VALIDATING A MEDITATION-BASED MIND WANDERING BCI USING THE UNICORN HYBRID BLACK: A PILOT STUDY

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Abstract

Brain-computer interfaces (BCI) have become a burgeoning field of research as computers become embedded in everyday life. Electroencephalography (EEG) is the preferred brain measurement device used in BCIs, though research- and medical-grade devices are prohibitively expensive. EEGs such as the Unicorn Hybrid Black (UHB) have entered the market as low-cost alternatives, albeit with electrode arrays of diminished density. The present study aims to assess the feasibility and usability of the UHB in BCI research and how it can or cannot be utilized as an accessible learning tool in academic, commercial, and public spheres. This was done by creating a BCI using the UHB and UHB Python API to assess various machine learning algorithms' classification accuracy of a meditation paradigms that uses self-caught experience sampling to capture mind wandering. Key findings suggest that the UHB is a demonstrably effective tool within research and academic spheres; however, its feasibility within consumer-grade BCIs may be limited. The machine learning classification accuracy was deemed acceptable with the ridge classifier emerging as the algorithm of optimal performance.

Keywords: BCI, machine learning, EEG, meditation, mind wandering, usability testing

List of Abbreviations and Symbols Used

Abbreviation	**Definition**
BCI	Brain-computer interface
DMN	Default mode network
ECoG	Electrocorticography
EEG	Electroencephalography
ERP	Event-related potential
fMRI	Functional magnetic resonance imaging
fNIRS	Functional near-infrared spectroscopy
MLP	Multi-layer perceptron
MMN	Mismatch negativity
PET	Positron emission tomography

Glossary

Term	Definition
Brain-computer interface	a system that translates brain signals into instructions or commands that are subsequently interpreted by an external device, thereby allowing for direct communication between brain and computer
Alpha waves	neural oscillatory activity from the range of 8-13 Hz
BCI illiteracy	a phenomenon in which a non-negligible minority of BCI users are unable to produce detectable patterns of brain activity that is required from some paradigms
Beta waves	neural oscillatory activity from the range of 13-30 Hz
Decision tree	a supervised machine learning algorithm that continuously splits data based on specific rules or conditions
Default mode network	a resting state network that exhibits consistent deactivation during goal-directed tasks
Delta waves	neural oscillatory activity from the range of 0.1-4 Hz
Electrocorticography (ECoG)	a device that measures electrical activity in the brain through electrodes that are placed directly on the surface of the cortex
Electroencephalogram (EEG)	a device that measures neural activity through the placement of electrodes on the scalp that detect the electrical impulses generated by neurons
Event-related potential (ERP)	neural activity that temporally corresponds to a sensory, cognitive, or motor event describe through its polarity, amplitude, latency, and scalp distribution

Term	Definition
Extra-physiologic artifact	artifacts in an EEG signal resulting from the external environment such as technical preparation problems, movements in the recording environment, and powerline noise
Feature extraction	a process that highlights pertinent signals from a signal
Function near-infrared spectroscopy (fNIRS)	a device that measures changes in the oxygenated and deoxygenated hemoglobin levels in the brain using near-infrared-range light
Functional magnetic resonance imaging (fMRI)	a device that measures brain activity by detecting changes in the brain associated with blood flow
Gamma waves	neural oscillatory activity from the range of 30-100 Hz
K-fold cross-validation	a method to evaluate a machine learning algorithm's performance
K-nearest neighbour	a supervised machine learning algorithm that is non-parametric and classifies new data points by choosing the class closest in distance to a number of predefined training samples
Machine learning	a branch of computer science concerned with enabling computers to "learn" without being directly programmed
Meta-awareness	the explicit awareness of the contents of one's consciousness
Mind wandering	the disengagement from active attention due to spontaneous thought
Mismatch negativity (MMN)	an ERP shown to be exhibited during auditory change detection tasks

Term	Definition
Multi-layer perceptron	a supervised and neural network machine learning algorithm that operates by creating a network of nodes arranged in layers
Multitaper power spectral analysis	a feature extraction technique operating in the frequency domain that reflects the amount of power per unit volume of a random signal at a particular frequency
Naïve Bayes	a supervised machine learning algorithm that is based on the Bayes Theorem and is used to calculate conditional probabilities
Oddball auditory protocol	a method of eliciting mind wandering in which a sequence of repetitive "standard" tones is interspersed occasionally with "oddball" tones that differ in some way from the standard tones, typically in frequency (i.e., pitch)
Physiologic artifact	artifacts in an EEG signal resulting from eye movement, the heart, sweat, tongue movement, and muscular movement
Probe-caught experience sampling	a method of measuring mind wandering in which a random prompt or probe is presented to a participant at random points through a task asking whether they are experiencing mind wandering or not
Self-caught experience sampling	a method of measuring mind wandering in which a participant self-reports their conscious perception of mind wandering through methods such as a button press
Supervised learning	a category of machine learning classification that makes inferences from labelled training data
Support vector machine	a supervised machine learning algorithm that is often used for classification and regression purposes

Term	Definition
Theta waves	neural oscillatory activity from the range of 4-8 Hz
Unicorn Hybrid Black (UHB)	a consumer-grade eight-channel wet/dry EEG

Chapter 1 Introduction

With the increasing ubiquity and embeddedness of computers in everyday life, many researchers of varying disciplines have endeavoured to enhance and reimagine the ways in which we operate and communicate with computers. One such method is to communicate with computers directly with one's brain rather than relying on peripheral devices such as a computer mouse or keyboard. This approach, coined brain-computer interface (BCI), involves a system that translates brain signals into instructions or commands that are subsequently interpreted by an external device, thereby allowing for direct communication between brain and computer. Though there have been significant strides towards integrating BCIs into everyday life, the utility and usability of such systems remains an ongoing exploration. Likewise, the actual hardware used in BCIs is constantly evolving, thereby necessitating continuous investigation into the interplay between the neurophysiology and engineering on which BCIs hinge. Since the goal of BCI research is to redefine how we access and interact with information, the field has considerable potential as an information technology artifact as well as for information science research in general.

1.1 Background

Though BCI research is considered to have been founded in the 1970s, one must consider research as early as the 19th century in order to understand the theoretical background of the field. The first neural electrical signals were recorded from animals in 1875 by Richard Caton which led to the invention of the electroencephalogram (EEG) by Hans Berger in 1924. In the 1930s, the presence of alpha and beta waves were confirmed (Hermann et al., 2016; Kawala-Sterniuk et al., 2020; Stone & Hughes, 2013). By the beginning of World War II, most neuropsychiatric centres across the globe possessed an

EEG laboratory (Herrmann et al., 2016; Kawala-Sterniuk et al., 2020; Stone & Hughes, 2013). After 30 years of improving and expanding upon EEG as a neural measurement instrument, the field of BCI was conceived in the 1970s and the term first coined by Jacques J. Vidal (Kawala-Sterniuk, 2021; Vidal, 1973). Even so, the first attempts to create a functioning BCI with humans as subjects did not occur until the 1990s and the field was not operationalized until 2000 by Jonathan Wolpaw (Kawala-Sterniuk, 2021).

Even though initial BCI research used EEG as its primary neural measurement device, subsequent research has used a multitude of other instruments such as: electrocorticography (ECoG), magnetoencephalography (MEG), functional near-infrared spectroscopy signals (fNIRS) and functional magnetic resonance imaging (fMRI), among others (Hong & Santosa, 2013; Kawala-Sterniuk, 2021). Though all instruments have their own benefits and drawbacks, EEG is the preferred method in BCI research due to its non-invasive and inexpensive nature as well as its relative portability (Hong & Santosa, 2013; Jin, Ji, & Wenyan, 2019; Liang et al., 2020; Värbu, Muhammad, & Muhammad, 2022; Yin et al., 2022). Even though EEG is inexpensive compared to other options, commercial BCIs still remain limited to the public due to their high cost. Though there are smaller and more cost-effective EEGs available, they vary in the size of electrode arrays, the type of data transfer, the signal-noise ratio, and spatio-temporal resolutions. Compared to their research- and medical-grade alternatives, consumer-grade, low-cost EEG systems are often inaccurate and have a low transfer rate (Kawala-Sterniuk et al., 2021; Maskeliunas et al., 2016). However, with the initiative in medicine towards smaller, more capable, and cost-effective systems, over time, BCI devices will become more inexpensive and inconspicuous. Before this can occur, issues and deficiencies with EEGs must be identified so that they can be improved upon.

The most commonly used headsets in BCI research and development are created by the following companies: Emotiv Inc., Ant Neuro, Cognionics, Neurosky Inc., OpenBCI, interaXon, g.tec, and CREmedical (Kawala-Sterniuk et al., 2021). Each company offers multiple devices at varying costs and varying sizes of electrode arrays. In addition, the devices do not perform identically in practice and some devices are more suited to specific tasks than others (Kawala-Sterniuk et al., 2021). These companies among others have developed functioning BCIs that are available for consumer purchase. For instance, Neurosky headsets have a library of apps that can be used with their headsets that offer entertainment, wellness, and utility value (Neurosky, 2023). In addition, Muse is an assistive meditation tool that detects mind wandering and uses audio cues to return focus (Muse, 2023). Recently, Apple has been approved for a patent for AirPods equipped with 17 active electrodes capable of measuring neural activity, including other biological signals (Cruise, 2023). While it is still in development, this suggests that a next generation of consumer-grade EEG is on the horizon.

1.2 Purpose

The field of BCI research, while comparatively new as a discipline, is rapidly developing with the advent of new technologies. While BCI technology has seen limited success in the consumer market, with the pace at which it is growing, in the foreseeable future BCI systems may soon be a popular and ubiquitous consumer item. As such, it is of increasing importance to evaluate not only the feasibility and efficacy of consumer-grade EEGs in BCI systems, but also the usability and utility of both the EEGs and the

BCI systems themselves. There are many consumer-grade EEGs on the market, all of which have different features and specifications including the quality of the measurements they can record (resolution), the number of sensors they have (size of the electrode array), and how quickly they collect data (the sampling rate). Though these EEG systems are typically inexpensive and thereby make brain-measurement technology more accessible to a wider audience, the variability in the quality of the measurements can impact both the accuracy and reliability of the data collected. For instance, EEG devices providing lower resolution or smaller electrode arrays might limit the range of signals captured, potentially providing unclear or noisy data. Thus, it is important that the differences, benefits, and drawbacks of each EEG be evaluated in order to optimize the efficacy of the device in a particular BCI context. However, since there is no accepted standardized testing protocol, the quality of a signal is dependent on the paradigm and experimental conditions; a meditation paradigm wherein the participants are required to keep their eyes closed would yield fewer signal artifacts related to blinking than would an experiment in which participants are required to keep their eyes open, for example (Niso et al., 2023).

Though there often tends to be a focus on the signal and technical specifications of an EEG, the usability from the experience of a user is just as important. This holds especially true in the context of a BCI intended for the mass market—if a consumer cannot figure out how to work the system nor enjoys using it, it has little viability as a successful product. In a study assessing the user experience of a selection of EEGs, Izdebski et al. (2016) report that participants rated most EEGs with an average score of

3.5 or lower on a 5-point Likert scale. This suggests that many of the EEGs available on the market could benefit from usability improvements.

Though it is important to test the efficacy and feasibility of the specific EEG to be integrated in the BCI, it is also necessary to validate the usefulness and practicality of BCI systems themselves. A BCI must be demonstrably reliable in the long-term, easy to set up, use, and maintain, and through its use benefit mood, quality of life, and productivity (Wolpaw, 2013). If a BCI is unable to meet these criteria, no matter how affordable, effective, and accurate the hardware is, there is little purpose or motivation in using the system. Thus, a BCI must not be designed thoughtlessly without due consideration to both the hardware, software, and purpose of the system.

One popular BCI design is an assistive meditation system, such as the previously discussed Muse. Neurosky also has multiple meditation apps available in its app store (Neurosky, 2023). This type of interface is popular not only because a meditation paradigm can control for signal artifacts resulting from movement and eye blinks, but also because a single electrode is sufficient to detect attention, thereby decreasing the need for larger and more complex EEG devices (van der Wal & Irrmischer, 2015). Furthermore, meditation has been found to enhance the efficacy of BCI system control (Eskandari & Erfanian, 2008; Lo, Wu, & Wu, 2004; Tan et al., 2015; Liang & Shastri, 2018). Thus, a meditation-based BCI is an excellent choice for a BCI in the early consumer market, not only because of the simplicity of the hardware and paradigm, but also because such a system would train users for success in subsequent BCIs.

Likewise, a system that can detect and correct mind wandering would prove to be an exceptionally helpful device. Mind wandering is defined as the disengagement from active attention due to spontaneous thought. Since mind wandering can negatively impact performance, it can be detrimental in the context of academic lectures and even dangerous in high-risk situations such as driving or operating heavy machinery (Lee, 2014; Mooneyham & Schooler, 2013; Wammes et al., 2016). However, mind wandering can be difficult to measure without disrupting the user. One approach to measuring mind wandering is through the use of a probe that prompts participants intermittently to collect information on whether or not they are experiencing mind wandering. While this has been shown to effectively capture mind wandering, it comes at the cost of disrupting the cognitive processes of the participants (Conrad & Newman, 2019). Another approach to measure mind wandering is with self-caught experience sampling in which participants self-report whether they are experiencing mind wandering using a button press, for example (Rodriguez-Larios & Alaerts, 2020). Since this is not as disruptive as a probe, it would be a preferable method in a BCI designed with the purpose of improving attention. Thus, determining whether self-caught experience sampling is a sufficient measure of mind wandering could assist in creating more accurate BCIs in the future.

