged tasks, developing effective interventions to counteract this decline could significantly improve the effectiveness of online learning.

2.1.1 Measuring Engagement

To better understand engagement, various methods have been developed to measure users' engagement. These methods can be categorised into direct and indirect approaches. Indirect methods include questionnaires, behaviour logging, observation, task outcomes, and interviews [16]. A study did a systematic review of engagement on 351 articles and 102 definitions [16]. They found that questionnaires are the most commonly used, with 124 applications recorded, followed by behaviour logging with 69 applications, and observation with 44 applications [16].

While widely used, these indirect methods are often subjective and susceptible to bias. Questionnaires, for example, rely on self-reported data, which can be affected by misremembering or personal bias. In contrast, direct measurement techniques such as eye tracking (19 applications), galvanic skin response (8 applications), and EEG (10 applications) provide more objective data [16]. This research uses explicitly EEG for real-time monitoring of brain activity, as it offers a direct measure of engagement, which is less susceptible to the biases associated with self-reported data.

2.2 Brain Computer Interfaces

The human brain reveals much about people's thoughts, actions, emotions, and motor functions. This information can be retrieved using BCI. BCI is the field of acquiring, analyzing, and translating brain signals to create a direct interface with external devices [17]. Gathering this information can give valuable insights into how people make decisions and perceive the world.

2.2.1 Electroencephalogram (EEG)

EEG is a subset of BCI, dedicated to capturing and interpreting the brain's electrical activity. During cognitive activity, the brain generates electrical signals in the region in which it is active. EEG uses electrodes to detect these signals, which are amplified for analysis. These electrodes are either attached directly to the scalp using adhesive stickers or incorporated into specialized EEG headsets designed to ensure stable and consistent contact [18]. These signals are then further processed and interpreted. This process is demonstrated in Figure 2.1.

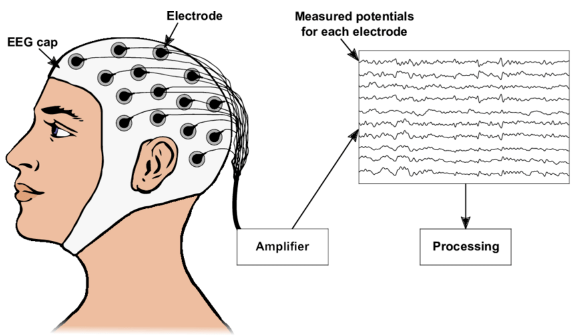


FIGURE 2.1: Illustration of EEG Recording Setup [19]

For this research, EEG is preferred over other BCI methods because of its several advantages [20] over other BCI methods. First, EEG has a high temporal resolution, which allows for capturing brain activity in the milliseconds range [21]. This allows for detecting rapid changes in engagement levels.

In addition, EEG is a non-invasive method, meaning it does not require surgical procedures or implants. This feature ensures a safer and more accessible option for research participants.

Additionally, EEG does not require large devices to work. This allows it to be portable and deployable in various settings outside the laboratory, such as a classroom or study

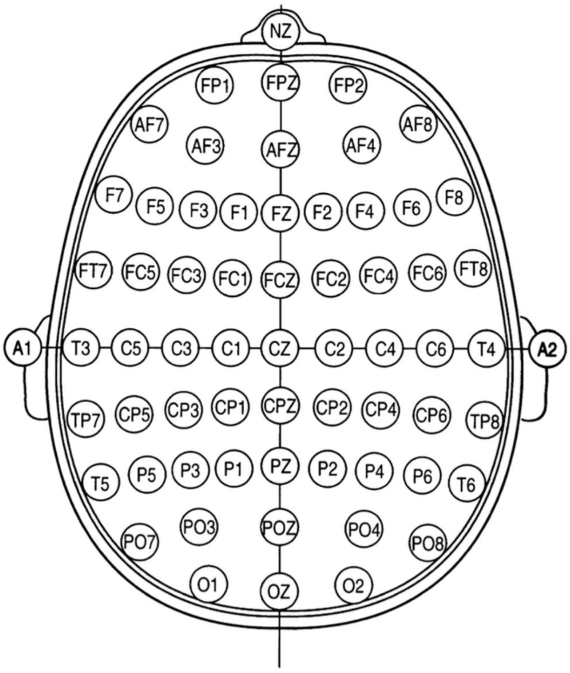


Figure 2.2: Electrode placement according to the 10-10 EEG system [23]

room. Dry measurement systems further enhance accessibility, as these systems do not require specialised gels for electrode application.

Despite its advantages, EEG has limitations compared to other BCI methods like functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG). EEG has a lower spatial resolution, which makes it difficult to precisely identify the location of brain activity. Additionally, EEG is limited to measuring the electrical signals from the surface of the brain and is less effective for detecting activity deeper in the brain. However, these limitations are not a significant concern for the present study, as the focus is on overall trends in brain activity rather than localizing brain activity in specific neural regions.

Overall, the high temporal resolution, non-invasiveness, portability and direct measurement capabilities make EEG a good fit for this research. Especially with dry measurements.

2.2.2 Electrode Placement

To ensure consistency in EEG measurements across research, electrodes are placed at specific, standardised locations on the scalp. A standardised system, known as the 10-20 EEG system, has been developed. Each electrode placement is assigned a unique identifier, which includes a name and a number, reflecting the region of the brain where the electrode is positioned [22].

The precise placement of these electrodes is crucial. Incorrect positioning can capture signals from adjacent brain regions, leading to inaccurate data and potentially false conclusions. This can compromise the validity of the research findings [22].

In some cases, the 10-10 system (Figure 2.2) is used for electrode placement, which is an extension of the 10-20 system [23]. This research uses a subset of the 10-10 system, explicitly using the nodes Fz, Cz, Pz, Oz, C3, C4, PO7, and PO8.

To align the electrodes with the head of the participants, anatomical landmarks such as the inion, nasion, and the left and right pre-auricular points are used, ensuring that the central electrode (Cz) is approximately aligned with the vertex [24].

2.2.3 The EEG Engagement Index

The EEG Engagement Index is a measure of mental engagement and sustained attention [25]. It is calculated by examining the relationship between the different frequency bands of brain activity. Higher frequency bands, such as the Beta band (β), are associated with increased engagement, while lower frequency bands, such as the Alpha (α) and Theta (θ) bands, are linked to lower engagement. The EEG Engagement Index is determined by dividing the Beta band by the sum of the Alpha and Theta bands, as shown in Formula 2.1 [26].

$$EngagementIndex = \frac{\beta}{\alpha + \theta} \tag{2.1}$$

In this formula, β, α, and θ represent the power of the EEG signal within the Beta, Alpha, and Theta frequency bands, respectively.

2.2.4 EEG Frequency Bands

To analyse EEG signals, spectral analysis can be employed to break down the EEG signal into frequency bands. Spectral analysis is the process of estimating the power spectrum of a signal from its time-domain representation [27]. After calculating the Power Spectral Density (PSD), the signal is divided into frequency bands by range. The ranges are Delta (0-4Hz), Theta (4Hz-8Hz), Alpha (8-12Hz), Beta (12-30Hz) and Gamma (30-80Hz) [28].

Each of these different frequency bands is correlated with a different behavioural process. For instance, Delta waves are associated with deep sleep, whereas Gamma waves are associated with tasks that involve higher cognitive functions [29]. Research shows a negative correlation between students performance and the Theta/Alpha and the Delta band [30].

2.3 Haptic Feedback

Haptic feedback encompasses a range of feedback technologies that use the sense of touch [31]. It is defined as the "sensory and/or motor activity of the skin, muscles, joints, and tendons" [32]. There are several types of Haptic feedback: vibrotactile, thermal, pressure, and electrotactile feedback [32]. A summary of these different haptic feedback modalities can be seen in 2.3.

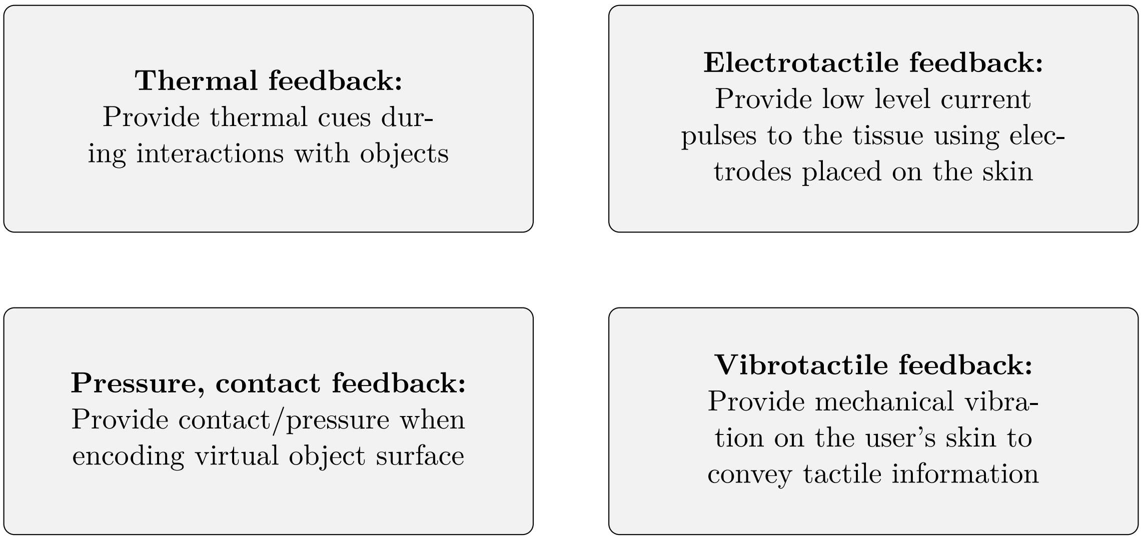


FIGURE 2.3: Haptic interface classification [32]

2.3.1 Vibrotactile Feedback

Vibrotactile feedback is the most common form of Haptic feedback, where vibrations convey information to the user [33]. This technology is prevalent in mobile and wearable devices, such as smartwatches, where continuous vibrations effectively notify users of messages and incoming calls. Additionally, discrete vibration bursts are often used as a substitute for the tactile feedback that physical keyboards provide during typing [32].

