# EEG in the wild: Using real-world tasks to measure changes in EEG rhythms related to human attention

by

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## Abstract

Understanding attentional processes in everyday environments is an important step to further understanding the EEG rhythms that, for decades, have been studied in isolated indoor chambers. The present dissertation aimed to investigate the dynamics of EEG oscillations using mobile settings. The dissertation starts with an overview of the state of the mobile EEG field. We next present a novel skateboard paradigm where participants can freely navigate while completing a concurrent attentional task. While we could reliably record ERPs using this new method, we found no significant differences in ERPs related to increased motor demands. In another study, we demonstrated that during outdoor cycling, there is a significant increase in the N1 ERP amplitude when participants were exposed to the greatest traffic volume. This effect suggests an increase in auditory filtering in environments with greater traffic sounds. To account for previous mixed results regarding the role of alpha power during motor tasks, we conducted an analysis of four selected mobile studies in our workgroup. We found across studies that increases in environmental complexity are associated with decreases in alpha power. Behaviorally, we found that participants can better process target stimuli when located indoors or in a quiet park. Taken together, these findings show that sing the N1 ERP and modulations in alpha oscillations, increases in environmental complexity can be accurately estimated. We also discussed several methodological considerations to improve the current state of mobile EEG literature.

# Preface

The research project, of which this thesis is a part, received research ethics approval from the University of Alberta Research Ethics Board, Project Name “Electrophysiological markers of cognitive processes”, Study ID: Pro00050069, 08/08/2014 to 03/29/2022.

The content of Chapters 1, 2, 3, and 4 are my own original work. The EEG collection methodology from chapters 2, and 3 was originally developed by Joanna Scanlon and Kyle Mathewson. The skateboard EEG idea from Chapter 4 was originally proposed by Pete Hurd and Nathan Bartlett, and the methodology was developed by myself, Kyle Mathewson, and Jonathan Kuziek. Chapter 2 of this thesis has been published as Daniel Robles, Jonathan W. P. Kuziek, Nicole A. Wlasitz, Nathan T. Bartlett, Pete L. Hurd, Kyle E. Mathewson (2021). EEG in motion: Using an oddball task to explore motor interference in active skateboarding. *European Journal of Neuroscience*. 2021; 54: 8196– 8213. Kyle Mathewson proposed the idea for chapter 3. I was responsible for the data collection and analysis as well as the manuscript composition.

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# Chapter 1 - Introduction

## 1.1 Making a case for mobile EEG research

Humans have been interested in mental processes for hundreds of years (Rocca, 2003), yet, historically, our capacity to understand cognitive processes has been linked to the available technology of the times. For example, while the early days of psychophysics and experimental psychology relied on less sophisticated tools, contemporary psychophysiology enjoys a vast range of modern tools to study mental phenomena. However, even in times of significant technological advancements, we still face technical challenges in brain imaging, particularly when it comes to active behaviors such as walking and moving (Jungnickel & Gramann, 2016). At the center of these challenges is the ability to measure reliable brain signals of interest while subjects perform complex mobile tasks.

### *Why mobile paradigms?*

Electroencephalography (EEG) is a technique that uses scalp electrodes to record neuronal activity. This technique records the coordinated postsynaptic activity of cortical neurons (Olejniczak, 2006). Since the development of EEG in the 1920s, scientists have validated several classic paradigms to record brain activity in research laboratories (Cohen, 2017; Shipton, 1975). EEG can accurately capture fast voltage changes in the scalp; therefore, this technique is widely recognized as having superior temporal resolution relative to other techniques (Burle et al., 2015; Louis et al., 2016). Signals such as EEG produce very low electrical potentials under 100 microvolts (*Neuroergonomics*, 2008; Parasuraman et al., 2011). Due to the low voltage in EEG signals, electrical potentials from eyeblinks and movements can also get recorded along the EEG signal resulting in increased data noise (Luck, 2014; Thompson et al., 2008). To illustrate this, an eye blink generates noise in the order of millivolts which are larger than the microvolt scale of EEG signals (Çınar, 2021). Eye movements, including blinks, generate temporary shifts in electric fields that travel around the head surface. These artifact noise signals pose major problems for researchers. For example, artifacts are impossible to completely minimize, and still, they are larger than EEG signals of interest recorded during an experiment (Gratton, 1998).