The purpose of the present study is to create a BCI using the Unicorn Hybrid Black (UHB), a relatively low-cost consumer-grade EEG, and to assess its performance, feasibility, and usability within the context of the system. Likewise, the utility and practicality of a meditation-based paradigm within the context of a BCI will be assessed. We will also endeavour to delineate how such a device can or cannot be utilized in academic, commercial, and public sectors. The main research questions to be investigated are as follows:

1. Is an 8-channel EEG sufficient for the identification of mind wandering?

2. Does a BCI intervention enhance meditation attention?
3. Is self-caught experience sampling sufficient for the detection of mind wandering in a meditation-based BCI?
4. What are the best approaches to machine learning classification in a mind wandering BCI?

Chapter 2 Literature Review

2.1 Measuring Neural Activity

As the name suggests, one of the primary components of a BCI is some sort of instrument that can detect and measure brain activity. The instrument most used in BCI research is typically EEG due to its non-invasive and inexpensive nature as well as its relative portability, though electrocorticography (ECoG) and more recently functional near-infrared spectroscopy (fNIRS) are also popular choices (Hong & Santosa, 2013; Jin, Ji, & Wenyan, 2019; Liang et al., 2020; Nicolas-Alonso & Gomez-Gil, 2012; Värbu, Muhammad, & Muhammad, 2022; Wang, Nakanishi, & Zhang, 2019; Yin et al., 2022).

An EEG measures neural activity through the placement of electrodes on the scalp that detect the electrical impulses generated by neurons. Historically, EEG has required that a conductive medium, typically a gel, be placed between the electrode and the scalp. However, advances in EEG technology have led to the development of so-called “dry” electrodes that do not require such a conductive medium (Cruz-Garza et al., 2017). Because of its placement on the scalp, EEG signals suffer from poor spatial resolution and a low signal-noise ratio brought on by the interference of background activity (Vaid, Singh, & Kaur, 2015). Additionally, due to its poor spatial resolution, EEG does not excel at localizing brain activity. Though there are EEGs with dense electrode arrays with up to 512 channels or more that are specialized at localizing activity, these devices are expensive and thus are not currently used outside of research contexts. That said, EEG is exceptionally precise when it comes to temporal measurements (Burle et al., 2015; Kim, Richter, & Uğurbil, 1997; Song et al., 2013; Vaid, Singh, & Kaur, 2015). This is because EEG measures electrical activity as opposed to other brain measurement instruments like fMRI or positron emission tomography (PET) that rely on the measurement of regional cerebral blood flow which, while considered a correlate of neural activity, presents a number of compounding issues when it comes to temporal resolution (Kim, Richter, & Uğurbil, 1997; Roy & Sherrington, 1890). Since a BCI often must respond to inputs in real time, it is much more productive to have a device that is temporally precise than spatially precise. As such, EEG's precise temporal resolution makes it a compelling method of data collection in a BCI.

Another neural measurement technique is ECoG which measures electrical activity in the brain through electrodes that are placed directly on the surface of the cortex. While it has increased temporal and spatial resolution and is less vulnerable to artifacts as compared to EEG, it requires a craniotomy to be utilized and therefore its use is incredibly invasive and hazardous (Nicolas-Alonso & Gomez-Gil, 2012). Successful BCIs created using ECoG include a system that controls a two-dimensional cursor and a system that classifies motor actions (Levine et al., 1999; Schalk et al., 2007). The utility of these BCIs as well as the incredibly invasive nature of ECoG suggests that it is an option better suited for people with severe motor disabilities rather than for everyday use.

fNIRS is another measurement technique that measures changes in the oxygenated and deoxygenated hemoglobin levels in the brain using near-infrared-range light. Like EEG, it is portable and relatively inexpensive compared to other available options. When compared to EEG, it is not susceptible to electromagnetic noise, but is more vulnerable to signal issues caused by motion. While it is more spatially precise than EEG, it is less temporally precise. One compelling disadvantage of fNIRS is the lack of standardization when it comes to data analysis (Naseer & Hong, 2015; Pinti et al., 2020).

Though there may certainly be a future for fNIRS in BCI research, at present there are very few consumer-grade devices on the market. Thus, while the primary focus of this study will be EEG, fNIRS should also be investigated once there are more consumer-grade options available.

BCIs built using EEGs typically involve the measurement of two different forms of brain activity: oscillatory activity and event-related potentials (ERPs). There are five frequency bands that are well-established within EEG oscillation: delta (0.1-4 Hz), theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-100 Hz) (Kumar & Bhuvaneswari, 2012; Teplan, 2002). These oscillations are associated with different cognitive functions depending on their location, amplitude, frequency, phase, and coherence (Herrmann et al., 2016; Kumar & Bhuvaneswari, 2012; Teplan, 2002). An ERP, on the other hand, is reflective of neural activity that temporally corresponds to a sensory, cognitive, or motor event and is described through its polarity, amplitude, latency, and scalp distribution (Handy, 2005; Kam et al., 2022; Luck, 2012). Whether or not a researcher chooses to measure oscillatory activity or ERPs depends largely on the paradigm associated with the BCI and what the system is attempting to accomplish.

2.2 Mind Wandering

2.2.1 Definition

A BCI must have a specific function or purpose to work effectively. Paradigms must be used to elicit a certain neural response in order to achieve a BCIs purpose. One commonly used paradigm in BCI research is one that detects mind wandering and alerts users to recover attention. Mind wandering is defined as the disengagement from active attention due to spontaneous thought. It is characterized by the absence of strong constraints on both the contents of and transitions between mental states and is often defined by its absence of explicit intent (Christoff et al., 2016; Compton, Gearinger, & Wild, 2019; Dehais et al., 2020; Fox & Christoff, 2018). However, there is a growing body of research that acknowledges that there are two primary types of mind wandering—intentional and unintentional—and that one must be cautious not to conflate the two (Klesel et al., 2021; Seli et al., 2016). That said, unintentional mind wandering will hereafter be referred to as mind wandering, keeping in mind that the focus of this paper is not on intentional mind wandering. While mind wandering is considered to have adaptive functions in autobiographical planning and creative problem solving, it also poses a significant cost to performance and can be dangerous when occurring in high-risk situations such as driving (Fox & Beaty, 2019; Lee, 2014; Mooneyham & Schooler, 2013; Oschinsky et al., 2019; Park et al., 2021; Smallwood & Andrews-Hanna, 2013; Smallwood et al., 2011). Therefore, attention-recovery BCIs could prove to be an important tool to implement in such high-risk situations should they reach viability in the consumer market.

Though mind wandering falls under the inattention umbrella along with effort withdrawal, preservation, and inattentional blindness and deafness, it is differentiated from other inattentional neurocognitive states in both how it is evoked and its manifestation. Typically, mind wandering results from both low to mid task engagement and low physiological arousal (Dehais et al., 2020; Lee, 2014; Park et al., 2021; Smallwood & Schooler, 2006). However, mind wandering can occur during more cognitively demanding tasks at the cost of deficits in performance (Smallwood & Schooler, 2006). In essence, mind wandering occupies a middle ground of constraint between dreaming and creative thinking (Christoff et al., 2016). Hasenkamp et al. (2012) proposed a model that describes the cognitive fluctuations that occur between mind wandering and attentional states that consists of four intervals: mind wandering, awareness of mind wandering, shifting of attention, and sustained attention. This model was developed from the observation of meditation and provides key insights into the neural mechanisms associated with mind wandering, self-detection of mind wandering, and the return to meditation.

2.2.2 Measurement

Such meditation paradigms are often used in the detection of mind wandering and are particularly effective in its measurement since by nature it involves the dynamic fluctuation between attention and mind wandering. Likewise, given perfect experimental conditions, meditation does not involve a visual or auditory task and thus does not require the discernment between on-task and mind wandering that many other paradigms require (Hasenkamp et al., 2012; Lutz et al., 2015). There are two methods of measuring mind wandering during a meditation task: self-caught experience sampling in which a participant presses a button when they become aware of their mind wandering, and probe-caught experience sampling in which participants are probed at random points throughout the task as to whether they are presently experiencing mind wandering (Rodriguez-Larios & Alaerts, 2020). The former method requires the participation of meta-awareness (i.e., the explicit awareness of the contents of one's consciousness) whereas the latter is identified passively. Because of this, one can expect each method to produce different results even when performed under otherwise identical experimental conditions. Indeed, Liu et al. (2021) discovered significant differences in the ERPs induced by mind wandering between participants measured with self-caught experience sampling and those measured with probe-caught experience sampling, though the authors purport that these differences may result from differing visual stimuli. Though there are a variety of benefits and limitations to using self-caught and probe-caught experience sampling methods, self-caught experience sampling is particularly suited for meditation tasks because of the close relationship between meditation and meta-awareness and mindfulness (Chu et al., 2023; Weinstein, 2018).

Because of the delay between mind wandering and the awareness of mind wandering, EEG's enhanced temporal resolution is particularly appropriate for measuring neural correlates of mind wandering. Some research suggests that increased alpha band activity is considered the strongest indicator of mind wandering (Baldwin et al., 2017; Compton, Gearinger, & Wild, 2019; Kam et al., 2022). Conversely, Braboszcz and Delorme (2011) found that alpha power was decreased during mind wandering whereas theta and delta power were increased. Similarly, Rodriguez-Larios and Alaerts (2020) found that mind wandering was associated with increased amplitude and decreased frequency of theta bands whereas alpha bands exhibited decreased amplitude and increased frequency. In studies conducted on fatigue and inattention in various vehicle operators, only the theta band was shown to have consistently increased power (Park et al., 2021). On the other hand, in Kam, Rahnuma, and Hart's (2022) meta-analysis on spectral band activity during mind wandering, only eight of 13 studies reported increased theta activity. Less importance has been placed on delta, beta, and gamma bands but research shows mixed results (Kam, Rahnuma, & Hart, 2022). In sum, there is little agreement within past literature on the oscillatory activity associated with mind wandering, though alpha and theta bands seem to be most implicated.

One can also analyze ERPs to measure mind wandering. While some research posits that ERP amplitude is the most compelling and replicable indicator of mind wandering, others find that oscillatory activity is the most significant (Conrad & Newman, 2021; Kam, Rahnuma, & Hart, 2022). However, ERPs by nature are elicited from the presentation of stimuli and are not an appropriate or viable method of neural measurement in a meditation task that does not involve some sort of auditory, motor, or visual stimulus.

2.2.3 Neuroanatomy

Insofar as the neuroanatomical regions associated with mind wandering, most of these areas (such as the posterior cingulate cortex, ventral medial and dorsal medial prefrontal cortex, precuneus, and lateral parietal cortex) belong to the default mode network (DMN), a resting state network that exhibits consistent deactivation during goal-directed tasks (Christoff et al., 2016; Hasenkamp et al., 2011; Raichle et al., 2001; Raichle, 2015). The DMN is located bilaterally in the medial prefrontal cortex and in the medial and lateral parietal and temporal cortices (Raichle, 2001). As such, we can expect the spectral band activity associated with mind wandering to be localized in these areas. Indeed, in joint EEG-fMRI research, alpha activity is reported to be involved both with the DMN and with internally directed cognition (Christoff et al., 2016; Compton, Gearinger, & Wild, 2019; Hasenkamp et al., 2011; Knyazev et al., 2011; Mo et al., 2013; Raichle, 2015). Indeed, in Kam, Rahnuma, Park, and Hart's (2022) meta-analysis, they found that alpha band activity is often reported to be attenuated across both posterior sites and frontocentral and temporal sites during mind wandering. Likewise, the authors report that mind wandering often results in greater theta activity in frontocentral areas. While this suggests that the DMN is implicated in these changes, this cannot be confirmed with EEG alone due to its poor spatial resolution.

2.3 Computer Interface

The second main component of a BCI, as the name suggests, is the computer. Once the neural signals have been collected, a computer is required to interpret, process, and send feedback to the user. Using the breath counting task used by Braboszcz and Delorne (2011) to detect mind wandering as an example, a BCI could be created by first collecting training data from participants by asking them to engage in the task, self-caught experience sampling and oddball auditory protocol included (whereby participants are presented with two tones of different frequencies, one of which is presented significantly fewer times, leading to its designation as an "oddball" auditory tone). An algorithm can then be trained on this data so that the system can appropriately determine the neural correlates of mind wandering. Subsequently, the system could then fit this data to data collected from the users in real-time as they repeat the breath counting task (excluding the self-caught experience sampling and oddball auditory protocol) and initiate some sort of stimulus when it detects a user's mind wandering. Though this is one example of how a mind wandering BCI might operate, there are many different ways in which a BCI might be designed.

2.3.1 BCI Classification

BCIs are classified in various ways with increasing levels of specificity. At the broadest level, BCIs are classified as either invasive or non-invasive and can be further classified by the method of measuring neural activity (e.g., EEG, fMRI, fNIRS, etc.). Within the context of this paper, the focus will be on EEG-based BCIs. This particular type of BCI can be further categorized based on the paradigm the interface uses and/or the BCI categorization. Paradigm-based subdivisions are that a BCI can either be actively controlled (e.g., through motor imagery, visual evoked potential, auditory evoked potential, vibrotactile evoked potential, imagined speech, or error-related potential) or passively controlled (e.g., analysis of EEG spectral changes) (Abiri et al., 2019; Al-Nafjan et al., 2017; Vărbu, Muhammad, & Muhammad, 2022).