2.3.2 Thermal Feedback

Thermal feedback involves using temperature changes to deliver sensory information. This type of feedback can create distinct sensations by altering the temperature of a device or surface in contact with the user's skin [32].

2.3.3 Pressure And Contact Feedback

Pressure or contact feedback uses applied pressure or physical contact on the skin, typically through motors, to convey information or prompt a response [32].

2.3.4 Electrotactile Feedback

Electrotactile feedback gives feedback to users through electrical pulses transmitted via electrodes placed on the user's skin [32]. This type of feedback stimulates the nerves directly, creating a touch sensation.

Chapter 3

Related Work

This research aims to enhance engagement during online lectures. This chapter reviews related studies on the EEG Engagement Index and feedback modalities.

3.1 EEG-Engagement Index

The EEG Engagement Index is a well-established metric used in research to assess sustained attention [34]. The EEG Engagement Index has also been proven useful in the context of cognitive engagement, which is the extent to which students can learn [35]. Research shows that differences in cognitive task demand have different levels of cognitive engagement, which can be measured through the EEG Engagement Index [36]. This can even be done with dry measurements [34]. Because of its ability to detect variations in cognitive engagement, the EEG Engagement Index is a valuable metric for monitoring student engagement, as it allows for real-time monitoring of students' cognitive behaviour during learning activities.

3.2 EEG-based Engagement Measurement And Feedback Systems

The EEG Engagement Index is often combined with a sensory feedback mechanism to detect and address declines in sustained attention.

One prominent application is in high-focus environments where maintaining alertness is critical. For example, a study developed a system for Unmanned Aerial Vehicle (UAV) operators to prevent them from falling into inattention [6]. The researchers proposed a system composed of three components. First, a signal processing unit to collect and preprocess the EEG signals of the user of the system. Based on these signals, it could be determined whether the user was paying attention. If it were detected the user was not paying attention anymore, the user would receive visual and audio cues to start paying attention again. They tested the accuracy and effectiveness of their proposed system on four participants with a flight simulator. Based on their test, it was shown that their system helped users focus when attention was lost. However, because of the small number of subjects, statistical significance could not be established.

One study investigated the impact of visual feedback based on the EEG Engagement Index in an educational setting [5]. The researchers developed a BCI system that provided real-time feedback during an educational video. Participants watched three videos with visual, false, or no feedback. Although the study did not find a statistically significant difference between the three feedback conditions, the researchers suggested that this result could be due to several factors, including the limited sample size, the variability in individual attention patterns, artefacts in the EEG signal, and the design of the feedback and lecture content. The researchers suggested exploring alternative modalities, such as haptic feedback (vibrotactile and thermal), for potentially greater effectiveness [5].

Most studies have focused on visual or auditory stimuli, engaging the same brain regions in online learning. This overlap can be problematic if users are distracted from the screens or audio, as they might miss the feedback, reducing its effectiveness [7].

There is also research that looks at haptic feedback as a feedback mechanism for sustained attention. Haptic feedback has been extensively utilized in various forms in combination with BCI within the context of learning. One such form is thermal feedback, which has been explored in an online engagement setting [37]. In this study, researchers tested the effectiveness of using thermal feedback to notify presenters about audience engagement. Despite the small sample size, the researchers observed positive results, suggesting that informing users of their engagement levels may also be feasible.

Vibrotactile feedback has also been explored in BCI as a haptic feedback mechanism. One study proposed a two-part system consisting of an EEG headband and a scarf equipped with subtle vibration mechanisms that activate when the user's EEG Engagement Index drops below a certain threshold [38]. Participants watched three online lectures or attended three face-to-face lectures on different subjects. They received either accurate, false or no feedback, comparing the results across these conditions. The findings indicated that the vibrotactile feedback positively influenced engagement and led to improved performance on subsequent tests.

This research aims to directly compare vibrotactile and thermal haptic feedback in the context of online learning. By looking at the effect of these haptic feedback modalities on student engagement, this study attempts to understand how different forms of haptic feedback can support cognitive engagement in educational settings.

Chapter 4

Methodology

This chapter proposes a method to investigate how sustained attention can be enhanced using haptic feedback during online learning. By integrating BCI with haptic feedback, real-time feedback can be provided to learners, possibly improving their attention and engagement. The primary dependent variable in this study is the EEG Engagement Index, which is the measurement of the sustained attention of the participants. The EEG Engagement Index will be examined during three different conditions of the independent variable: no feedback, vibrotactile feedback, and thermal. The mean of each condition is compared using a two sided paired t-test. This is done to assess the impact of haptic feedback on engagement.

4.1 BCI Pipeline

The research makes use of the Unicorn EEG hybrid black EEG headset (Figure 4.1) which is used to measure brain activity using eight EEG channels (Fz, Cz, Pz, Oz, C3, C4, PO7 and PO8) [39]. This headset is chosen for its availability at the university and quick setup. This headset was selected for its availability at the university, ease of setup, and ability to perform dry measurements. Since participants will be seated and the data is recorded in 5-second windows across the head, the dry measurements are expected to suffice. Because of this, the preparation will take less time compared to other EEG methods while still yielding valid results [40].

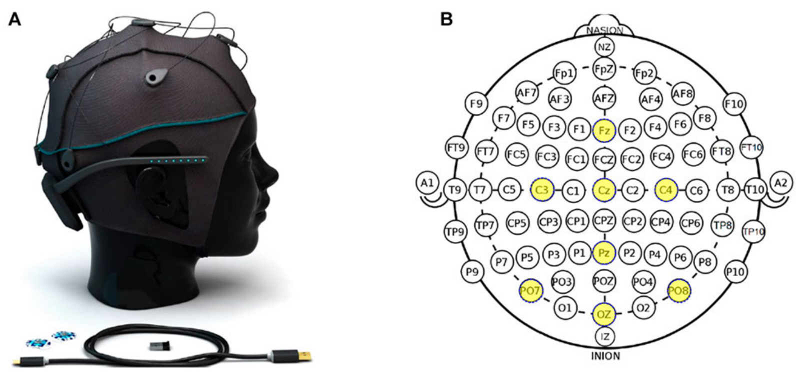


FIGURE 4.1: (A) The Unicorn Hybrid Black system (B) The available channels of the system. The ground and reference electrodes are placed on the mastoids using disposable sticky electrodes. [41]

The feedback is delivered through a vibration motor for vibrotactile feedback and a Peltier element to create a cold sensation on the wrist as thermal feedback. A cold sensation is chosen because the cold range is safer than the heat range. Cold is also associated with boredom, which participants may more easily associate with a lack of attention [42, 43]. These devices are connected to an Arduino Uno and controlled via Pulse-Width Modulation (PWM). Communication with the Arduino is established through a serial connection.

4.1.1 Data Processing

Raw EEG signals are recorded in 5-second intervals, called epochs. To reduce high-frequency noise and minimize artefacts caused by movements, blinks, and other disturbances, each epoch is processed using median filtering [44]. A median filter protects the edges of the signal and removes random noise [45]. The median filter uses a window size of 3, meaning that the median is calculated using each data point and its two nearest neighbours [5]. This process smooths the signal by removing noise while preserving its overall trend, as shown in Figure 4.2. In Figure 4.2, the blue line represents the filtered signal, while the red dotted line shows the unfiltered signal. After filtering, many of the peaks caused by noise are removed, but the general shape and trend of the signal remain intact.