The traditional approaches to dealing with artifacts include restricting participant movements during experimental blocks and offline analyses to either discard or correct artifact-related noise (Gwin et al., 2010; Hoffmann & Falkenstein, 2008). While these solutions increase the data quality of the EEG, conceptually, the isolated and passive environments under which experiments take place make it difficult to generalize findings to everyday situations. For instance, in everyday life, people are bombarded by large amounts of outdoor stimuli and can move freely (Ladouce et al., 2017). The interaction with the environment is one crucial aspect of human cognition that traditional laboratory approaches are not well suited to explore, given the complexity of real-world environments and hardware limitations (Jungnickel & Gramann, 2016). To illustrate this problem, consider a conventional laboratory; it cannot emulate the sensation of riding a bicycle downhill at a very fast speed using an indoor paradigm. It is also impossible to obtain an fMRI recording from someone riding a bicycle downhill outdoors. For these reasons, developing appropriate mobile and outdoor EEG paradigms can be beneficial to the study of cognitive processes.

In a world where rigorous experimental control has long been considered the standard, why would cognitive neuroscientists want to move away from laboratories into unstructured naturalistic environments? Previous studies have argued that cognitive processes have evolved to facilitate interaction with our immediate environment (Jungnickel et al., 2019). For example, the concept of active externalism proposes that the interaction between a human organism and the external environment creates a coupled system (Clark & Chalmers, 1998). This coupled system is analogous to a cognitive system that influences behaviors and actions. Furthermore, (Makeig et al., 2009) have also proposed that cognitive processes have evolved to guide behaviors in the physical environment. These authors argue that there is a strong link between perception and motor control that facilitates visually guided behavior. For example, environmental information continuously shapes an individual's situational awareness to guide behaviors, whereas objects from the environment can be integrated into bodily cognition (for example, a player's racket). Moreover, evidence of mirror neurons might also support the argument that cognitive and motor areas are interdependent (Gramann et al., 2014).

When studying attention during motion, an important consideration is a potential interdependence between sensory, motor, and cognitive processing during the execution of behaviors and actions. Since traditional laboratories require subjects to sit still, researchers have previously questioned the degree to which traditional theories remain valid under more ecologically valid paradigms, such as in an outdoor or naturalistic setting (Debener et al., 2012). Ecological validity can be thought of as the degree to which real-world and experimental phenomena overlap (Schmuckler, 2001). With the development of mobile EEG techniques, we now have an opportunity to explore aspects of human attention in more dynamic environments relative to isolated laboratories.

### *Achieving portability in EEG research: From consumer gear to MoBI.*

The development of portable, low-cost, and commercially available EEG devices has contributed to the study of cognitive processes under a range of naturalistic behaviors (Xu & Zhong, 2018)**.** Critically, attention scientists rely on the crucial assumption that laboratory-based findings reflect true attentional mechanisms that the EEG can capture (Biasiucci et al., 2019). One crucial step in developing optimal mobile EEG paradigms is replicating classic laboratory phenomena in less structured settings. For example, in humans, EEG can record several markers of endogenous attention, such as the event-related potential (ERP) known as the P300 or P3. This refers to the positive deflection of the EEG signal occurring approximately 300 ms after the onset of a target stimulus (Picton, 1992). The amplitude of this ERP component has been previously linked to stimulus processing (Sur & Sinha, 2009) and the allocation of cognitive resources devoted to experimental tasks (Polich & Comerchero, 2003). Generally, a reduction in P3 voltage is associated with increased task efforts which could reflect the reallocation of limited cognitive resources (Kok, 2001). Since the oddball P3 effect has wide replicability in traditional laboratory settings (Zamrini et al., 1991), mobile studies have deployed these paradigms to less structured research settings while participants perform physical tasks. One central assumption in these studies is that there are shared resources between areas of motor control and cognitive processing (Leone et al., 2017). For instance, a complex motor task should demand a higher allocation of cognitive resources than a simple motor task. The increase in cognitive demands should be reflected in changes in P3 amplitude relative to conditions where participant effort (either cognitive or physical) is lower. For a review of common ERP components, refer to (Luck, 2014).