A BCI can be classified as either dependent in that it relies on muscles and peripheral nerves or independent wherein only changes in brainwaves are observed without any required muscle movement (Machado et al., 2010; Pasqualotto, Federici, & Belardinelli, 2011; Vărbu, Muhammad, & Muhammad, 2022). Similarly, a BCI can be defined as either evoked/exogenous or spontaneous/endogenous. The former category is dependent on external stimulation whereas the latter does not require a stimulus (Padfield et al., 2019; Vărbu, Muhammad, & Muhammad, 2022). Lastly, a BCI can be classified as either synchronous in which the BCI only analyzes signals within specific time intervals and thus commands can only be made during specific windows or asynchronous in which neural activity is constantly analyzed and commands can be issued at any time (Nicolas-Alonso & Gomez-Gil, 2012; Vărbu, Muhammad, & Muhammad, 2022). A mind wandering detection BCI, at least in instances of unintentional mind wandering, is passively controlled and independent because it involves the detection of a user's internal state and does not require any muscle movement. A mind wandering detection BCI can be either evoked/exogenous or spontaneous/endogenous and may also be synchronous or asynchronous depending on the constraints of the paradigm.

The operation of a BCI typically involves four stages: signal acquisition, signal pre-processing, feature extraction, and classification and computer interaction (Hong & Santosa, 2013; Vaid, Singh, & Kaur, 2015; Värbu, Muhammad, & Muhammad, 2022). Signal acquisition, as discussed previously, involves collecting neural data with a measurement device (an EEG, in this context) then storing it in an accessible format (Vaid, Singh, & Kaur, 2015).

2.3.2 Signal Pre-Processing

Because EEG data is vulnerable to signal artifacts, the collected data must then be processed to prevent the distortion of the signal (Padfield et al., 2019; Vaid, Singh, & Kaur, 2015). There are two different types of signal artifacts: extra-physiologic and physiologic. Extra-physiologic artifacts are those that result from the external environment such as technical preparation problems (e.g., insufficient electrode grounding, incorrect electrode placement), movements in the recording environment, and powerline noise. Physiologic artifacts include the interference of signals generated from eye movement, the heart, sweat, tongue movement, and muscular movement (Elsayed, Zaghloul, & Bayoumi, 2017; Jiang, Bian, & Tian, 2019; Reddy & Narava, 2013). The type of pre-processing performed largely depends on the artifacts present in the signal. For instance, the removal of eye movement artifacts is not necessary in a meditation-based BCI, since the eyes are closed during meditation. Most commonly, the techniques used for artifact removal are as follows: linear filtering, blind source separation, empirical-mode decomposition, and wavelet transform (Jiang, Bian, & Tian, 2019). Since most EEG-based BCIs required real-time signal processing, it is important that a pre-processing method that is both automatic and has a low computational cost is selected (Vaid, Singh, & Kaur, 2015). Linear filtering is a particularly popular approach to artifact removal because of its ease of implementation from both a hardware and software perspective and because it does not require the identification of artifacts nor other identifying information (Elsayed, Zaghloul, & Bayoumi, 2017).

2.3.3 Feature Extraction

The feature extraction stage of a BCI exists because the features of a sought-after signal are masked by noise. Rather than use an immense number of resources to analyze a massive dataset that may contain irrelevant data, feature extraction simplifies analysis by highlighting only those signals which are pertinent. In order to extract the signal or differentiate it from noise, a distinguishing property or recognizable measurement represented by a feature can be extracted from a section of a pattern (Suleiman & Fatehi, 2011; Al-Fahoum & Al-Fraihat, 2014; Vaid, Singh, & Kaur, 2015). There are a variety of feature extraction methods that can be used in a BCI that use both linear and non-linear methods. Such methods can occur in a number of different domains: time, frequency, time-frequency, and space-time-frequency (Al-Fahoum & Al-Fraihat, 2014; Hosni et al., 2007; Vaid, Singh, & Kaur, 2015). The feature extraction technique used depends on the experimental paradigm, the desired signals to be extracted, and the relevant domains. A popular feature extraction technique often used in bioengineering and neuroscience is multitaper power spectral analysis, an analysis that arose from non-parametric spectral analyses as an answer to inherent issues pertaining to variance and bias and is therefore a well-suited approach to time series data (Babadi & Brown, 2014; Bokil et al., 2006;

Thomson, 1982). This analysis exists in the frequency domain and produces a metric called power spectral density which is a reflection of the power density (the amount of power per unit volume) of a random signal at a particular frequency. Since it is an analysis of the frequency domain, it allows one to determine the prevalence of specific frequency bands within the context of specific paradigms.

2.3.4 Machine Learning Algorithms and Computer Interaction

Classification and computer interaction is the last stage of a BCI wherein data is fed to a machine learning algorithm. Machine learning is a branch of computer science concerned with enabling computers to "learn" without being directly programmed. This process is done with statistical algorithms that employ a variety of methods to fit models to data such that future data can be predicted accurately (Bi et al., 2019). There are many algorithms that classify data in a variety of ways, and there is no single algorithm that works in all circumstances (Mahesh, 2020). The selection of a classifier largely depends on the data and experimental paradigm of the BCI, and due consideration must be given to the algorithm's hypothesis space to ensure that the theoretical model suits the data to which it is applied. The machine learning algorithm used is the main player behind the predictive performance of a BCI—arbitrary or uninformed selection can significantly hinder predictive performance.

Machine learning algorithms fall under one of the following categories: supervised learning, unsupervised learning, semi-supervised learning, reinforcement learning, multi-task learning, ensemble learning, neural network, and instance-based learning (Mahesh, 2020). Of these categories, only supervised learning models and to a lesser extent neural nets will be discussed since they are the most used machine learning models in the context of EEG-based BCIs (Aggarwal & Chugh, 2022).

Supervised learning algorithms make inferences from labelled training data and require that the dataset be split into a training dataset and a testing dataset (Mahesh, 2020). Though there are various methods to do this, most machine learning frameworks split the dataset statically wherein neither the training nor evaluation stage of the model can use all available data (Bai et al., 2021). Decision tree, Naïve Bayes, support vector machine, k-nearest neighbour, and multi-layer perceptron algorithms are all examples of supervised learning yet employ drastically different methods.

A decision tree continuously splits data based on specific rules or conditions and is typically used to solve classification and regression problems, though suffers from issues with stability and has a disposition to sampling error (Mahesh, 2020; Pedregosa et al., 2011; Ray, 2019). Decision trees are optimized for relatively simple classification tasks with fewer unrelated data features.

Naïve Bayes, by contrast, is a machine learning approach based on the statistical Bayes Theorem, which is used to calculate conditional probabilities. This algorithm assumes that all predictors are conditionally independent from one another—that is, the presence of a specific feature is unrelated to any other feature (Joyce, 2003; Mahesh, 2020; Pedregosa et al., 2011; Ray, 2019). The Naïve Bayes approach is easy to implement, can be effective with smaller samples of training data, scales linearly with the number of predictors, and is generally used to solve binary and multi-class classification problems and probabilistic predictions. However, its simplicity is its downfall since it can be difficult to apply Naïve Bayes to a dataset that, for example, has a continuous variable feature (Mahesh, 2020; Pedregosa et al., 2011; Ray, 2019).

Support vector machine algorithms are used for classification and regression purposes, though they can classify non-linear data by using kernels which separate objects that belong to different classes. This approach excels with both structured and semi-structured data, has reduced probability of over-fitting due to its adoption of generalization, and can be utilized in complex manners if the appropriate kernels are adopted. However, support vector machine algorithms also suffer from noticeable increases in training time for large datasets, struggle to analyze noisy data, and do not provide probability estimates (Mahesh, 2020; Pedregosa et al., 2011; Ray, 2019).

K-nearest neighbour algorithms are non-parametric and are used for both classification and regression problems. This algorithm classifies new data points by choosing the class closest in distance to a number of predefined training samples. While this algorithm is both simple and flexible, using larger datasets is computationally intensive and therefore hinders performance (Mahesh, 2020; Pedregosa et al., 2011; Ray, 2019).

Multi-layer perceptron (MLP) algorithms, while classified as supervised learning, can also be classified as a neural network. Used for either classification or regression, MLP operates by creating a network of nodes arranged in a minimum of three layers (input, hidden, and output) with each node in the nonlinear hidden and linear output layer possessing an associated threshold and weight. The input layer distributes the inputs to subsequent layers such that an input is multiplied by a weight to a certain threshold then passed to a linear or nonlinear function. While an MLP is flexible enough to solve a variety of problems, they are non-monotonic, there is no standard way to initialize and train additional hidden units, and net control parameters are arbitrary (Delashmit & Manry, 2005).

2.3.5 Evaluation

Once a machine learning model has been applied, it should be evaluated to assess its performance. Though there are a number of techniques that evaluate an algorithm's predictive performance, henceforth referred to as generalization error, one of the most common is *k*-fold cross-validation. This method iterates over the dataset *k* times, each time splitting the dataset into *k* parts where one part is used for validation and the remaining *k* – 1 parts are merged into a training subset for model evaluation. This is done for each part such that the model is fit to distinct yet partially overlapping training sets. The score produced from this process is the mean *k* generalization error. The value of *k* can therefore greatly affect the resulting generalization error and its value should therefore be fixed intentionally. Generally, the value of *k* is assigned a large value (usually 5, 10, or 20) in order to analyze a greater number of patterns for training, though larger *k* values result in loose generalization error estimations (Anguita et al., 2012; Raschka, 2018).

2.4 Summary

In sum, BCIs employ a diverse array of techniques and technologies to operate efficiently. When determining which methods to employ, it is crucial to consider the intended purpose and function of the BCI so that the technology and underlying processes can synergistically optimize its performance.

EEG was chosen as the primary neural measurement device because of its low cost, relative portability, enhanced temporal resolution, and popularity as a tool in BCI research. Furthermore, a meditation paradigm that detects and corrects mind wandering was chosen for a number of reasons. Firstly, meditation-assistance BCIs are some of the most common BCIs available in the consumer market at present and investigating the utility and usability of such a device would provide a look into the current state of the market. Secondly, meditation paradigms are particularly easy to implement by merit of their simplicity and that the lack of motor movements yields a signal less vulnerable to signal artifacts caused by noise. Lastly, mind wandering, while it can be positive and helpful in some contexts, can be disadvantageous or dangerous in high-risk situations; investigating ways in which mind wandering can be interrupted and corrected could lead to research that can benefit the development of future mind wandering intervention BCIs. We will measure mind wandering with self-caught experience sampling because of its minimized disruption of cognitive processes as well as the close relationship between meta-awareness and meditation.

The neural signal to be investigated is oscillatory activity, with a particular focus on alpha and theta activity. Though there is discourse on whether oscillatory activity or ERPs are the most compelling and replicable indicator of mind wandering, ERPs by nature are elicited from the presentation of stimuli and are not an appropriate method of neural measurement in a meditation task that does not involve an auditory, motor, or visual stimulus. The acquired signal will then be processed with linear filtering due to its ease of implementation and because it does not require the identification of signal artifacts. Features will then be extracted with a power spectral density analysis since this analysis operates in the frequency domain and is therefore well-suited for extracting oscillatory activity.

The machine learning classifiers to be used are all classified as supervised learning models and are as follows: decision tree, Naïve Bayes, support vector machine, k-nearest neighbour, and multi-layer perceptron. The decision to use only supervised learning models was made because they are the algorithms most often used in EEG-based BCIs. The performance of the algorithms will be assessed using *k*-fold cross-validation which is a popular method to calculate generalization error that is effective on supervised learning models.

Table 1. A summary of the key technologies and processes that will be used in the present study.

Process	Approach	Rationale
Signal acquisition	EEG	• Low cost • Portability • Enhanced temporal resolution • Popularity
Paradigm	Mind wandering detection during meditation	• Exists in consumer market • Fewer signal artifacts • Mind wandering can be dangerous
Mind wandering measurement	Self-caught experience sampling	• Close relationship between meditation and meta-awareness
Neural signal	Oscillatory activity (alpha and theta in particular)	• Reliable indicator of mind wandering
Signal pre-processing	Linear filtering	• Ease of implementation • Does not require identification of artifacts

Process	Approach	Rationale
Feature extraction	Power spectral density	• Operates in frequency domain; well-suited for oscillatory activity
Machine learning classification	Supervised learning models	• Most used approach in EEG-based BCIs
Evaluation	*k*-fold cross-validation	• Popular approach • Effective on supervised learning models

Chapter 3 Methods

3.1 Instruments

The developed BCI employs a Unicorn Hybrid Black EEG (UHB) as its neural measurement device. The UHB is an eight-channel EEG with electrodes situated at the international 10-20 system electrode positions FZ, C3, CZ, C4, PZ, P7, 0Z, and P8 (American Clinical Neurophysiology Society, 1991; Figure 1). The UHB supports both wet and dry recording—the first recording was obtained with dry electrodes, though data were deemed poor quality and subsequent recordings were obtained with wet electrodes (See Appendix 1 for wet/dry recording comparison for the first task). The device connects to a computer via Bluetooth using a USB dongle and as such is wireless, excluding the wired electrodes (Unicorn Hybrid Black, 2022). The device was paired with the UHB Python API in order to control the device from within the Python environment. The Python library PyGame was used for the design of the user interface and forms the primary framework of the BCI. The library MNE-Python was used for EEG processing and analysis, and the library scikit-learn was used to apply the machine learning algorithms. According to the previously outlined classification criteria, the BCI developed in this study is classified as independent, spontaneous, asynchronous, and measures passive spectral changes.