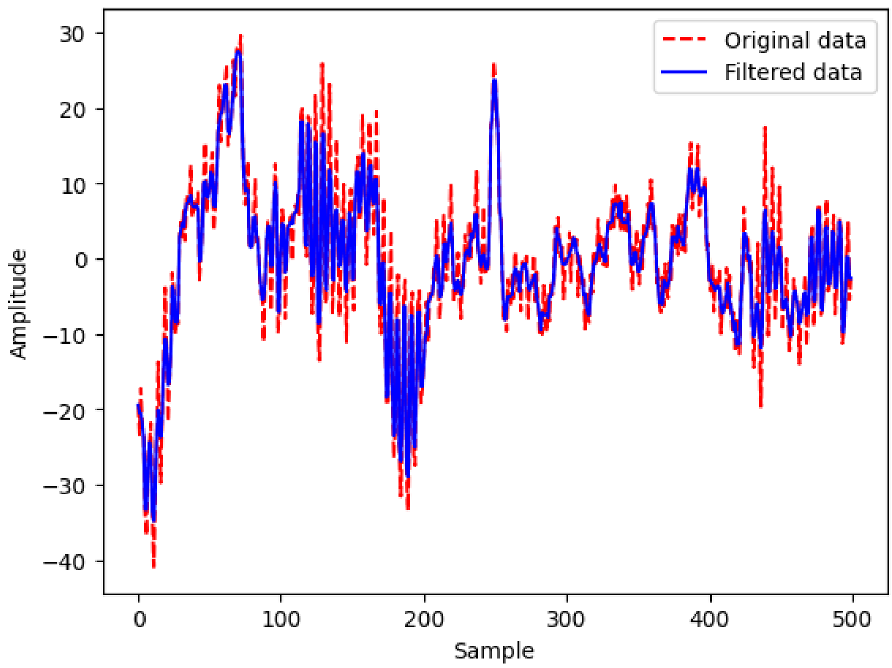


FIGURE 4.2: Visualisation of median filtering of the EEG data with a window size of 3.

The filtered signal's PSD is calculated using Welch's method [46], with a bandpass filter applied to exclude frequencies below 1 Hz and above 50 Hz. This is done because the frequencies outside of this range are not relevant for the frequency bands Theta, Alpha and Beta; and thus not needed for the analysis. The data is then divided into the specific frequency bands (see Section 2.2.4) and visualized as seen in Figure 4.3. The mean value for each frequency band is computed for every channel, preserving local frequency characteristics. A peak at 25 Hz can be observed, this corresponds with a sub-harmonic of the 50 Hz power grid, which must be filtered out.

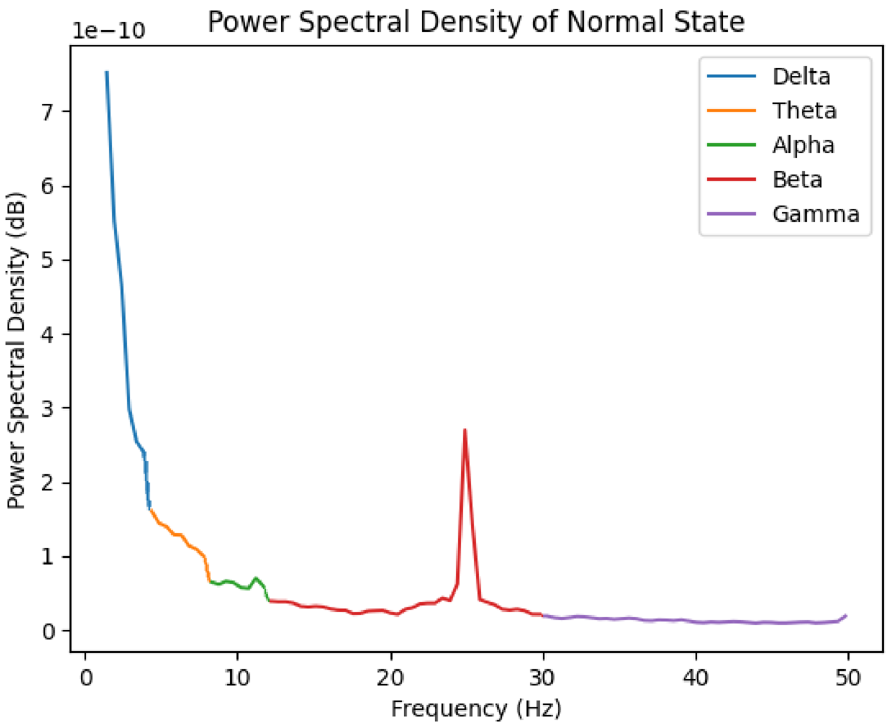


FIGURE 4.3: Visualisation of the PSD using Welch's method and the division into different frequency bands, with a minimum threshold of 1 Hz applied to the delta band to mitigate low-frequency noise; Peak at 25 Hz because of sub-harmonic frequency of 50 Hz power grid.

The EEG Engagement Index is calculated using Equation 2.1. Signal smoothing is applied using an Estimated Weighted Moving Average (EWMA) with $\alpha = 0.2$ [5], as shown in Equation 4.1. Because the EWMA references previous values, the first time it is used, the first time it is initialised by being set to the value of the EEG Engagement Index instead of calculating the EWMA. From that point on, the EWMA can be calculated.

$$EI_{\text{EWMA}} = \begin{cases} \alpha \cdot EI + (1-\alpha) \cdot EI_{\text{EWMA}} & \text{if } EI_{EWMA} \text{ has been previously computed} \\ EI & \text{otherwise} \end{cases} \tag{4.1}$$

Engagement threshold

A threshold is introduced to detect drops in engagement. It is calculated by taking the mean of the calibration period and removing outliers from the measurements by using a threshold of two standard deviations. This step is graphed in Figure 4.4.

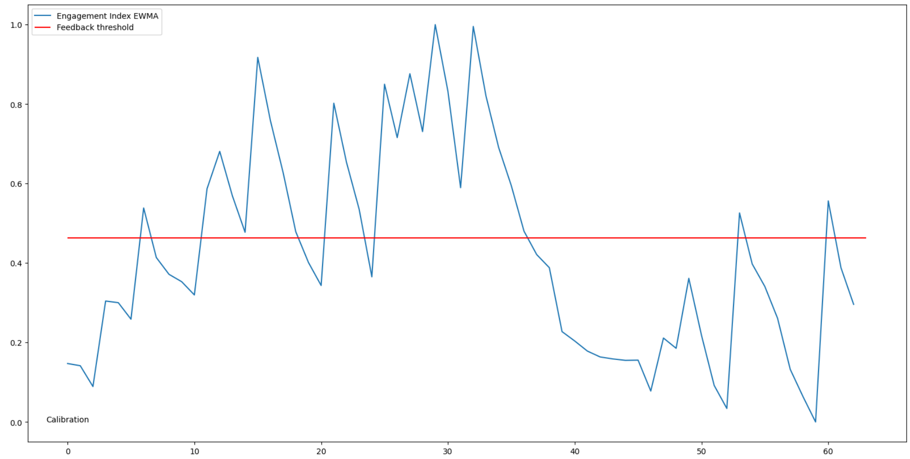


FIGURE 4.4: Visualization of the threshold of the calibration. The threshold is marked in red.

The complete data processing pipeline is depicted in Figure 4.5.

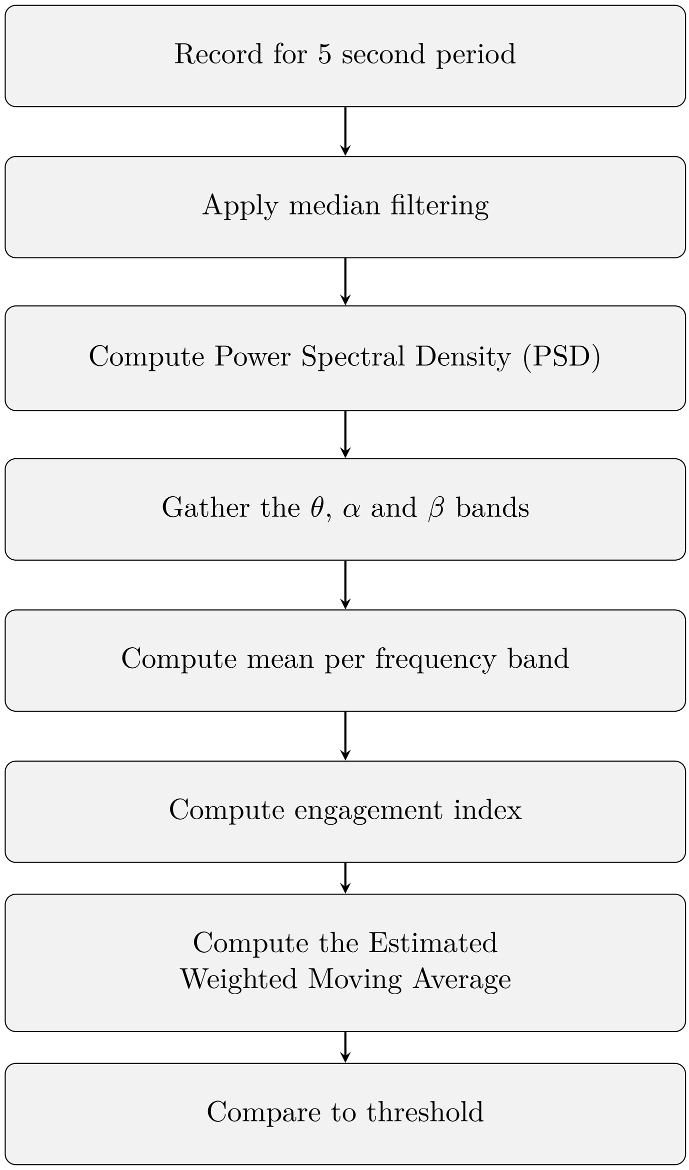


FIGURE 4.5: Data processing steps [5]

4.2 Data Acquisition

The Unicorn Hybrid Black EEG headset records EEG signals and connects to a laptop for processing using Bluetooth. The device can be controlled using the provided Unicorn Hybrid Black Python Application Programming Interface (API) [39]. Feedback devices (vibration motor and Peltier element) are controlled by an Arduino Uno, which communicates with the laptop through a serial connection. The experimental setup is shown in Figure 4.6.