Crucially, mobile setups, including consumer EEG systems such as the Emotiv (https://www.emotiv.com/) have been previously modified in walking paradigms to yield laboratory-grade quality oddball P3 indoors and outdoors and demonstrating that single-trial EEG data quality can be achieved using non-laboratory grade hardware (De Vos et al., 2014; Debener et al., 2012). The Emotiv system has also been deployed to collect EEG over extended periods outside the laboratory setting, such as in classrooms (Dikker et al., 2017). Other commercially available devices, such as the meditation tool called Muse Headband (Figure 1), have been previously used for EEG research inside and outside of the laboratory. The Muse has been used to record and quantify well-known ERPs related to attentional processes, such as the N2 and the P3, (Krigolson et al., 2017). In this study, the authors focused on P300 and replicated the P300 oddball effect using this portable setup while also finding a reliable reward-positivity effect in a reward paradigm. Our workgroup used the Muse as part of a large longitudinal multisensor study to record EEG in remote villages in Malawi (Neto et al., 2021). In this study, we showed the reliability of the muse headband to collect EEG to perform frequency band analyses in the alpha frequency. Oscillatory EEG activity in the alpha frequency, along with other frequencies such as beta, have been previously associated with alertness and expectancy (Klimesch et al., 2007), cortical excitation, and attention (Sauseng et al., 2009), and cognitive processes related to attention (Başar & Güntekin, 2012). In the context of oscillatory activity, power refers to the amount of activity conferred to a given frequency in the EEG spectrum (Xiao et al., 2018). In many tasks, increases in task demands tend to result in a decrease or desynchronization of alpha power (Klimesch, 1999). In another study by our workgroup, (Wilkinson et al., 2020) demonstrated the feasibility of the Muse to predict stroke severity by EEG recording the patient's EEG for 3 minutes using an analysis of different EEG frequency ratios. These results suggest that consumer gear EEG tools can produce reliable EEG signals both inside the research lab and in external settings. While there are undeniable challenges in collecting EEG outdoors (e.g., less experimental control, increased artifacts) as well as reduced data quality in consumer-grade devices (e.g., data quality does not compare to laboratory-grade hardware), their accessibility and ease of use could help expand EEG research to novel scenarios (Krigolson et al., 2017).

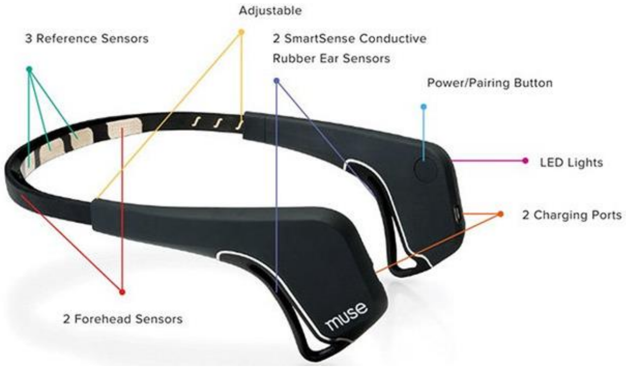

Figure 1.1 Muse Headband diagram.

Besides the development of consumer EEG gear, advancements in portable minicomputers and smartphones have played a key role in developing mobile paradigms (Lau-Zhu et al., 2019). For example, the Raspberry Pi minicomputer (https://www.raspberrypi.org/) has been used by researchers to successfully record ERP components yielding similar results to traditional laboratory gear (Kuziek et al., 2017). Likewise, the implementation of tablets (Ladouce et al., 2017) and Android-based smartphones (Bleichner & Debener, 2017; Blum et al., 2017; Debener et al., 2015) used for task presentation and data recording represent a significant advancement in mobile research for the following reason: Bluetooth based connection reduces the use of cables that constraint subject movement, also, due to increased portability, these devices can be deployed to the field (Dehais et al., 2019). As mentioned previously, this largely increases the potential for scientists to explore attention in the “wild”. While consumer gear and minicomputers offer simple alternatives to study attentional processes, some scientists have adopted a more complex approach to investigate brain/body dynamics under active behaviors.