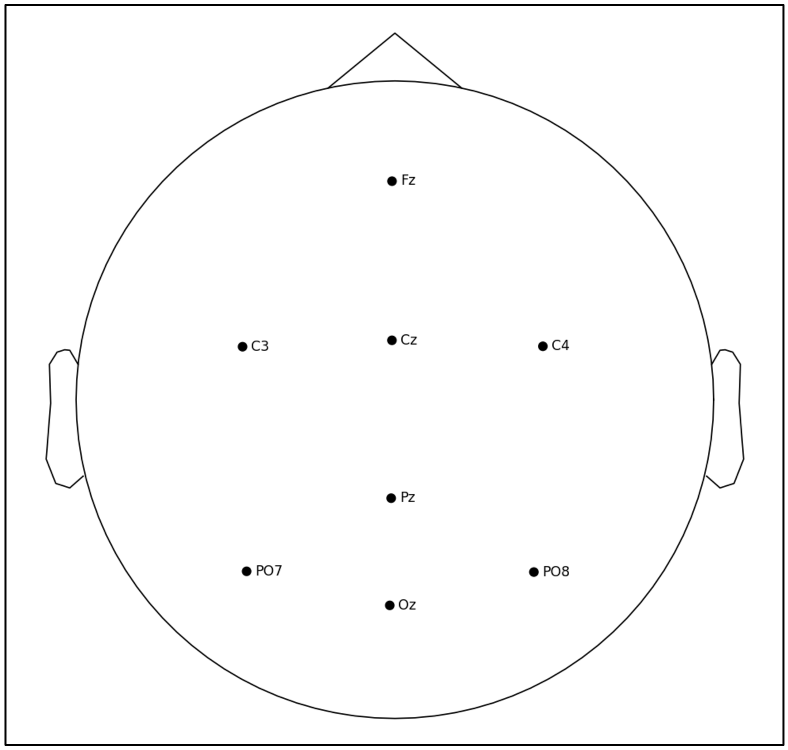

Figure 1. UHB electrode positions, in adherence with the international 10-20 system electrode positions (American Clinical Neurophysiology Society, 1991).

3.2 Participants

Participants (n = 5) were recruited from within the Neurocognitive Imaging Lab and the Quantitative Science Studies Lab at Dalhousie University on a first come, first served basis. Participants were subject to screening criteria to ensure they were fluent in English, able to use a computer keyboard, had no history of neurological disorders, were not taking medications that affect brain activity, and were comfortable removing religious headgear. No information was collected on the level of experience that participants had with meditation. Though it has been found that meditation training leads to fewer episodes of mind wandering, this was ultimately not deemed relevant since it exists outside the scope of this study (Feruglio et al., 2021; Zanesco et al., 2016). Though this is an interesting avenue for future research, the present study is grounded in more technical aspects related to BCI research.

3.3 Experimental Design

The experimental task consisted of two primary stages: data collection and application. In the data collection and training stage, participants were fitted with the UHB then asked to engage in meditation for 20 minutes. Mind wandering was measured using self-caught experience sampling by asking participants to respond with a key press when they became aware of their mind wandering. Additionally, birdsong was played throughout the task. Subsequently, in the application stage, the participants were again asked to engage in meditation for 20 minutes with the exception that they do not button press when they become aware of their mind wandering. Instead, the BCI was programmed to interrupt the birdsong to play traffic noises at the 7-, 12-, and 17-minute marks for 20, 30, and 10 seconds, respectively. Upon completion of these two tasks, the participants were finally asked to complete a short questionnaire to record their subjective experience using the BCI (Figure 2; Appendix 2).

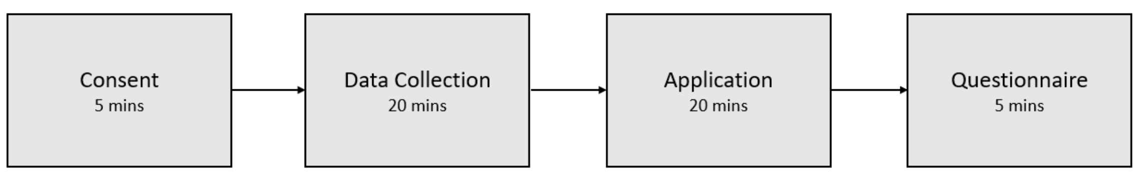

Figure 2. An illustration of the experimental design.

The method in which the auditory stimuli are presented is modelled loosely after the oddball auditory protocol in which a sequence of repetitive "standard" tones is interspersed occasionally with "oddball" tones that differ in some way from the standard tones, typically in frequency (i.e., pitch) (Braboszcz & Delorne, 2011). The intention for presenting the audio stimuli in this way was to test whether a disparate sound presented at intervals (i.e., the traffic noises) is sufficient to bring participants out of a mind wandering state. The Muse headband uses thunderstorm and birdsong when users are in a mind wandering and meditation state, respectively (Vekety, Logemann, & Takacs, 2022). This was inspiration for the selection of our audio cues, though we selected traffic noises both to differentiate ourselves from the Muse system and as a creative choice. Based on the literature reviewed, there does not appear to be a significant body of research aimed at whether specific audio noises are more or less inclined to correct mind wandering.

We selected the 20-minute duration interval for meditation because mind-wandering results from both low task engagement and low physiological arousal (Dehais et al., 2020; Lee, 2014; Park et al., 2021; Smallwood & Schooler, 2006). It was our intention to design the study in such a way to ensure that the length of meditation was long enough to elicit low task engagement, thus creating more opportunity for mind wandering. However, we did not want the meditation task to be overly long so that we could control for the effects of fatigue—though the task may not be cognitively demanding, 40 minutes is a long time to be meditating.

3.4 BCI Design

In order to run two different stages of the experimental task, two separate scripts were created. The scripts are very similar, with a few key differences. Both scripts utilize the same primary graphical interface that is of a relatively simple design. Upon initialization of both programs, there is a welcome screen that shows task-relevant information and instructs the participant how to properly operate the BCI. Following this screen is one in which the participant is prompted with a text-input box to enter the amount of time they would like to meditate. Though within the context of the study each participant was instructed to meditate for 20 minutes, the option to run the program for any amount of time was included for future research involving the developed BCI and in the event that the BCI is developed for consumer use. Once this information is entered, the BCI then enters its primary experimental loop and shows a timer on the screen while the participant performs the task. Throughout the task, birdsong audio is played which stops once the entered duration elapses, thereby notifying the participant that the task is complete. The primary difference between the two scripts is that the application script for the second stage of the experimental task will interrupt the birdsong audio with traffic noises at specified intervals. Otherwise, the two scripts are virtually identical. Upon completion, the raw EEG data is stored in a comma-delimited format for processing and algorithm training.

Separate from the primary BCI, a script was created to process the data, train the machine learning algorithms, and conduct relevant analyses. Since this script is an offline analysis, it is important to note that the BCI created within the context of this study is not a true BCI, but instead a framework upon which a BCI can be implemented. However, the offline analysis tests the feasibility of the BCI and its various components even though they do not exist as a cohesive whole. In order to create a true BCI, parts of the offline analysis script can be nested within the application script to detect and correct mind-wandering in real time. However, since this is a pilot study, it was not pertinent to complete the interface but rather to assess the performance of each of its individual parts. Depending on the results, the paradigm may or may not be modified to enhance the performance and efficacy of the BCI.

3.5 Data Processing and Analysis

The raw EEG data obtained during this task was processed using tools from the MNE-Python library. Since MNE-Python assumes EEG data to be in volts, the data collected from the UHB were converted from microvolts to volts. A one-pass, zero-phase, non-causal bandpass filter was then applied to converted data using the windowed time-domain method. A hamming window with a 0.0184 passband ripple and 53 dB stopband attenuation was used. The bandpass filter was applied such that it filtered low frequency signals below 2Hz and high frequency signals above 30Hz. The converted and filtered data was then sectioned into 10 second epochs. Rejection criteria were set for epochs with a maximum peak-to-peak signal amplitude of 1e-3. Features were extracted by calculating power spectral density using a multitaper method then converting the values to decibels.

Using the sci-kit learn library, the processed data from the collection phase of the task was validated using the train test split procedure then was subsequently used to train seven classifiers, as follows: linear discriminant analysis, ridge classifier (sometimes referred to as a least squares support vector machine with a linear kernel), k-nearest neighbours, support vector machine, decision tree, multi-layer perceptron, and Naïve Bayes. These classifiers were then applied to the data collected during the application stage of the task in order to determine how well the classifiers can predict mind wandering. To assess the performance of the classifiers, an accuracy score and a mean k-fold cross-validation score ($k = 5$) were computed for each classifier. A cross-validation score was only calculated for the data collection phase data since it is only relevant to use on data that has been split for training.

The power spectral density analysis was then undone to leave us with the filtered epochs. Evoked objects were created for each condition by averaging together all epochs for each respective condition. From here, there were two separate analyses that were performed on the data: a subtraction analysis and a time frequency analysis. The subtraction analysis will provide information on the difference between the on-task conditions and the mind wandering conditions, and the time frequency analysis will allow us to evaluate how the presentation of the traffic noise stimulus modulates neural oscillations over time. The latter of the analyses will only be applied on the application task data since the collection task data does not contain the traffic noises that are pertinent to the analysis. The subtraction analysis was performed by subtracting the mind wandering condition evoked objects from the on-task evoked objects, thereby creating a new evoked object containing the features specific to the mind wandering condition. The resulting object also underwent feature extraction by calculating the power spectral density with a multitaper method. The second analysis was to calculate the time frequency representation of the evoked objects for each condition using a Morlet transform method which utilizes a fast Fourier transform, which is functionally identical to the calculation of power spectral density (Cochran et al., 1967). Since the traffic noise stimuli were administered at specific time points, this analysis thereby required operation in the time-frequency domain.

The post-task questionnaire consisted of four questions, two of which use a 5-point Likert scale (Q1, Q2), one of which is designed to capture relevant keywords pertaining to the participants' experience with the BCI (Q3), and the last of which offers an opportunity to provide user feedback regarding the BCI (Q4) (Appendix 2). Since the post-task questionnaire was administered via pen and paper, results were transcribed into an Excel worksheet. The mean and median scores were calculated for the Likert-based questions (Q1, Q2). For Q3, keywords were manually extracted and a simple sentiment analysis using a dictionary-based approach was conducted. Though Q4 underwent no specific analysis, participant responses were individually considered within the context of the discussion.

Chapter 4 Results

4.1 Classification

On average, the overall classification accuracy for the training data was 52% with no classifier obtaining an accuracy score above 60%. The algorithms with the highest accuracy overall were the decision tree (60%), ridge classifier (59%), Naïve Bayes (57%), and nearest neighbours (57%). Once cross-validated, the classifiers with the highest accuracy were the ridge classifier (62%), Naïve Bayes (59%), and nearest neighbours (57%). However, some classifiers had greater accuracy for specific participants. For instance, the ridge classifier classified the data for participant 2 with 100% accuracy as did the Naïve Bayes for the data for participant 5. The corresponding mean cross-validation scores for these two classifiers, however, are 73% for the ridge classifier and 80% for the Naïve Bayes (Figure 3).

The application data had noticeably lower accuracy scores than the training data with an average accuracy score of 45%. The algorithms with the highest accuracy scores were the ridge classifier, decision tree, and multi-layer perceptron in a three-way tie, all with an accuracy score of 50%. Since the application data was not split for training, there are no cross-validation scores to report. Unlike with the application data, there are few individual scores that performed significantly higher than average. The decision tree and ridge classifier algorithms had accuracy scores of 67% for two separate participants, whereas the linear discriminant analysis and Naïve Bayes each had an individual accuracy score of 67% for one single participant (Figure 3).

Some participants had data that on average had higher classification accuracy than others. For instance, participant 5 had the highest total classification accuracy (78%) and mean cross-validation score (68%) for the training data as well as the highest classification accuracy (52%) for the application data. The classifiers for the data of participant 4 had the lowest accuracy (36%) on the training data, though participant 3 had the lowest cross-validated score (48%) and participant 2 had the lowest accuracy for the application data (36%) (Figure 3).

		Accuracy						Mean Cross-Validation					
		Participant						Participant					
Task	Classifier	1	2	3	4	5	Grand To..	1	2	3	4	5	Grand To..
meditation	Decision Tree	50%	75%	40%	50%	86%	60%	59%	48%	47%	48%	70%	54%
	Linear Discriminant ..	67%	25%	40%	25%	71%	46%	56%	42%	51%	55%	74%	56%
	Multi-layer Perceptr..	50%	25%	75%	25%	57%	46%	49%	47%	53%	40%	50%	48%
	Naïve Bayes	50%	50%	35%	50%	100%	57%	55%	63%	48%	47%	80%	59%
	Nearest Neighbours	50%	50%	50%	50%	86%	57%	67%	47%	46%	58%	65%	57%
	Ridge Classifier	67%	100%	45%	25%	57%	59%	69%	73%	43%	58%	68%	62%
	Support Vector Mac..	50%	25%	25%	25%	86%	42%	49%	47%	51%	53%	68%	54%
	Total	55%	50%	44%	36%	78%	52%	58%	52%	48%	51%	68%	56%
evaluation	Decision Tree	33%	67%	67%	33%	50%	50%						
	Linear Discriminant ..	50%	33%	0%	50%	67%	40%						
	Multi-layer Perceptr..	50%	50%	50%	50%	50%	50%						
	Naïve Bayes	50%	17%	67%	50%	50%	47%						
	Nearest Neighbours	17%	17%	50%	50%	33%	33%						
	Ridge Classifier	33%	33%	67%	50%	67%	50%						
	Support Vector Mac..	50%	33%	50%	50%	50%	47%						
	Total	40%	36%	50%	48%	52%	45%						
Grand Total		48%	43%	47%	42%	65%	49%						

Figure 3. The accuracy and mean cross-validation scores for each participant and classifier per task with associated averaged totals.

Note. Evaluation task classifiers do not have cross-validation scores.

4.2 Questionnaire

The results of the questionnaire are summarized in Table 1. For Q1, using a 5-point Likert scale, all participants but one agreed that they successfully accomplished the task, while the remaining participant responded that they found they neither agreed nor disagreed (mean = 4.2, median = 4). Similarly, for Q2, also using a 5-point Likert scale, all participants but one reported that they found the BCI easy to use, while the remaining participant found that it was neither challenging nor easy to use (mean = 4.4, median = 5).

Table 2. Participants' responses to the post-task questionnaire.