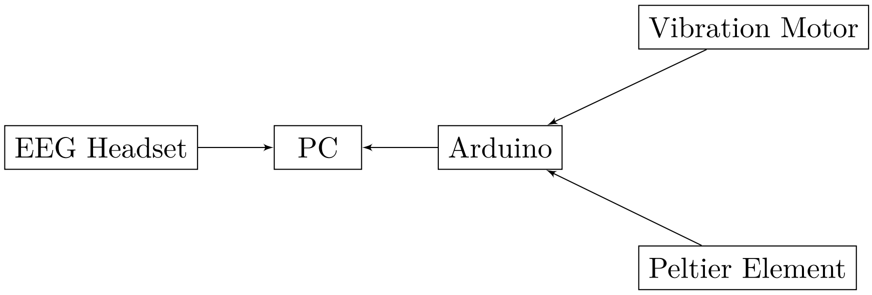


Figure 4.6: Experiment setup: The EEG headset is connected to a laptop, which controls the Peltier element and vibration motor via an Arduino.

4.3 Validation

The pipeline was validated by replicating the validation step of a prior study [5]. Since the same results were obtained, it was assumed that the two methods were similar. This allowed for a direct comparison of the results of the two studies.

To validate the system, a driver fatigue detection dataset [47] was used. This dataset included EEG data collected from 12 participants during a simulated driving task, divided into normal and fatigued states [5].

The hypothesis was that as the drivers became fatigued, their alertness decreased, leading to a lower EEG Engagement Index. This decrease was expected to be detectable by the EEG Engagement Index values.

The data were segmented into 5-second epochs to align with the experimental setup of this study. The first 10 minutes of the standard and fatigued data were processed for each participant, and the results were averaged over the 10 minutes for each state. The results were validated using a one-sided paired sample t-test with a significance level of $\alpha = 0.05$. The t-test revealed whether there were any significant differences between the three methods.

4.4 Experiment Setup

Before participating, participants were provided with an information sheet (Appendix B) detailing the study. Before proceeding, they were required to sign a consent form (Appendix A). Participants were allowed to ask questions at any time.

4.4.1 Installation

It was essential to ensure the electrodes of the headset were positioned correctly for accurate measurements. Two sticky electrodes were placed behind each of the mastoid bones behind the ears [48]. These sticky electrodes were replaced for every participant. The electrodes were turned clockwise and counterclockwise to ensure they reached the head through the hair. A waiting time of three minutes was observed according to the headset's instructions to ensure signal accuracy [48]. The signal strength was tested with the software suite provided with the headset. If signals were unclear, the electrodes were adjusted again until the signals became mostly clear.

During the experiment, participants were instructed to sit upright with both arms resting on the table and to remain as still as possible. This minimized noise in the EEG signal caused by movements and helped ensure cleaner data.

The vibration motor was attached to the participant's right wrist. After the vibrotactile feedback experiment was completed, the vibration motor was replaced with the Peltier element for the thermal feedback experiment. The Peltier element was mounted with the cold side in contact with the wrist and the heated side facing away. The order of the feedback modalities was alternated between participants.

4.5 Participants

Ten participants were selected for this study. While this sample size was insufficient for statistically significant results, it provided insights into how future research could be structured to explore how haptic feedback may raise engagement. The participants in this study were primarily university students to ensure a consistent education level. An equal number of male and female participants were recruited to help balance the results.

4.5.1 Ethical Approval

This study received ethical approval from the Ethics Committee of the University of Twente. Before the experiments, participants were provided with an information sheet (Appendix B) explaining the purpose of the study and the procedure. They were also required to sign a consent form (Appendix A) before participating. Participation in the study was entirely voluntary, and participants were allowed to withdraw at any time without consequences.

All collected data were anonymized and could not be traced back to the participants.

4.5.2 Experiment Task

Participants were required to watch a video lecture on economics [49]. This subject was intentionally chosen because the participantsmostly students from a technical universitywere presumed to have little to no prior knowledge of the topic. This ensured that participants had roughly equal experience with the content, minimizing variability in engagement due to prior knowledge. The selected video was an introductory lecture from a university bachelor's program, making the material accessible and understandable for all participants given their academic backgrounds [49].

The lecture lasted 35 minutes, allowing participants time to lose attention over its duration. The video was divided into three equal parts, with three different methods tested across these segments. In one segment, engagement was measured without administering feedback. In another, participants received a vibration when the EEG Engagement Index dropped below a certain threshold. In the final segment, participants received thermal feedback instead.

The same video was used across all conditions to eliminate bias related to specific topics. The video always started without feedback, serving as a baseline for the experiment. Additionally, the order of vibrotactile and thermal feedback was alternated between participants to control for order effects. Table 4.1 shows the order in which participants were tested. The order of the feedback was randomized, but it was made sure that both vibrotactile and thermal feedback occurred equally often in the first and last segments.

Test #	First Position	Second Position	Third Position
1	N	V	T
2	N	V	T
3	N	T	V
4	N	V	T
5	N	T	V
6	N	T	V
7	N	T	V
8	N	T	V
9	N	v	T
10	N	V	T

TABLE 4.1: Test sequences with feedback conditions: V (Vibrotactile Feedback), T (Thermal Feedback), and N (No Feedback).

4.5.3 Calibration Period

Before beginning the main experiment, participants underwent a brief calibration period. This calibration was important for establishing the upper and lower bounds of the EEG Engagement Index so the results can be normalised. The EEG Engagement Index values are also used to calculate a threshold threshold to be used for the remainder of the video by taking the mean over that period. During this phase, participants were asked to watch the first five minutes of the video. This initial period allowed for the collection of engagement data under relatively consistent conditions, providing a reference point against which subsequent engagement levels could be compared. Based on this calibration the results can be normalised using formula 4.2.

$$\mathrm{EI}_{\mathrm{normalised}} = \frac{\mathrm{EI} - \min(\mathrm{EI}_{\mathrm{calibration}})}{\max(\mathrm{EI}_{\mathrm{calibration}}) - \min(\mathrm{EI}_{\mathrm{calibration}})} \tag{4.2}$$

4.5.4 Statistical Analysis

To examine the effect of haptic feedback on sustained attention during an online lecture, a paired two-sided t-test was conducted on the mean EEG Engagement Index across three conditions: no feedback, vibrotactile feedback, and thermal feedback.

The mean and standard deviation of the EEG Engagement Index were calculated for each condition. Because of the large sample size of the EEG Engagement Index measurements ($n > 30$), the measurements were assumed to be normally distributed based on the Central Limit Theorem (CLT) [50]. A two-sided t-test was used to compare pairs of conditions: no feedback, vibrotactile feedback, and thermal feedback. The t-test used α=0.05 as the threshold for statistical significance. The test determined whether there were significant differences in sustained attention across conditions in this experiment.

A boxplot was generated to visualise each of the different conditions for each participant. This boxplot was used to identify outliers through visual inspection. If outliers were detected, they were removed.

The analysis aimed to determine whether haptic feedback modalities significantly enhanced engagement compared to the no-feedback baseline. All statistical analyses were performed using Python, with SciPy for hypothesis testing and Seaborn and PyPlot for data visualization.

Chapter 5

Results

This chapter discusses the results of the research. The study's primary objective was to find out how haptic feedback could improve sustained attention in university students during online lectures. The study is concerned with the EEG Engagement Index, which serves as a measure of sustained attention.

The chapter is split up into two sections. The first section presents the results of an online dataset, where the findings of previous studies are replicated. The second section addresses the main and subquestions by presenting the results for each feedback condition: vibrotactile, thermal, and no feedback. The results are shown with data visualizations and statistical analyses.