Since individuals’ external environment constantly shapes human behavior (e.g., to better guide behaviors, and attention), researchers have been interested in exploring these body/environment dynamics (Gramann et al., 2011). As a result, the mobile brain/body imaging (MoBI) approach (Makeig et al., 2009) was developed to analyze brain signals, motor behavior, and events within the subject’s environment during attention/motor tasks. This approach obtains synchronized recordings from multiple sources, including EEG, noise artifacts, Electromyography, movement trackers, and timed events the participant experiences during the experimental paradigm. The challenge of integrating synchronized data required the development of a toolbox for MoBI studies called MoBILAB (Ojeda et al., 2014). This toolbox uses Lab Streaming Layer (LSL) technology to synchronize the events from the different sensors by estimating the relative event offsets. The different data formats, such as EEG and EMG, are stored separately, allowing for the individual processing and visualization of each. The MoBI approach aims to link the relationship between unconstrained behavior, cognitive function, and brain dynamics by analyzing synchronous activity (Jungnickel et al., 2019). Along with the simpler consumer gear approach mentioned above, the MoBI approach radically breaks away from traditional laboratory research, where behaviors are generally limited to responses on a computer, such as a button pressing.

Our research group developed another simple yet effective approach. Microsoft-based tablets such as the Surface and USB connections can power a Raspberry pi computer to reliably administer the EEG task (Kuziek et al., 2017). By reducing the set-up to two portable computers and a Brainvision V-amp (Brain Products GmbH) with a full electrode set, we can fit the basic elements of an EEG laboratory in a backpack that participants can wear outdoors (Figure 2A). In this setup, the Surface laptop launches the EEG software and records the data while the Raspberry Pi computer runs an auditory oddball task and stamps the triggers in the EEG corresponding to task events (Figures 2B, 2C)**.** One of the advantages of this setup is that participants can comfortably wear a 16-channel EEG system for outdoor activities. Previous studies by our workgroup (Scanlon et al., 2017; Scanlon, Townsend, et al., 2019; Scanlon et al., 2020) have shown that this setup is convenient for outdoor bike riding as the bicycle suspension system makes it possible to navigate smoothly while avoiding movement artifacts from ground walking outdoors.

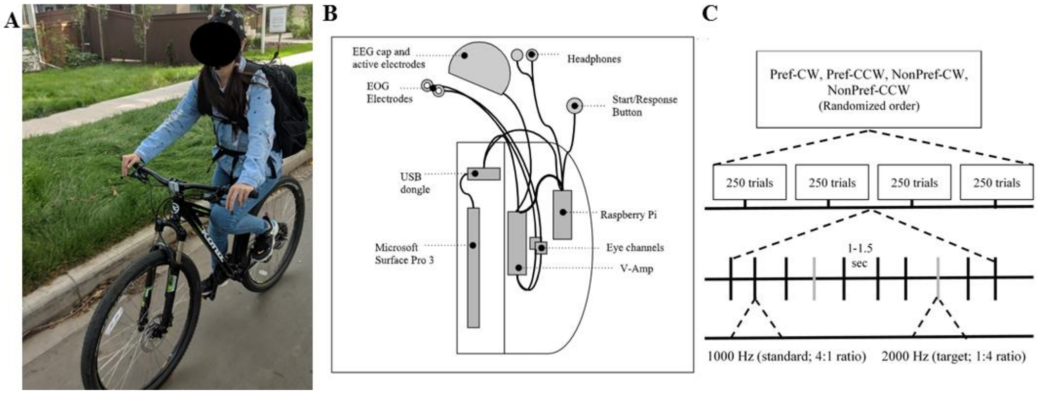

Figure 1.2. Applab Mobile EEG setup. (a): Cycling participant. (b): Backpack Setup Schematic Map. (c) Oddball task diagram.

The reviewed studies reveal several points regarding the contributions of mobile EEG to the field of selective attention. First, these studies show that even though motion and outdoor environments reduce the quality of EEG data, these factors do not necessarily compromise the validity and reliability of studies if suitable paradigms are developed. Even when there are no gold standard benchmarks in mobile research, these studies demonstrate that it is possible to transition studies beyond the stationary laboratory into less structured environments without sacrificing validity and reliability. Furthermore, we need to consider whether outdoor studies validate or contradict the large body of knowledge accrued over decades of indoor research. By showing specific task modulations of attentional components originally validated in laboratory-based studies (e.g., alpha power, P3), mobile paradigms serve as evidence that the body of knowledge gained over decades is valid under highly ecologically valid settings. An important point raised by (Reiser et al., 2019) and others is that high ecological validity does not compromise the quality of the signals collected during mobile studies. This ability to use portable technology to collect data in outdoor non-laboratory settings would provide experienced EEG researchers an opportunity to validate paradigms under novel settings.