Were you able to successfully accomplish the task?	**How challenging did you find using the BCI?**	**If you found the BCI challenging to use, what challenges did you encounter? If you found it easy to use, what made it easy to use?**	**How do you think this tool can be helpful to use when meditating? How may it not be helpful?**
Strongly Agree (5)	Easy (4)	I found it easy as it was a wireless setup and could run it within a couple of minutes of starting it up. Also what was required of me was very simple.	If users could see after one use what their brain looks like when they get off track from meditating, then in subsequent uses they could use the BCI to help them successfully meditate. It may not be helpful for those who already find it hard to meditate, as wearing the cap and running software could distract them further.
Agree (4)	Very easy (5)	It seems reasonably easy to set up & start/stop.	Being responsive to users' state of mind could be helpful, but it's possible that their awareness of the tool may be distracting (both physical sensation and knowledge that it's in use).
Neither agree nor disagree (3)	Neither challenging nor easy (3)	The first half was easy except the birds were annoying. I typically do guided meditations that are more silent. I got a headache during the second half so I wasn't able to focus on much else.	Maybe… I think a big part of practicing meditation is letting your mind wander while paying attention to how your mind and body feels. Now that I think about it, that might be mindfulness, not meditation.
Strongly Agree (5)	Very easy (5)	No challenges. Apart from my own concentration skills. Very straightforward; relaxing even.	Keeps the participant aware and cognizant of when they're off-task, which is helpful. Keeps you alert to the external environment which could be distracting.
Strongly Agree (5)	Easy (4)	A little uncomfortable	It would be helpful if it could capture/predict when your mind is wandering and provide you with some kind of reminder to stay focused.

Keywords extracted from Q3 were coded as either positive (1), neutral (0), or negative (-1). Of the 11 keywords that were extracted, 7 were of positive sentiment, 1 was of neutral sentiment, and 3 were of negative sentiment. The median keyword sentiment was 1, suggesting that the most common response was positive. Two out of five participants had an overall negative sentiment, while the remaining three had a positive sentiment (Table 2).

Table 3. The sentiment for each keyword per participant.

Participant	Keyword	Sentiment
1	Easy	1
	Simple	1
	Wireless	0
2	Easy	1
3	Annoying	-1
	Easy	1
	Headache	-1
4	No challenge	1
	Relaxing	1
	Straightforward	1
5	Uncomfortable	-1

Legend

Sentiment

-1 0 1

Note. 1 = positive, 0 = neutral, -1 = negative sentiment.

4.3 Mind Wandering

When creating the epochs from the EEG data, some epochs met the predefined rejection criteria (as discussed in Chapter 3) and were dropped (Table 3).

Table 4. The number of epochs that were dropped for each participant and each task.

	Participant					
Task	*1*	*2*	*3*	*4*	*5*	**Total**
Meditation	5	1	1	5	0	**12**
Evaluation	0	0	0	0	0	**0**
Total	**5**	**1**	**1**	**5**	**0**	**12**

4.3.1 Training Data

The subtraction analysis for the training data shows varied results, though there are some consistencies. Alpha band power is generally elevated across all participants, except for participant 4 wherein only theta bands show increased power. Participant 3 shows the most robust increase in alpha power with a marked peak at 10 Hz. In all participants, theta power is generally higher than other frequencies, though alpha power is higher than theta in participants 3 and 5 (Figure 4).

Legend

Delta	0.1 – 4 Hz	**Alpha**	8 – 13 Hz
Theta	4 – 8 Hz	**Beta**	13 – 30 Hz

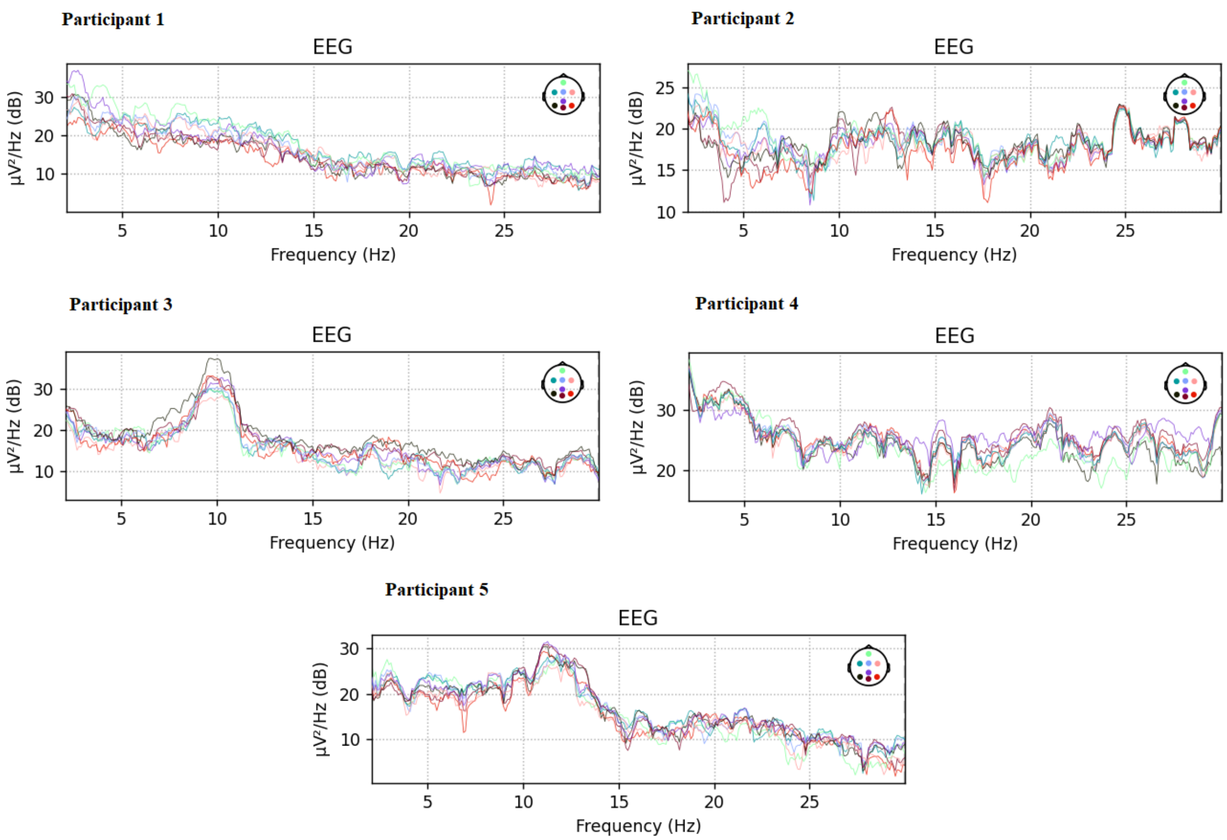

Figure 4. The average evoked power spectral densities of the mind wandering condition subtracted from the on-task condition for each participant for the training data.

Insofar as space localizations, most theta is frontal with the exception of participants 3 and 4 who exhibited theta power in the left temporal and occipital regions, respectively. Alpha power showed varied localization, with areas ranging from left frontal in participant 1, left temporal in participants 2 and 3, parietal in participant 4, and occipital in participants 4 and 5. Beta power was generally constrained to the occipital and left temporal areas, though there was a left frontal effect in participant 1 and a more central parietal effect in participant 4 (Figure 5).

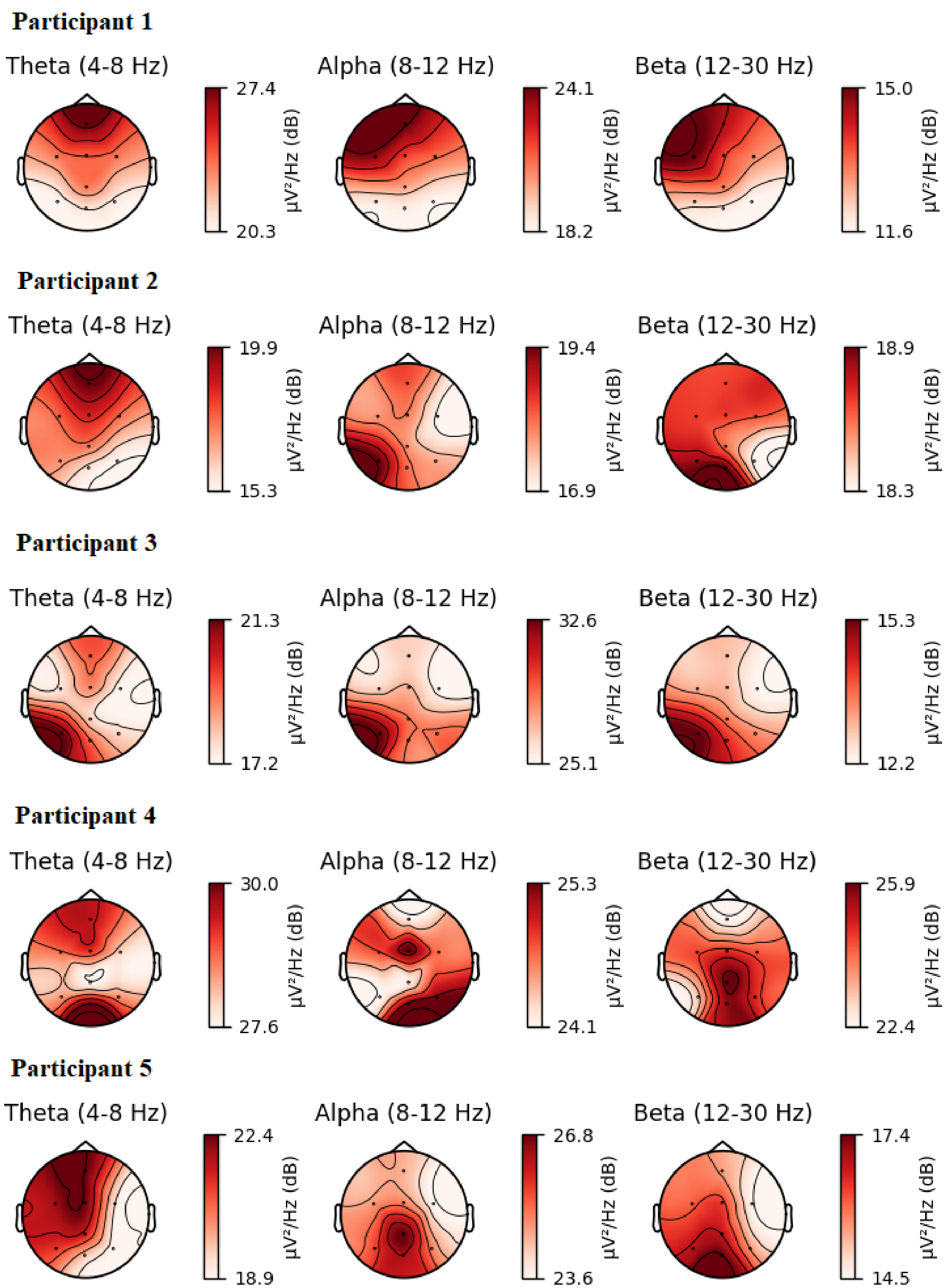

Figure 5. The average evoked power spectral densities of the mind wandering condition subtracted from the on-task condition for each participant during the training task, plotted topographically to visualize the space dimension.

Taken together, participants 1 and 2 showed the greatest difference in frontal theta power, participant 3 showed a robust left parietal alpha power difference, participant 4 showed a slight occipital alpha power difference, and participant 5 exhibited a parietal alpha power difference.

4.3.2 Application Data

The subtraction analysis for the application data generally shows a marked alpha power with some strong theta effects with some key exceptions. Participant 1 had equally strong theta and alpha power whereas participants 2 and 4 did not have any power bands that appeared higher than the others. Both participants 3 and 5 had very pronounced alpha activations (Figure 6).

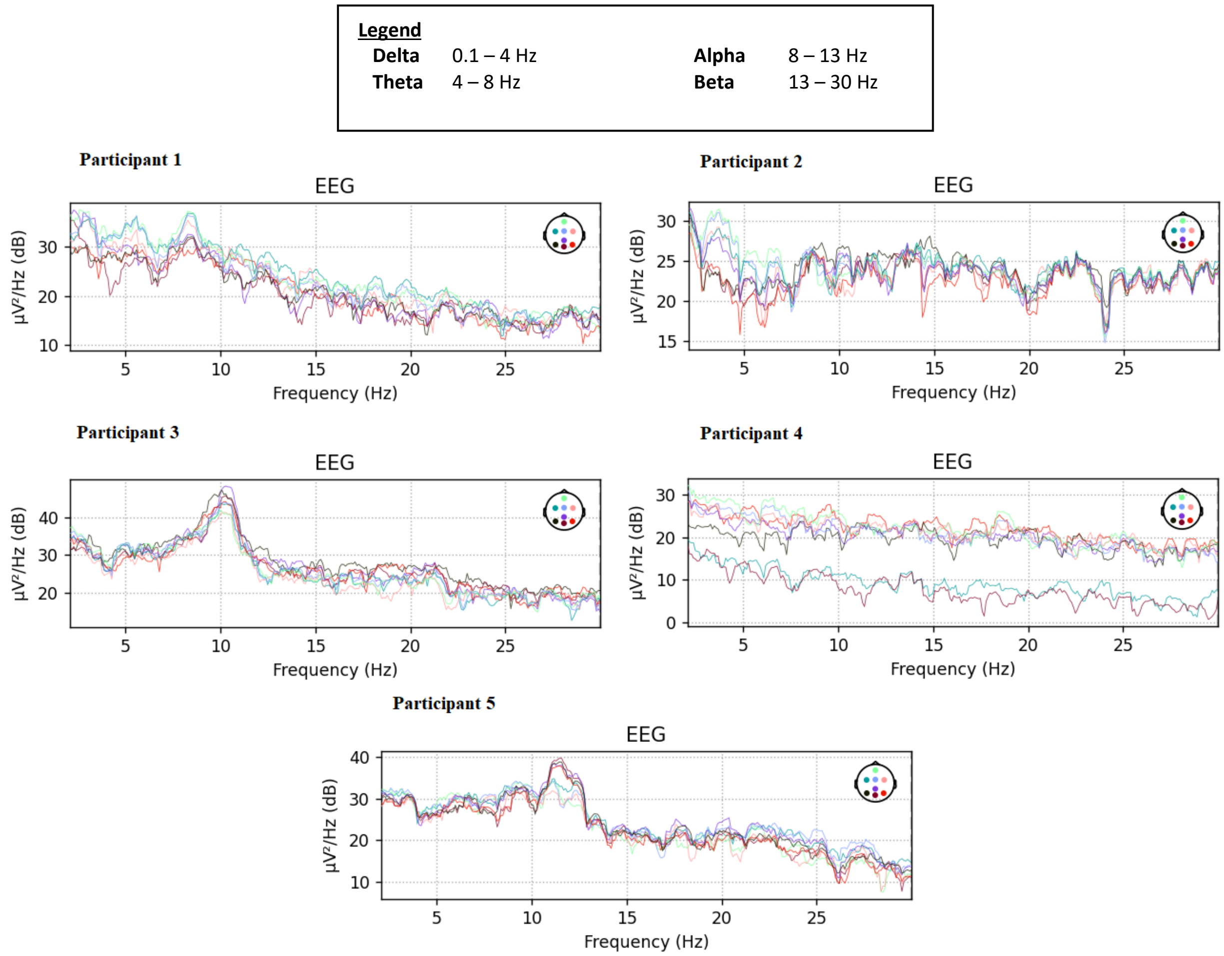

Figure 6. The average evoked power spectral densities of the mind wandering condition subtracted from the on-task condition for each participant for the application data.