5.1 Validating Against Previous Research

Participant	Normal Mean	Fatigue Mean	Difference Mean
1	1.471	0.434	1.037
2	0.694	0.944	-0.250
3	1.114	0.935	0.179
4	0.605	0.896	-0.291
5	0.796	1.354	-0.558
6	0.839	0.909	-0.070
7	1.062	0.998	0.064
8	0.798	0.541	0.257
9	0.798	0.541	0.257
10	1.703	1.833	-0.130
11	1.343	1.040	0.304
12	1.102	1.222	-0.120
Mean	1.027	0.971	0.057

TABLE 5.1: Comparison of Driver EEG Engagement Index Between Normal and Fatigued States

Metric	Value
Number of participants	12
Degrees of freedom	11
Alpha	0.05
Mean difference (Normal - Fatigued)	0.057
Standard deviation of difference	0.404
Standard error of difference	0.117
T-value	0.485
T-critical	1.796
P-value	0.319

TABLE 5.2: Inferential statistics summary for comparing Normal and Fatigued groups.

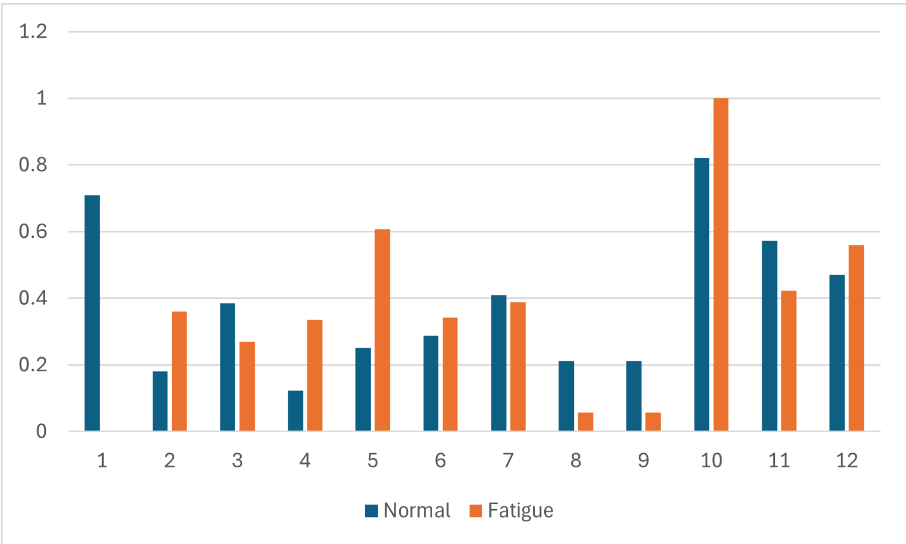


FIGURE 5.1: Comparison of driver alertness between normal and fatigued states by normalised engagement index

Table 5.1 lists the difference in alertness levels of the participants during the driving simulation before and after they were labelled as fatigued. This data is visualised in Figure 5.1. On average, the participants had an EEG Engagement Index of 1.027 during the normal state, which decreased to an average of 0.971 during the fatigued state (Table 5.1). Although the participants had a lower EEG Engagement Index while fatigued, results showed no significant difference in engagement levels between the normal and fatigued data ($t = 0.465, p = 0.319$, see Table 5.2).

These results are similar to the results of the previous study [5]. However, while this study did not find any significant differences between the normal states and fatigued states, they found significantly larger EEG Engagement Index values for the normal states than the fatigued states [5].

Although the validation was designed to replicate the setup of the original research as closely as possible [5], certain details, such as the chosen 10-minute segment of the dataset used in the original study, were unavailable. This means that the setup was likely not identical, which may account for any differences in the results. The differences in data selection between the two studies make direct comparisons of the methods challenging.

5.2 Experimental Results

The experiment aimed to investigate the effect of haptic feedback on sustained attention during online lectures. To address this, the study examined the impact of the three feedback conditions: vibrotactile, thermal, and no feedback on the participants' sustained attention, as measured by the EEG Engagement Index. This section presents the results of the experiment, structured as follows. First, the trends in sustained attention across the three conditions, including the identification and handling of outliers to ensure data validity. Next, the mean EEG Engagement Index is analysed for each condition to show the differences and variability in participant responses. Finally, the results of the participants are graphed in Figure 5.5 to show how the EEG Engagement Index behaved throughout the research. Statistical analyses are included to evaluate the significance of the observed differences.

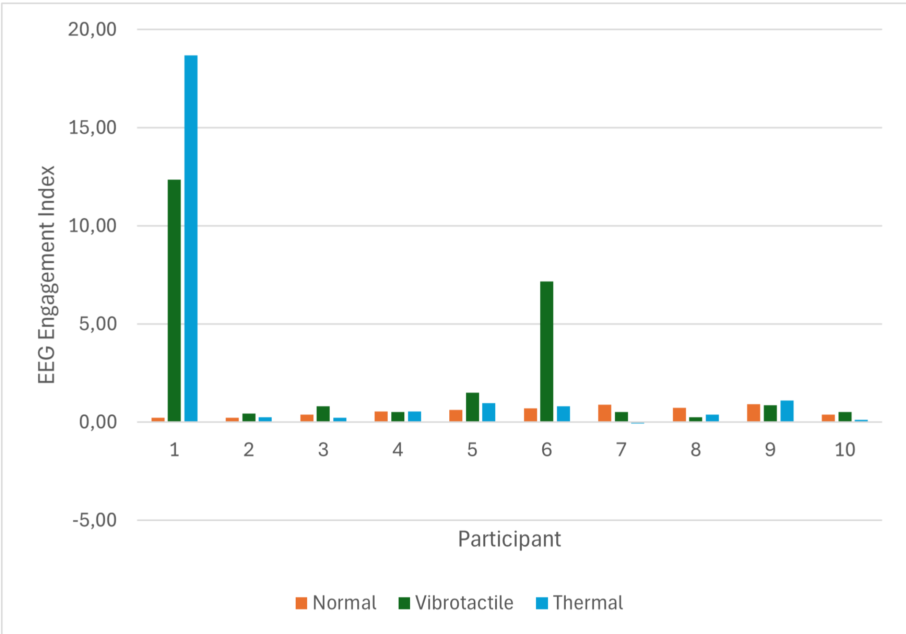


FIGURE 5.2: Normalised mean EEG Engagement Index of participants during the video across different conditions: normal, vibrotactile, and thermal.

Figure 5.2 shows the participants' mean EEG Engagement Index, normalised according to Formula 4.2 between the minimum and maximum EEG Engagement Index value of the calibration period. Note that the engagement index for participants 1 and 6 is extremely high. The measuring equipment is sensitive to noise and movement. As shown in Figures 5.5a and 5.5f, the data for these participants is capped at 1 towards the end of the recording, indicating that the values exceeded this threshold for the remaining duration.
The results of participant 10 were invalid because of errors with the headset. hese errors could have been resolved by restarting the headset, this was not possible during the experiment. Restarting the headset could not be done with the EEG headset's Software Development Kit (SDK) and had to be done manually, which would have disrupted the ongoing experiment. As a result, the issue could not be addressed in real-time.
Due to these recording errors, the data from participants 1, 6, and 10 were excluded from

further analysis to maintain the validity and reliability of the results.

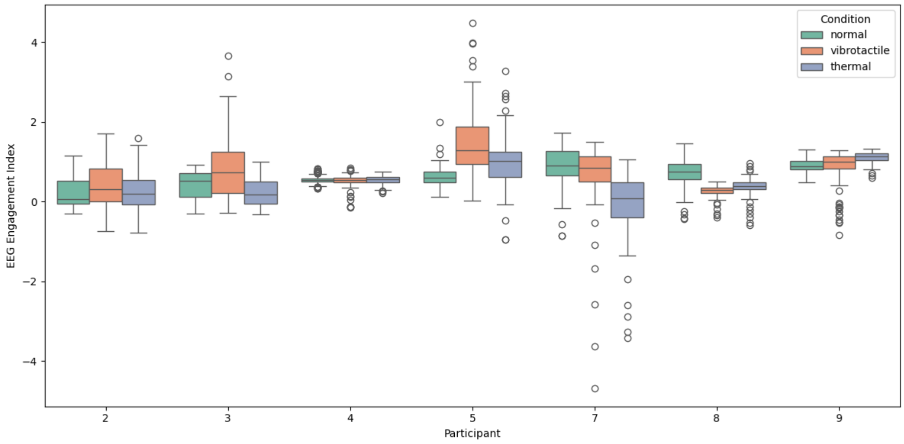


FIGURE 5.3: Normalised EEG Engagement Index of participants during the video across different conditions: normal, vibrotactile, and thermal.

Figure 5.3 shows a boxplot of the EEG Engagement Index of participants during the experiment. The EEG Engagement Index is shown on the y-axis while the participants' number is shown on the x-axis, with the colours representing the different conditions. Note that participants 1 and 6 are removed because they were labelled as outliers.

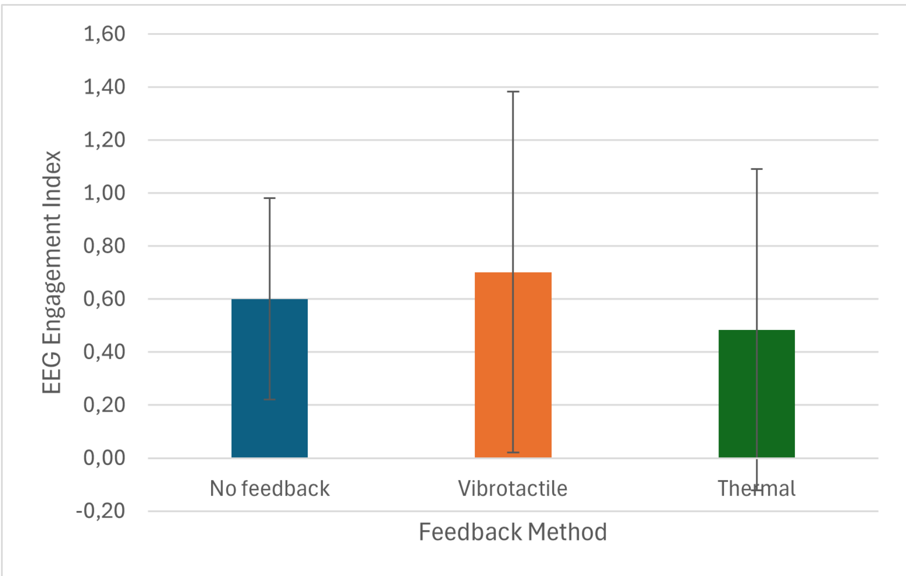


FIGURE 5.4: Mean EEG Engagement Index of participants during the video across different conditions with error bars representing standard deviation.

Figure 5.4 shows the mean EEG engagement index across conditions, with error bars indicating standard deviation. The vibrotactile feedback condition had the highest mean engagement index ($\bar{x} = 0.70$), followed by the no-feedback condition ($\bar{x} = 0.60$) and the thermal feedback condition ($\bar{x} = 0.48$). However, the differences between baseline and vibrotactile, baseline and thermal, and vibrotactile and thermal were not statistically significant ($p = 0.864$, $p = 0.308$, and $p = 0.262$, respectively; $\alpha = 0.05$).

Notably, the standard deviation increased for the vibrotactile feedback condition. This means there EEG Engagement Index and thus the engagement of the participants more at the later parts of the study. This shows that participants transitioned between focusing on the lecture and not focusing more frequently compared to the beginning of the video when the no feedback baseline was recorded, which signals that participants had shorter sustained attention at the end of the lecture.

Figure 5.5 shows the normalised EEG Engagement Index of the participants, with values limited between zero to one. Four different phases of the experiment can be seen as indicated by the dotted vertical lines. The four phases were calibration, no feedback, thermal feedback and vibrotactile feedback. The graph also shows a red line, which is the average of the calibration period and serves as the threshold for the feedback. The points where feedback is administered are recorded alongside the EEG Engagement Index and are displayed by the red dots.

5.3 Statistical Analysis

Table 5.3 shows the EWMA of the participants' EEG Engagement Index across the four experimental phases: calibration, no feedback, vibrotactile feedback, and thermal feedback.

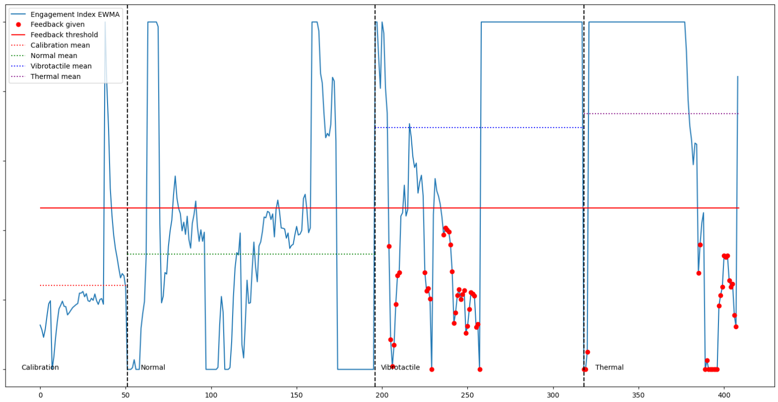
Participant #	Calibration	No Feedback	Vibrotactile	Thermal
Participant 2	0.133	0.116	0.135	0.118
Participant 3	0.065	0.058	0.083	0.048
Participant 4	0.086	0.089	0.086	0.088
Participant 5	0.059	0.064	0.083	0.071
Participant 7	0.081	0.083	0.079	0.072
Participant 8	0.107	0.146	0.103	0.114
Participant 9	0.059	0.068	0.067	0.073
Mean	0.084	0.089	0.091	0.083

Table 5.3: Mean EWMA of the participants' EEG Engagement Index across the different experimental phases. Data from participants 1, 6, and 10 were excluded due to errors.

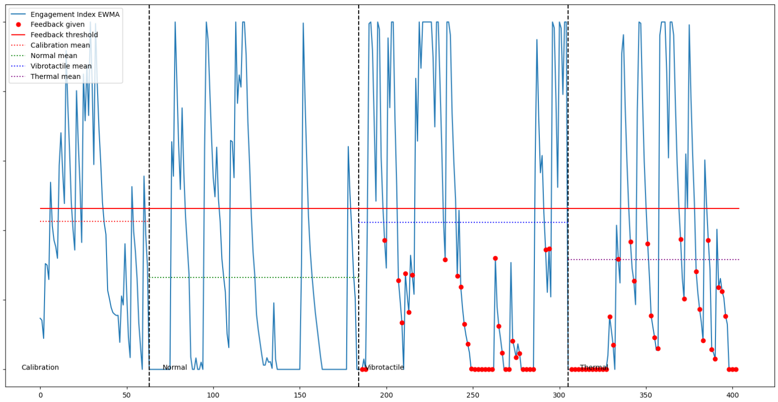
Metric	No feedback vs Vibrotactile	No feedback vs Thermal	Vibrotactile vs Thermal
Number of participants	7	7	7
Degrees of freedom	6	6	6
Alpha	0.05	0.05	0.05
Mean difference	-0.002	0.006	0.007
T-value	0.178	1.112	1.239
P-value	0.864	0.308	0.262

Table 5.4: Inferential statistics summary for comparing No Feedback, Vibrotactile Feedback and Thermal Feedback.

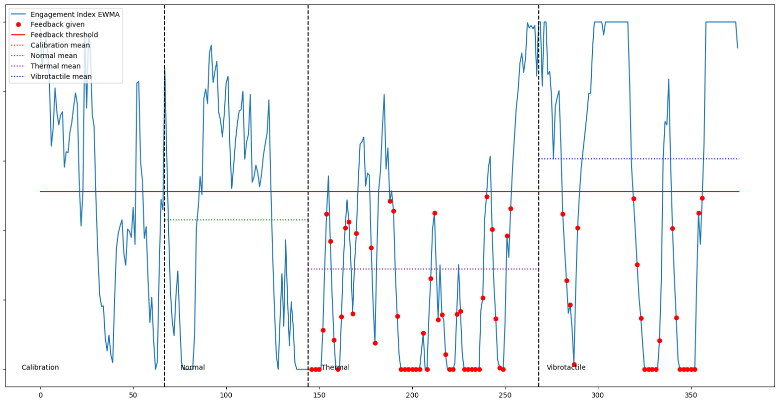
Table 5.4 shows the statistics for the paired t-test that was used to compare the different methods, each with an alpha level of 0.05. The results indicate no statistically significant differences between the conditions. For instance, the comparison between no