Insofar as spatial localizations, most theta activations were in frontal areas but for the exception of participant 3 who exhibited a marked left temporal activation and participant 4 who in addition to frontal theta also exhibited right temporal theta. During this task, though there were instances of frontocentral theta activation, both participants 1 and 5 showed a frontolateral theta activation in the left hemisphere. Alpha band powers were generally focused in the left parietal area but for the exception of participant 1 and participant 5 who exhibited a left frontal activation and an occipital activation, respectively. Participant 4 presented both frontocentral and right temporal alpha activations. Lastly, beta was mostly localized in the left hemisphere but for a bilateral activation in participant 4 and a midline parietal activation in participant 5 (Figure 7).

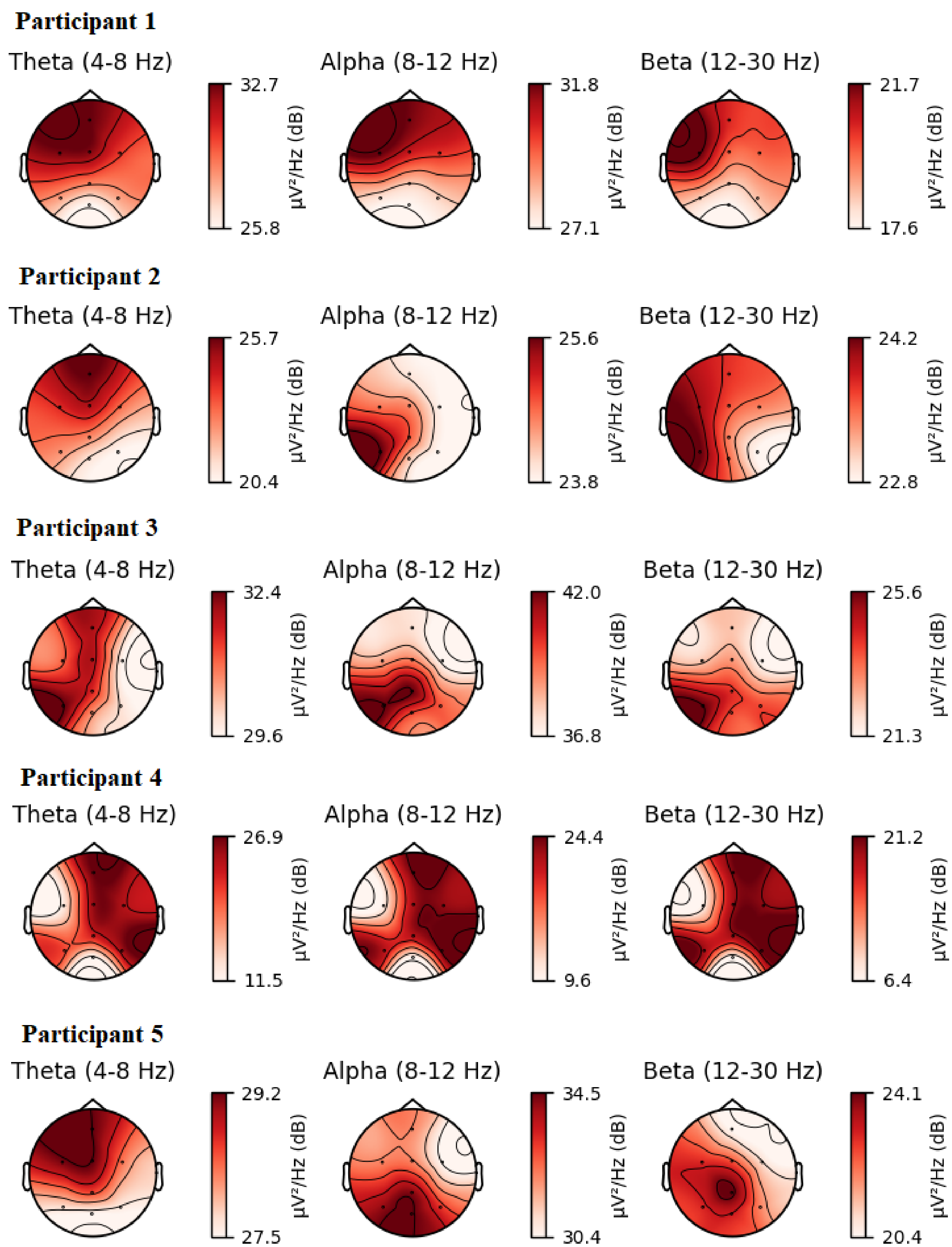

Figure 7. The average evoked power spectral densities of the mind wandering condition subtracted from the on-task condition for each participant during the application task, plotted topographically to visualize the space dimension.

Taken together, results indicate that alpha and theta frequencies were of a relatively equal power, with theta activations elicited primarily from frontocentral regions and alpha activations most often originating from left temporal regions. Beta power bands, while not as present as other frequencies, generally occurred in the left hemisphere but showed no particular localization.

Since the epochs for the application data were structured around the presentation of auditory stimuli at specific points in time, an analysis into the time-frequency domain was required. Because of this structure, the end of a mind wandering evoked object corresponds to the time preceding the presentation of the stimulus and the beginning of an on-task evoked object corresponds to the time directly after the presentation of the stimulus.

Time frequency representations were calculated on the evoked application data using Morlet wavelets for both on-task and mind wandering conditions. Topographic maps were created for areas of interest that showed the highest signal intensity in the four seconds directly preceding and following the stimulus. In general, participants exhibited frontal theta activation during the four seconds prior to the presentation of the disparate stimulus. However, theta and alpha activations in the left temporal theta area were also observed. There were varied results following the presentation of the stimulus. Some participants showed frontal theta attenuation (participant 1) while others showed frontal theta activation (participant 2). Participant 3 showed slight parietal attenuation of alpha shortly followed by a left temporal activation of alpha. Participant 4 showed slight frontal attenuation of theta followed by a strong parietal activation. Participant 5 showed a slight alpha activation in the frontal areas followed by a strong activation of alpha in the parietal areas. In general, the mind wandering condition showed greater intensity than the on-task condition (Figure 7).

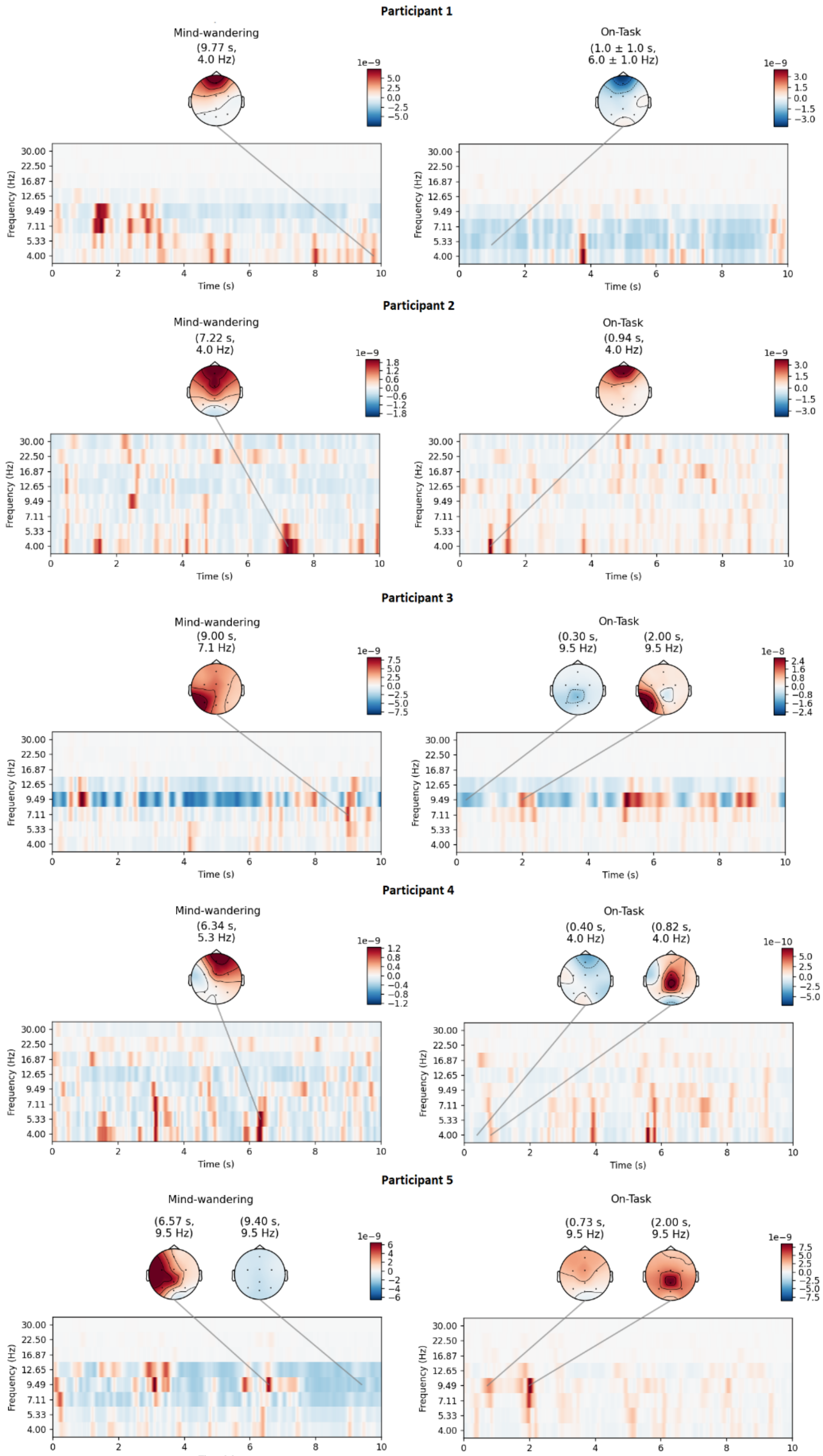

Figure 8. Morlet wavelet time frequency representations of evoked data at points of interest. End of mind wandering interval occurs just before the on-task interval.

Chapter 5 Discussion

5.1 UHB Device

5.1.1 Hardware

The UHB consists of a cloth cap with eight holes into which the eight electrodes can be slotted into. There is also a magnetic “dock” of sorts at the back onto which the UHB rests. The EEG device itself consists of the electrodes and receiving ends, which are connected to a plastic case which wraps around to the other side of the head. At the back of the device, there is a magnet which allows for docking onto the cap as well as a charging port, a power button, and an indicator light. The electrodes themselves have a ring of spiky protrusions that jut downwards and rest on the scalp and a raised ring at the opposite side that fits through the cap onto which the receiving end of the electrodes attach. The device can be used with either wet or dry electrodes. The device transmits data via Bluetooth and comes with a Bluetooth USB dongle.

The UHB only comes with a medium-sized cap, though small and large sizes are available for purchase for €69 ($101.48 CAD, at time of writing) (Unicorn Hybrid Black, 2023). No information on cap circumference or standard EEG cap size is available on the website, so there is guesswork involved in which sized caps will be required. For our purposes, we used a medium and a large size which generally fit most participants. That said, fitting participants with a cap was not as simple as measuring the circumference of their head and choosing the appropriate cap. Instead, it involved visually determining a participant’s cap size or asking them to try on both options for the best fit. The researchers tried on both sizes of cap and anecdotally report that neither of the sizes fit perfectly; on one researcher both caps were too small, and on the other researcher the medium was too small yet the large was too big. Having too large a cap can decrease electrode contact and can negatively effect signal quality whereas too small a cap greatly increases participant discomfort. The UHB could benefit from having available an array of varying cap sizes with information on the standard sizes or circumference of each cap for greater clarity.