(A) Participant 1

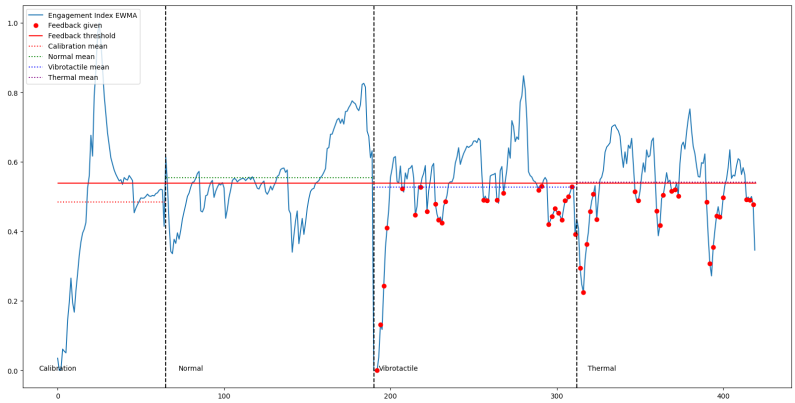


(B) Participant 2

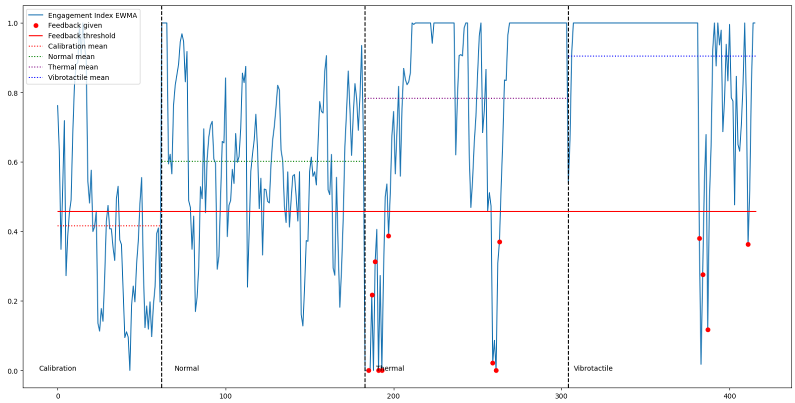


(C) Participant 3

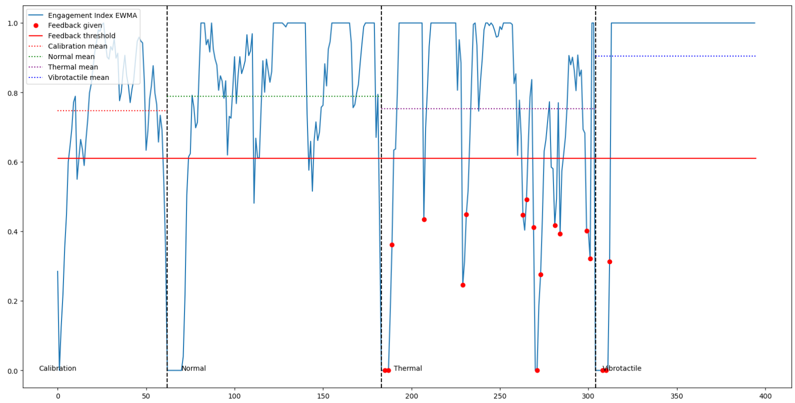
FIGURE 5.5: Normalised EEG Engagement Index of participants during the four different phases of the experiment. The red dots label the moment feedback is applied.



(D) Participant 4

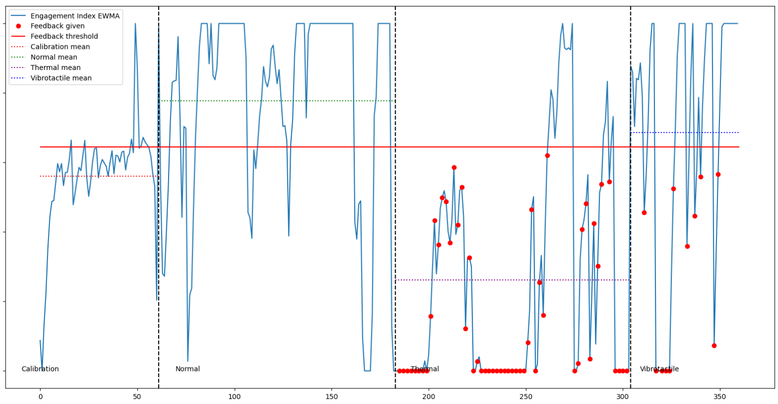


(E) Participant 5

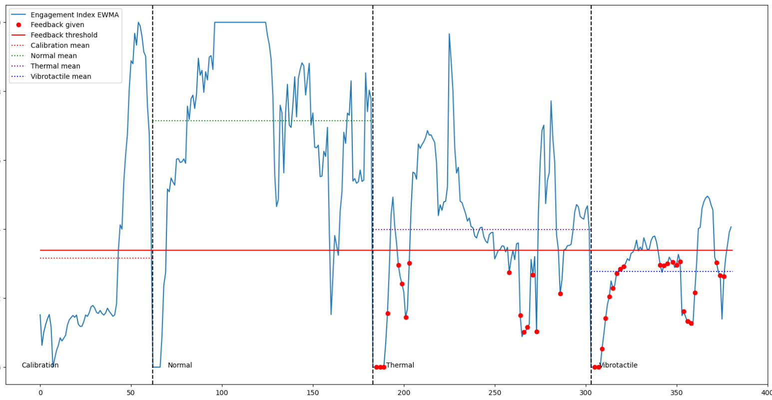


(F) Participant 6

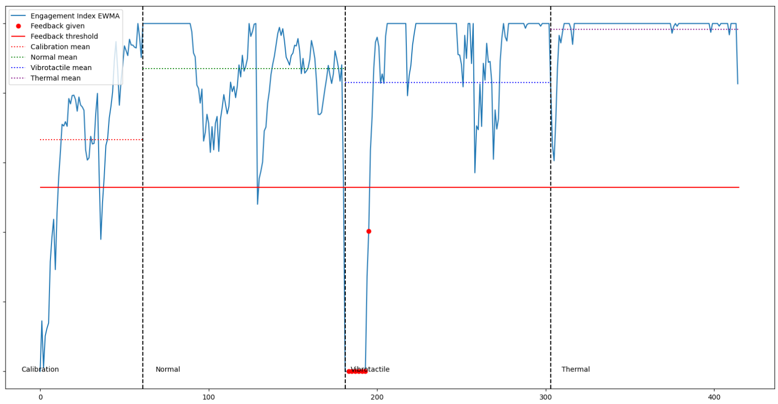
Figure 5.5: Normalised EEG Engagement Index of participants during the four different phases of the experiment. The red dots label the moment feedback is applied.



(G) Participant 7

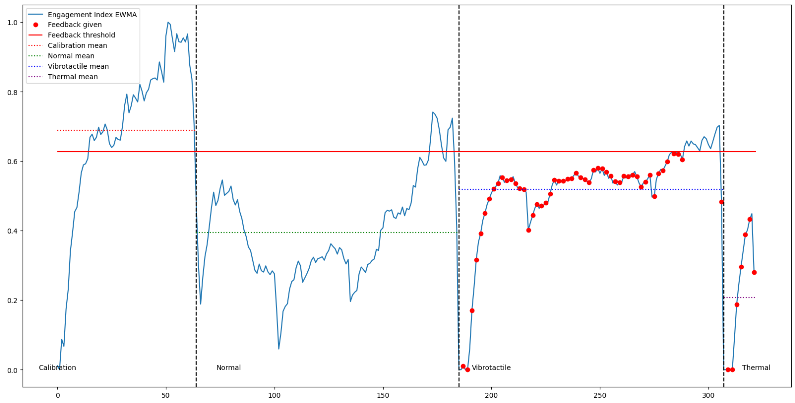


(H) Participant 8



(I) Participant 9

FIGURE 5.5: Normalised EEG Engagement Index of participants during the four different phases of the experiment. The red dots label the moment feedback is applied.



(J) Participant 10

FIGURE 5.5: Normalised EEG Engagement Index of participants during the four different phases of the experiment. The red dots label the moment feedback is applied.

feedback and vibrotactile feedback resulted in $p = 0.864$, while no feedback versus thermal feedback resulted in $p = 0.308$. Similarly, the comparison between vibrotactile and thermal feedback resulted in $p = 0.262$. These findings suggest that neither vibrotactile nor thermal feedback significantly impacted sustained attention compared to the no feedback condition.

Chapter 6

Discussion

This study has provided insights into the extent to which haptic feedback modalities, namely vibrotactile and thermal, affect sustained attention in university students during an online lecture. It is important to note the study's limitations, which will be discussed in detail in this chapter. Because of this, the findings of this study should be interpreted with caution. This chapter will also compare the results with existing research and conclude with recommendations for future studies.

6.1 Method Validation

The method of a previous study was replicated to validate whether the methodologies of both studies were consistent [5]. Because the EEG Engagement Index lacks a standardized scale, comparing results between studies can be challenging. If the research methods of the studies had been found similar, it would have allowed for a direct comparison between the results. However, the differing results between the two studies suggest differences in their methods.

Both the previous research and this study used 120 instances of 5-second long epochs [5]. However, the timeframe of the dataset was not specified. It was assumed that the first ten minutes were used, but given the dataset's length of 12 hours, it is likely that a different segment was analyzed [47].

Regarding the findings, the previous study reported a correlation between the EEG Engagement Index and fatigue, which was not observed in this study [5]. These differences may be because the first ten minutes of the dataset were selected, where fatigue might not yet have been apparent, which could account for the differences in results. Differences in the pipeline can also be the reason for the differences in the results. The study used a random sooth effect to account for variability of the different participants which this study did not [5].

As for the results of this study, engagement is influenced by factors other than fatigue (see Section 2.1). Thus, while participants may have experienced fatigue, it did not necessarily result in reduced engagement which could explain the lack of a correlation between fatigueness and a reduced EEG Engagement Index.

6.2 Experiment Results

The results of this experiment revealed no statistically significant differences in the EEG Engagement Index across the no-feedback, vibrotactile feedback, and thermal feedback conditions. Vibrotactile feedback showed the highest mean EEG Engagement Index, indicating it could possibly be used to enhance engagement. Thermal feedback resulted in a lower mean EEG Engagement Index, suggesting that it may be less effective in maintaining attention during online lectures. However, because of the lack of statistical significance due to the small sample size, the current dataset is insufficient to draw definitive conclusions about the effectiveness of these feedback methods.