The design of the UHB is quite fragile and as such the device should be handled with care. The electrode wires are thin and easily tangled and rough treatment could easily break them. The electrode receivers are constructed of a plastic casing over the circuit board and when removing them from the electrodes the plastic casing can sometimes pop off, leaving the circuitry of the electrode receiver behind attached to the electrode. Though this would be acceptable and perhaps expected from a more inexpensive EEG, the UHB is available for purchase for €990 ($1,443.21 CAD, at time of writing) (Unicorn Hybrid Black, 2023). Though this is a tenth of the price of a typical medical- or research-grade EEG, it is still quite a costly piece of equipment and as such one would expect a more durable design.

One issue encountered during the study is the battery life of the UHB device. The device ran out of battery in the middle of the task for one participant, therefore making their data unusable. The charging port of the UHB is located on the underside of the magnetic docking station such that it cannot be worn while charging and likewise will not turn on when connected to a power source. Thus, one must ensure discipline in charging the device in advance of use. On the other hand, the UHB user manual suggests that the device be stored in a 50% charged state to maintain battery lifespan. Though the fact that it operates on battery provides benefits in mobility and flexibility, one must be sure to charge the device after every use.

In order to operate the Bluetooth dongle that comes with the UHB, the computer to which it is inserted must either not have Bluetooth capabilities or have Bluetooth entirely disabled. The PC that was used for the study, like many PCs, had an internal Bluetooth drive which needed to be disabled prior to using the UHB. Rather than simply turning off Bluetooth in settings, the built-in PC Bluetooth adapter had to be entirely disabled in device management (thereby necessitating a restart) in order for the dongle to operate. While inconvenient, it also proved unnecessary—in the process of designing the interface, the dongle stopped working with the UHB and so the built-in Bluetooth adapter was used. This was the adapter that was used to collect all data used in the study. The rationale behind creating a Bluetooth dongle is clear since the UHB designers could not account for every make and model of Bluetooth adapter. However, it would be helpful to include those Bluetooth adapters that have been tested and proven to work with the device to save the inconvenience of rooting around in system settings. Furthermore, there are some systems, such as newer models of iMac, that have foregone USB ports in favour of USB-C, thereby requiring a USB-C to USB adapter to operate the dongle. These drawbacks aside, working with a wireless EEG is much easier than the cumbersome tethers of more traditional research and medical-grade EEGs.

Some participants expressed in both the post-task questionnaire and conversationally with the researchers after the task that they found the UHB uncomfortable. This is likely in part due to the spiky nature of the electrodes as they press into the scalp, but also due to ill-fitting cap sizes. This user discomfort can limit the amount of time the UHB is able to be used and therefore has implications for its viability on the consumer market.

As previously mentioned, the UHB has both wet and dry electrode capabilities. Initially, we intended to record all participants with dry electrodes. Wet electrode EEGs, which use a conductive medium such as saline or gel inserted between the electrode and the participant's scalp, require a more involved and laborious set up and leaves behind a gelatinous residue in a user's hair (Cruz-Garza, 2017). For real-life applications of EEG, dry electrode would be preferable due to its relative convenience and its limited cleanup. Not only are dry electrodes easier to clean and set up, Hinrichs et al. (2020) report that between wet and dry electrode systems, most participants preferred using dry electrode headsets, particularly after use exceeding 60 minutes. As such, our first participant was recorded using a dry electrode headset. However, after further study on the differences between wet and dry electrodes, we had doubts that a dry electrode system would produce sufficient results. Since EEG is susceptible to signal noise from both physiologic and non-physiologic sources, the reduced impedance and potential loss of contact between the scalp and electrodes may enhance this susceptibility to produce more noise (Cruz-Garza, 2017; Laszlo et al., 2014). To confirm if there was indeed a marked difference between the quality of the recording, we tested the first task on one of the researchers with both wet and dry electrodes and found that the dry electrodes produced significantly more noise than did the wet electrodes (Appendix 1). This is consistent with past literature that reports that dry electrode recordings produce noisier signals (Cruz-Garza et al., 2017; Halford et al., 2016; Hinrichs et al., 2020; Johnstone, Blackman, & Bruggemann, 2012; Spüler, 2017).

Interestingly, our first participant and the only participant who was tested with dry electrodes did not have the data with the poorest classification accuracy. In fact, for the training data, cross-validated training data, and application data, the participant tested with dry electrodes had the second-best performing classifiers. While this result is unexpected, one possible explanation is due to BCI illiteracy, a phenomenon wherein a minority of BCI users are unable to produce detectable patterns of brain activity required by a particular BCI paradigm (Maskeliunas et al., 2016). This will be discussed more in depth later in the chapter. Moreover, when testing wet versus dry electrodes on a member of the research team, the same task was performed twice in a row, perhaps leaving room for the confounding effects of fatigue (Appendix 1). Therefore, future research should look at testing the UHB's dry versus wet electrodes between groups with a larger sample size to uncover any signal differences.

5.1.2 Software

The UHB Python API was used to create a bespoke BCI from the ground up. While this offered much in terms of flexibility, it was challenging to use due to the in-depth knowledge of Python that was required. This creates accessibility issues for researchers who intend to create BCIs that operate under specific paradigms. Though the UHB can be paired with other g.tec software for which the paradigms are already developed, one must purchase a license for each and are then constrained to the provided function, removing the flexibility that the Python API provides. As such, there is a trade-off between flexibility and difficulty that must be considered when using the UHB.

5.2 Classification

On average, most classifiers performed poorly enough to be considered insufficient for appropriate classification. However, some algorithms performed reasonably well, particularly on specific datasets. Classification accuracy was significantly poorer on the application data than it was on the training data, indicating underlying issues with the experimental design. In addition, the classifiers performed significantly better on some datasets than others, suggesting modulation from individual differences.

The best performing classifiers in terms of accuracy were the decision tree, ridge classifier, Naïve Bayes, and nearest neighbours. After cross-validation, the best performing classifiers were the ridge classifier, Naïve Bayes, and nearest neighbours. There is little consensus in the literature on what is the best performing and most appropriate classifier in an EEG-based BCI. For instance, consistent with the results reported presently, one study found that in an EEG-based passive BCI, a least squares support vector machine with a linear kernel (i.e., a ridge classifier) has superior accuracy after cross-validation than other classifiers (Acı et al., 2019). Furthermore, Myrden and Chau (2017) found that a linear discriminant analysis algorithm had higher classification accuracy than did a support vector machine in an EEG-based passive BCI. On the other hand, Akella et al. (2021) report that a support vector machine with a non-linear kernel outperforms other classifiers on EEG data from the Trier Social Stress Test. Though our results suggest that a ridge classifier is the best algorithm to use for our specific paradigm, our limited sample size does not allow us to make definitive conclusions.

Since classification accuracy was significantly poorer for the application data than it was for the training data, there is likely an issue with the interface design. The tasks for our training phase and application phase were fundamentally different; the training task relied on self-caught experience sampling whereas the application phase made use of a disparate audio stimulus intended to return participants to attention. We chose self-caught over probe-caught experience sampling because the latter comes at the cost of disrupting the cognitive processes of the participants (Conrad & Newman, 2019). In a meditation task, probe-caught experience sampling is particularly disruptive because it requires participants to open their eyes and respond to a probe on-screen rather than simply pressing a button when they become aware of their mind wandering.Firstly, self-caught experience sampling was used in the first phase of our task which relies on meta-awareness, defined as the explicit awareness of the contents of consciousness (Schooler at al., 2011; Seli et al., 2017; Smallwood, 2002). Past research has distinguished between two different states of unintentional mind wandering characterized by the presence of meta-awareness; "tune-outs" are mind wandering with meta-awareness, and "zone outs" are mind wandering without meta-awareness. Not only do these two states reflect different theoretical processes, but also different neurological processes (Christoff et al., 2009; Seli et al., 2017; Smallwood, McSpadden, & Schooler, 2007). Our first task, the data collection and training phase, since it is characterized by the presence of meta-awareness, can be said to be reflective of "zone outs". However, our second task involves the purposeful interruption of mind wandering which is more reflective of a "tune out". This could explain why the classifiers did not perform as effectively on the application data as they did on the training data—the tasks were reflective of different mental processes.

That said, our intention for designing the second task in this way was to test whether the disparate sound presented at intervals (i.e., the traffic noises) was sufficient to bring participants out of a mind wandering state. The present study is a pilot study that performs an offline analysis to assess the efficacy of the classifiers on the EEG data collected. When adapting the system into a true BCI, the intent is to use the disparate audio as a mind wandering intervention so that upon hearing it, the participant breaks from their mind wandering and returns to attention. One potential issue with this paradigm is that it assumes that participants are experiencing mind wandering prior to the presentation of the stimulus, which may not be the case.

Another issue to consider is that there is high performance variability in using BCI systems both between and within subjects, a phenomenon known as BCI illiteracy. A non-negligible minority of BCI users are unable to produce detectable patterns of brain activity required by some paradigms (Maskeliunas et al., 2016). In essence, there are always neurological differences between individuals; some may exhibit an expected response to a stimulus, while others may not. This effect is exacerbated by small sample sizes which could explain the poor classification accuracy observed within the training phase. As such, future research should endeavour to replicate these results with a larger sample size to evaluate whether the poor classification observed in this study is due to poor performance on behalf of the UHB, BCI illiteracy, or some other factor.

5.3 Mind Wandering

For the training data, mind wandering was found to be primarily associated with greater theta activity at frontocentral areas and secondarily with alpha activation in left temporal areas. Our observed theta observations are consistent with past research that posits that theta activity in frontocentral areas are a strong marker of mind wandering (Braboszcz & Delorme, 2011; Conrad & Newman, 2021; Kam et al., 2022). However, the observed alpha activation in left parietal areas is not what has been observed in past literature; typically, alpha band activity is often reported to be attenuated during mind wandering, particularly across posterior, frontocentral, and temporal sites (Braboszcz & Delorme, 2011; Kam et al., 2022; van Son et al., 2019). Interestingly, parietal alpha oscillations are associated with processes such as working memory and shifts in visuospatial attention, two mechanisms that are not expected to be at play during a meditation paradigm (Meyer, Obleser, & Friederici, 2013; Schuhmann et al., 2019). One possible explanation is that during a mind wandering episode, the participant may have opened their eyes, either consciously or unconsciously, to look at the interface on which there was a stopwatch keeping track of elapsed time, thereby causing a shift in their visuospatial attention.

Similarly, for the application data, mind wandering was also found to be most often associated with greater theta activity at frontocentral areas and secondarily with alpha activation in left temporal areas. While this suggests that mind wandering was indeed captured in this phase and perhaps successfully corrected, there is perhaps another explanation for this result. Since the application phase task involves the presentation of a mismatched audio stimulus at semi-random intervals (i.e., traffic noises versus birdsong), it can also be interpreted as an auditory change detection task. Auditory change detection is reflected in the ERP known as mismatch negativity (MMN). Past research has localized the MMN sources to the supratemporal cortex and the inferior frontal cortex, two areas that are near regions of interest implicated in mind wandering processes (Doeller et al., 2003; Marco-Pallarés et al., 2005; Rinne et al., 2005; Rosburg et al., 2005). Furthermore, theta oscillations have been observed during MMN events in frontal regions, suggesting that frontal theta plays a role in auditory change detection (Fuentemilla et al., 2008; Ko et al., 2012). Since frontocentral theta is a shared marker between mind wandering and auditory change detection, it cannot be said with certainty whether the frontocentral theta observed in the application phase of the task is resulting from one process or the other. To confirm this, a more in-depth analysis should be conducted that compares these two processes.

5.4 Usability

Generally, participants had a positive view of the system and considered it easy to use. Even so, they had valuable insights on ways in which the usability and function of the system could be improved. Many expressed a desire for a fully functional BCI and thus this questionnaire should be readministered once a true BCI is built to further investigate participant attitudes.

One participant discussed that the tool could be distracting, both because it is uncomfortable to wear and because of one's awareness of the tool. This latter point is of particular interest because of the previously discussed meta-awareness. One possible interpretation of this response is that the awareness of the tool creates a heightened meta-awareness, thereby leading to less instances of "zone outs"—not unlike a placebo effect.

Another participant expressed that the tool may not be helpful for those who already find it difficult to meditate because going through the preparation of wearing the cap and running the software could distract them further. In order for a BCI to be an effective system, it must be demonstrably reliable in the long-term, easy to set up, use, and maintain, and through its use benefit mood, quality of life, and productivity (Wolpaw, 2013). Though participants generally agreed that the BCI in the present study was easy to use, the fact that this participant indicates that it could be cumbersome to go through the preparation of the system suggests that the questionnaire administered requires more pointed questions about how useful such a BCI would be in their everyday life. This is not necessarily a characteristic inherent only to the UHB—while EEG technology is still making great strides in streamlining and improving the hardware, most if not all EEGs with satisfactory signal quality are rather cumbersome. It should also be noted that many of the participants were recruited from within the Neurocognitive Imaging Lab and perceived the UHB as an easy-to-use and convenient device relative to the research-grade EEGs they have experience with. In order to assess the UHB's convenience and usability from a consumer level, participants with no previous experience with EEG systems should be recruited so as to not affect the data. In addition, in a laboratory setting, the participant is neither putting the EEG device on themselves nor initializing the BCI and thus this does not replicate a real-world scenario. Perhaps if the participants were required to set up the system and equip the EEG device themselves, their responses would be different from what is reported here.

Another point of interest mentioned by a participant in the questionnaire is that the BCI keeps one alert to the external environment which may be distracting. One possible interpretation of this statement is that the audio inherent to the BCI necessitates a level of auditory focus that is not generally present in unassisted meditation, leading to heightened perception of environmental sounds and thereby increasing the number of external distractions. While it seems like a relatively simple solution to incorporate headphones into the BCI, this would increase the price, complexity, and comfort of the system. As discussed previously, participants already report that the BCI is both uncomfortable and perhaps cumbersome. Though headphones could resolve the issue of a distracting external environment, they would exacerbate the issues already present. In an academic setting, this is less of an issue; in a laboratory, it is generally easier to find a quiet space for testing. In a real-world scenario, however, this is far from ideal since many people live in environments with plenty of external noise, whether it be from family, pets, neighbours, traffic, or otherwise.

One participant expressed that the tool may not be helpful because the main purpose of meditation is to let one's mind wander while paying attention to how one is thinking and feeling. Though mind wandering can be disadvantageous in some situations and outright dangerous in others, it can also be a positive and creative process. This participant makes the point that an attention-recovery device is not particularly helpful during meditation since the goal of meditation is not necessarily to be focused on meditating with full intensity, but rather to be mindful of the thoughts and feelings resulting from mind wandering. A meditation BCI is useful in the context of academia and research since it is a simple paradigm and there are fewer visual artifacts from sensor data to process and filter. However, from a consumer perspective, not only is a meditation BCI uncomfortable, cumbersome, and inconvenient, but it also serves little practical function.

Chapter 6 Conclusion

In conclusion, the UHB is not well-suited for use in a mind wandering BCI at the consumer level due to issues arising from both its hardware and software. That said, its ease of use when compared to research- and medical-grade EEGs as well as the flexibility that the Python API provides would make it an effective learning tool in the context of academic institutions and laboratories. Though we can tentatively claim that our intervention can successfully correct mind wandering, future research should closely examine the processes at work in order to distinguish between mind wandering and audio change detection. Similarly, we can cautiously claim that self-caught experience sampling is sufficient for use in a mind wandering BCI, though perhaps not in conjunction with the selected mind wandering intervention described herein. Lastly, a ridge classifier was found to be the most effective machine learning algorithm in terms of accuracy within the context of this specific paradigm.

At the consumer level, the UHB would not excel in a meditation-based mind wandering BCI. Participants report that the device is uncomfortable and that there would be some level of burden if required to equip the device in a real-world situation. Furthermore, one participant indicated that the BCI meditation paradigm itself may not have practical use in the real world. In addition, even though the UHB is considered low-cost when compared to medical- and research-grade EEGs, it is a sizable investment for the average consumer. Since the hardware would also be paired with the actual BCI software, this would drive up the price even further. Thus, even in a scenario wherein the BCI provided real, practical value to the consumer, the inconvenience, discomfort, and cost associated with the BCI may not be able to justify its purchase.

That said, the UHB would perform reasonably well in an academic environment as a research or learning tool. Compared to traditional medical- and research-grade EEGs, the UHB is more portable, easier to set up, and dry electrode capabilities can provide more comfort. The Python API can provide a lot of flexibility to researchers experimenting with different paradigms or to those interested in exploring programming in the field of BCI research. The BCI meditation paradigm can also be useful in the realm of research due to its simple experimental design and the fact that the EEG signal is not affected by artifacts from blinking.

The evidence reported herein on the intervention designed to correct mind wandering is inconclusive and we cannot say with any degree of certainty whether it works as intended. While some participants showed evidence of it being effective, most did not. Though there are a number of reasons why this could be, it is important to stress that the small sample size of this study prevents us from drawing any definitive conclusions, whether that be that our intervention does work or does not work. Future research should examine this intervention in further detail with a larger sample to determine if it is an effective mind wandering intervention, perhaps outside of the context of a BCI. One potential study of interest would be to compare the results of the intervention used herein with the results produced by that of the oddball auditory protocol—does this protocol require tones be used or can its elicited neural activity by different auditory stimuli? Until the mechanisms at play are well understood, it is difficult to say exactly what should be changed about the design of this study.

Results indicate that self-caught experience sampling is an effective method of capturing the neural markers of mind wandering, though it is important that there is a distinction between “zone outs” and “tune outs”. It is possible that the mind wandering intervention returned inconclusive results because of potential mismatches between the neural signatures of these two different types of mind wandering. Future research should investigate if probe-caught experience sampling paired with the intervention described herein would return more conclusive results.

Finally, the ridge classifier algorithm showed the most promising results within this specific context, followed closely by the Naïve Bayes and decision tree algorithms. Whether these algorithms would retain their high performance once the paradigm undergoes the previously outlined changes should be investigated to determine if these particular classifiers are performing well due to the nature of the paradigm or due to the nature of the BCI.

In conclusion, this pilot study outlines the efficacy and practicality of the UHB EEG in a meditation-based mind wandering BCI and highlights some key insights into the design and theory behind the paradigm. Because of the exploratory nature of the study, conclusions drawn herein should be interpreted cautiously and future research should endeavour to confirm or deny these results.

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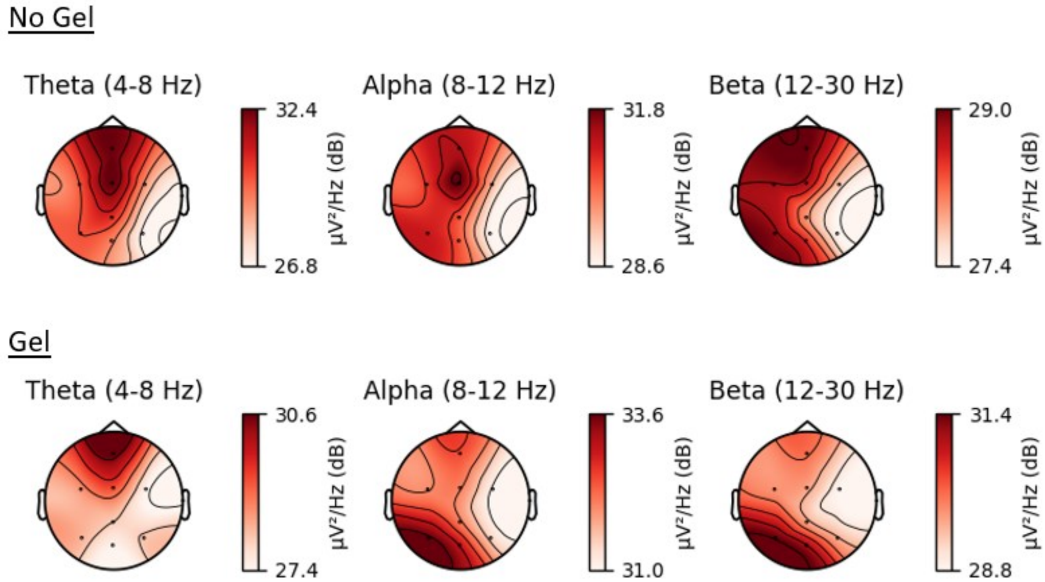
Appendix 1



Appendix 1. Power spectral density comparisons for both electrodes with gel and no gel.

Appendix 2

1) Were you able to successfully accomplish the task?

1	2	3	4	5
Strongly disagree	Disagree	Neither agree nor disagree	Agree	Strongly agree

2) How challenging did you find using the BCI?

1	2	3	4	5
Very challenging	Challenging	Neither challenging nor easy	Easy	Very easy

3) If you found the BCI challenging to use, what challenges did you encounter? If you found it easy to use, what made it easy to use?

4) How do you think this tool can be helpful to use when meditating? How may it not be helpful?

Appendix 2. The questionnaire administered to participants upon completion of the task.

Appendix 3

DALHOUSIE UNIVERSITY

Project title: Project FOCUS: A Free and Open Computer Program for User Meditation Success

Lead researcher:
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Introduction
We invite you to take part in a research study being conducted by, Dr. Colin Conrad, who is a researcher at Dalhousie University, and by Jenna Beresford, who is a graduate student at Dalhousie University. Choosing whether or not to take part in this research is entirely your choice. There will be no impact on your studies if you decide not to participate in the research.

The information below tells you about what is involved in the research, what you will be asked to do, and about any benefit, risk, inconvenience or discomfort that you might experience. You should discuss any questions you have about this study with Colin Conrad or Jenna Beresford. Please ask as many questions as you like.

Purpose and Outline of the Research Study
As brain-computer interface (BCI) research has become increasingly popular over the years, many researchers have been conducting research in the field of brain-computer interface (BCI). Electroencephalography (EEG) is the most popular method of neural measurement used in BCIs. However, most BCI-related research involves research- and medical-grade EEGs with dense electrode arrays which are very expensive for researchers who have minimal or no funding. As such, we are interested in if low-cost EEGs featuring a small number of electrodes are viable within the context of BCI research. In order to do so, we have built a simple BCI that aims to detect mind-wandering during meditation.

EEG measures electrical potentials in your cortical brain areas that will help us to determine the patterns in your brain when you experience mind-wandering. EEG is a silent and mobile measurement method which will be applied to your head like a cap. You will be asked to meditate while wearing the EEG cap to first collect information on the pattern your brain has during mind-wandering, then again while we use that information to test whether or not we can detect if and when your mind is wandering.

We wish to study this not just to test how a low-cost EEG functions, but also to determine whether a BCI can successfully decrease the amount of mind-wandering experienced, thereby increasing on-task attention. If successful, this study could encourage the development of a BCI used to maintain attention for individuals in high-risk situations such as pilots or drivers.

Therefore, this study aims to investigate whether a low-cost EEG can successfully detect mind-wandering and alert the user to recover attention.

What You Will Be Asked to Do

This study will take place in the Faculty of Management iLab, located in the Kenneth C. Rowe Management Building at 6100 University Avenue, Halifax. We expect that this session will take around 60 minutes total. The EEG headcap will be applied to your head and will be calibrated so that all electrodes have sufficient connectivity. During application, please inform the researcher if you feel any pain and discomfort due to the headcap. It will take about 10 minutes to prepare and test the EEG cap.

When all preparations are finished, you will be asked to meditate in front of our interface. As you're meditating, you will be asked to press a button when you become aware of your mind-wandering. After this, you will be asked to meditate again, but this time without the button press—just meditation. During this time, we will play sounds that indicate whether you are meditating or if your mind is wandering. When meditating, try not to move your head too much in order to prevent the movement of the EEG electrodes. Given the length of the study, however, it is understandable if you move your head from time to time. This procedure will take approximately between 60-75mins—20mins for set up, 20mins for the first meditation task, 20mins for the second meditation task, and a combined 15 minutes for a break between tasks and the administration of the questionnaire. When both meditation tasks are complete, the EEG headcap will be removed from your head.

Possible Benefits, Risks and Discomforts

Participating in the study might not benefit you, but we might learn things that will benefit others.

The EEG measures we are using simply record the electrical signals that your body generates. Please inform the researcher if you are uncomfortable with having your head being touched, as this is required to prepare the equipment. If you feel discomfort or distress caused by the EEG set-up or task that we are using, please inform the researcher immediately—the experiment will be temporarily halted, and actions will be taken to reduce the sensation of discomfort. You can also discontinue your participation in the study at any point.

Birdsong will be played during the first meditation task while a combination of birdsong and traffic noise will be played during the second meditation task. These noises may cause some discomfort or distress to some participants—if at any point you are feeling uncomfortable, again please inform the researcher immediately so we may halt the experiment to address your concerns.

Compensation / Reimbursement

To thank you for your time, we will give you $20. You will receive this even if you choose to discontinue participation in the study early.

How your information will be protected:
No personally identifying information about you will be kept by the research team other than your name on the consent form, which will be kept in a locked file cabinet in Dr. Colin Conrad's office for a period of two years, after which it will be destroyed. The data recorded from the experiment (EEG, questionnaire) do not contain any personally identifying information and will not be linked to your identity, including the name that you provide on this form.

Anonymous data generated from the information you provide in this research may be shared publicly (most likely in digital form via the internet) to advance knowledge. We plan to deposit the data in a public research database called the Dalhousie DataVerse repository and in a public research database called open science foundation (OSF). We will remove any personal information that could identify you before the data are shared in an effort to ensure that no one will be able to identify you. Despite these measures, we cannot guarantee your anonymity or predict how those who access the data will use them.

If You Decide to Stop Participating
You are free to leave the study at any time. If you decide to stop participating during the study, you can decide whether you want any of the information that you have provided up to that point to be removed or if you will allow us to use that information. After you leave the lab, however, it will become impossible for us to remove your data because the data is anonymous and can no longer be traced back to you.

How to Obtain Results
We will provide you with a short description of group results when the study is finished. No individual results will be provided. You can obtain these results by including your contact information at the end of the signature page.

Questions
We are happy to talk with you about any questions or concerns you may have about your participation in this research study. Please contact Colin Conrad (at (902) 494-8378, colin.conrad@dal.ca) or Jenna Beresford (jn856019@dal.ca) at any time with questions, comments, or concerns about the research study (if you are calling long distance, please call collect).

If you have any ethical concerns about your participation in this research, you may also contact Research Ethics, Dalhousie University at (902) 494-3423, or email: ethics@dal.ca (and reference REB file # 2023-xxxx).

Signature Page

Project title: Project FOCUS: A Free and Open Computer Program for User Meditation Success

Lead researcher:
Dr. Colin Conrad, Faculty of Management, Dalhousie University, colin.conrad@dal.ca

Other researchers
Ms. Jenna Beresford, Faculty of Management, Dalhousie University, jn856019@dal.ca

I have read the explanation about this study. I have been given the opportunity to discuss it and my questions have been answered to my satisfaction. I understand that I have been asked to take part in a laboratory experiment in which my subjective evaluations are assessed with questionnaires and my neural activity is assessed by means of electroencephalography (EEG).
I agree to take part in this study. My participation is voluntary, and I understand that I am free to withdraw from the study at any time during measurements. After the measurement has been completed, I can no longer withdraw from the study because my data has been anonymized and can no longer be traced back to me.

______________________________ ____________________________ ____________

Name Signature Date

If you like to receive a two-page results report from the study after all measurements have been made, please fill in your email address in the field below:

Email address: ___________________________________

Appendix 3. The consent form provided to participants prior to participating in the study.