None the less, it needs to be noted that the frequent administration of feedback may have overwhelmed or distracted participants, reducing its benefits. Participants mentioned outside of the experiment that the feedback could be removing their attention from the online lecture at times. Reducing the frequency of feedback interventions could minimize distraction and allow participants to better adapt to the stimuli, potentially yielding different results. Further research is needed to find the balance of haptic feedback to optimally keep the sustained attention of the participants high.

An important observation is the increased variability in EEG Engagement Index during the vibrotactile and thermal feedback conditions, as indicated by a larger standard deviation. This variability is presented in Figure 5.4 by the error bars in relation to the mean, the bars. This shows that while receiving feedback, there was more fluctuation in the data. This suggests that participants alternated between focused and unfocused states more frequently while receiving feedback. This can be seen in Figure 5.5. Because the feedback was given towards the end of the lecture, participants were already more easily distracted. This finding aligns with research indicating that our attention shifts from focussed to unfocused more frequently when time goes on [11].

6.3 Outlier Removal

The results of participants 1 and 6 were removed because of outliers due to abnormally high EEG Engagement Index. The high readings toward the end of their recordings were likely caused by headset displacement or movements of the participants, which led to a difference in the relation between the reference node and the rest of the nodes. Because of this the recordings experience EEG Engagement Index values that are well above expected. The results of participant 10 also had to be removed, because they were cut short by software-related errors of the EEG-headset itself. Removing these outliers improved the validity of the results by ensuring that the analysis better reflected genuine engagement patterns. However, this exclusion also reduced the sample size, which may have impacted the study's statistical power.

6.4 Improvemenets

6.4.1 EEG-headset

The equipment-related issues discussed in Section 6.3 emphasize the importance of proper headset placement and minimizing movements of the nodes during future experiments to prevent similar problems. These factors are critical for ensuring data accuracy and reliability. If the study were to be repeated, using a different EEG headset, preferably one with sticky electrodes, could improve measurement accuracy by keeping the electrodes stationary during the experiment. This could help mitigate the problems observed by Participants 1 and 6.

Additionally, addressing the technical issue with Participant 10, where the headset crashed, could also be resolved by using a more reliable EEG-headset.

6.4.2 Engagement Detection

In this study, the EEG Engagement Index was used as the primary metric for engagement, with comparisons made against a fixed threshold derived from the calibration period at the start of the experiment. This threshold represented the engagement level of participants when they just started watching the lecture and were still mentally fresh. However, engagement tends to decrease naturally over time, making it potentially unfair to compare later engagement levels to the initial threshold [11].

To address this limitation, recalibrating the threshold during the lecture could provide a more accurate representation of engagement over time. Instead of relying on a single calibration period before the study, the system could be recalibrated between different feedback modalities. This way the threshold can better reflect participants' current engagement levels, rather than being tied to their initial state.

Additionally, to maintain the flow of the experiment, recalibration could be done seamlessly without interrupting the lecture. For instance, calibration could occur during transitions between feedback modalities, ensuring that the video lecture continues uninterrupted. This continuous recalibration method would not only improve the accuracy of engagement measurements but also preserve the natural progression of the experiment.

Additionally, some studies propose alternatives to the EEG Engagement Index by leveraging frequency bands as features in machine learning models [51]. For instance, a k-NN classification method has been employed to assess user engagement. This approach may be more effective in certain cases, as it allows for training for specific target groups and removes the need for a set threshold.

6.4.3 Ojective Measurements For Learning

This study did not include pre- or post-tests to measure participants' knowledge of the lecture content. As a result, it was impossible to determine their understanding of the topic before and after the lecture. This limitation introduces potential variability, as participants with little to no prior knowledge or those with substantial knowledge might engage differently with an introductory lecture compared to participants with moderate familiarity.

Furthermore, without a post-test, the participants had little incentive to actively engage with the lecture, unlike in typical academic settings, where students are motivated to learn to pass exams or assignments. Because of the lack of knowledge assessments, it also remains unclear how much participants learned from the lecture or whether their learning outcomes differed when compared to lectures without the feedback system. The gain in learning can be used to compare this experiment to other research to see how effective it is in terms of helping with the learning progress.

6.4.4 Distraction From EEG And Feedback Systems

Several participants reported being distracted by the haptic feedback during the experiment. This distraction was attributed to the frequent vibrations and the repeated application of thermal feedback. These interruptions occasionally diverted participants' attention away from the online lecture, counteracting the intended goal of enhancing their engagement. This highlights a potential challenge in balancing the use of sensory feedback systems to ensure they support, rather than detract from, the learning experience.

Chapter 7

Conclusion

Maintaining sustained attention during online lectures can be challenging, especially in distracting environments. While previous research mostly looks at the potential of auditory and visual feedback [5], this research investigates whether haptic feedback, vibrotactile and thermal. This could effectively enhance sustained attention, without sharing the cognitive resources.

Vibrotactile feedback resulted in a higher mean EEG Engagement Index compared to the baseline, while thermal feedback showed a lower mean EEG Engagement Index than both the baseline and vibrotactile feedback. However, no significant differences were found between baseline vs. vibrotactile feedback, baseline vs. thermal feedback, or vibrotactile vs. thermal feedback. To answer the research question, "To what extent does haptic feedback, compared to no feedback, improve attention in university students during an online lecture, as measured by the EEG Engagement Index?" this study found no significant effect of haptic feedback on attention.

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Appendix A

Consent Form

Consent Form for 'Temperature and vibrating feedback during video lecture'

YOU WILL BE GIVEN A COPY OF THIS INFORMED CONSENT FORM

Authors: Stijn Kamp (based on template by BMS EC)
Last edited: 01-11-24

Please tick the appropriate boxes	**Yes**	**No**
Taking part in the study		
I have read and understood the study information dated dd-mm-yy, or it has been read to me. I have been able to ask questions about the study and my questions have been answered to my satisfaction.	○	○
I consent voluntarily to be a participant in this study and understand that I can refuse to answer questions and I can withdraw from the study at any time, without having to give a reason.	○	○
I understand that taking part in the study involves watching a video of around 30 minutes while wearing an EEG-headset and a bracelet for feedback and partake in an interview afterwards that is recorded using written notes.	○	○
Use of the information in the study		
I understand that information I provide will be used for reports, publication and follow up research.	○	○
I understand that personal information collected about me that can identify me, such as [e.g. my name or where I live], will not be shared beyond the study team.	○	○
Future use and reuse of the information by others		
I give permission for the anonymised recordings of the EEG-cap and written notes that I provide to be archived in in the report so it can be used for future research and learning.	○	○
I agree that my information may be shared with other researchers for future research studies that are similar to this study. The information shared with other researchers will not include any information that can directly identify me. Researchers will not contact me for additional permission to use this information.	○	○

Signatures

		dd-mm-yy
______________________	______________________	________
Name of participant	Signature	Date

I have accurately read out the information sheet to the potential participant and, to the best of my ability, ensured that the participant understands to what they are freely consenting.

Stijn Kamp		dd-mm-yy
_________________________	___________________	________
Researcher name	Signature	Date

Study contact details for further information: Stijn Kamp, s.kamp@student.utwente

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Appendix B

Information Sheet

Information sheet for 'Temperature and vibration feedback during video lecture'

Authors: Stijn Kamp (based on model by UCL Research Ethics)
Last edited: 01-11-24

Dear reader,

Thank you for your consideration of participating in this research project! Before you decide to participate, it is important for you to understand your part in the research and what the research is about. Please take your time to carefully read this information sheet. If anything is still unclear during or after reading the sheet, feel free to ask questions.

The aim of this research is to explore if sensory feedback, such as temperature changes or vibrations, can help regain and sustain attention during online lectures. This could potentially enhance learning experiences and outcomes in digital education environments. During the study, you'll wear a specialised cap, known as an EEG-cap, which will measure your brain activity to monitor your attention levels. If the EEG detects that your attention level is low, you'll receive feedback. During the video, you will either feel a vibration or a cold feeling, administered by a bracelet.

To test both methods, you are asked to watch a videos of around 30 minutes. During the video you'll have to wear the EEG-cap so your attention level can be measured. Afterwards I will ask you some questions about your experience with both methods.
The materials used for the testing setup have been extensively used in human research and are safe. While you might experience some discomfort from wearing the cap and the bracelet, there are no significant risks to this study.
Whilst there are not any immediate benefits for you in participating in this research for you, you'll help me by providing me with valuable information. This information consists of questions asked at the end of the tests and the recordings of the EEG-cap. This information will be published and could be used for follow up research. However, the information is strictly confidential and will be anonymised before publishing so it cannot be traced back to you.

The participation of this study is entirely voluntary. If you choose participate in this research, you are asked to fill out a consent form. You'll receive a copy of this sheet, the filled out consent form and the notes of the interview. At any time you are allowed withdraw from the research without any consequences.

If you have questions about your rights as a research participant, or wish to obtain information, ask questions, or discuss any concerns about this study with someone other than the researcher(s), please contact the Secretary of the Ethics Committee Information & Computer Science: ethicscommittee-CIS@utwente.nl

Thank you for your time!

Yours sincerely,
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