To summarize, though the mobile EEG field is in its infancy (Protzak & Gramann, 2018), the literature reviewed above can provide some answers to understanding attentional processes under unstructured real-world environments. Many mobile studies so far complement laboratory research even though the traditional laboratory approach is very restrictive, creating a limited subject experience (Ladouce et al., 2017). This opens new and exciting avenues for research where laboratory-based studies can serve as optimal control to then explore cognitive processes under less structured environments. Ultimately, given the replicability of lab-based findings outdoors, we can now create new paradigms and analyses to address questions regarding attention during motion better.

## 1.2 Looking at classic EEG markers of attention in motion: Walking and cycling studies using N1, P3, and alpha as indices of attention

Studies using dual-task paradigms involving motor control have proposed that there could be shared mechanisms between areas of cognitive resource and motor control (Al-Yahya et al., 2011; Leone et al., 2017; Sanctis et al., 2014). Therefore, in a dual-task paradigm, motor control refers to the level of cortical engagement required to maintain motor performance. Cognitive costs refer the increases in task effort/resource allocation that is indexed by temporal changes in the EEG signal. For instance, dual-task studies have explored the degree to which complex tasks can interfere with either cognitive or motor resources necessary for effective task performance. A recent EEG study by (Djebbara et al., 2019) provided evidence that behavioral affordances and actions affect how individuals perceive their external environment. In other words, movement influences our perceptual mechanism in an environment. Beyond human literature, animal studies exploring visual neuron activity have shown different activation dynamics in motion relative to idle or immobile states (Gramann et al., 2011). Overall, these studies show the importance of exploring cognitive and mental processes in dynamic environments relative to an isolated research chamber. The section below highlights several mobile EEG studies exploring various aspects of attention during motion.

### *Walking studies.*

In a mobile paradigm, (De Vos et al., 2014) used an oddball task to record the P3 on subjects during sitting and walking respectively. They found a 30% reduction of the P3 amplitude, a measure of attentional allocation, in the walking condition that could not be accounted for by the data noise in the sitting condition. The authors argued that the overall level of sensory/cognitive engagement during walking creates these differences in attentional allocation. In a study using a Go No/Go task during walking and standing, researchers found a lower P3 amplitude during the walking condition reflecting differences in cognitive processing while participants were in motion (Sanctis et al., 2014). The authors concluded that the observed differences in the EEG signal represent an adaptive mechanism to improve performance during walking (hence the lower P3 amplitude during motion). Similar results were obtained by (Scanlon et al., 2021) in a study where subjects completed an oddball task while walking and standing outdoors. They found a reduction in P3 amplitude during the walking condition. The authors concluded that the reduction in P3 amplitude could be due to sensory processing and motor activity in the walking condition. Using a walking visual task where participants respond to peripheral flashing lights, authors found differences in early visual processing between young and older subjects as measured by P1 latency and amplitude (Protzak et al., 2020). Interestingly, Protzak found that only young participants exhibited a more negative P3 amplitude during task completion, suggesting that the younger participants could better allocate cognitive resources during the task. One interesting finding in this study is that task performance during sitting and standing did not produce differential ERP amplitudes between these groups.

In a study manipulating motor difficulty while subjects completed a cognitive task, authors found that the reduction in P3 amplitude was a combination of cognitive and motor processes (Liebherr et al., 2018). These results are supported by a recent study where participants completed an oddball task while standing, walking, and completing an obstacle course (Reiser et al., 2019). In this study, researchers observed a smaller P3 amplitude during the moving conditions. The authors concluded that this change in the P3 amplitude during the motor conditions was the result of increased cognitive demands during motion. Additionally, they found an event-related decrease of power in the theta frequency during motion. The authors interpreted this decrease in theta power as a decrease in sustained attention during movement relative to standing. In a different oddball study where subjects either stood or walked while completing an oddball task, (Ladouce et al., 2019) concluded that the reduction in P3 amplitude was driven by both inertial and visual processing more so than by increases in motor demands. Taken together, walking studies show it is possible to record ERP components to explore attentional reallocation in humans. Critically, these studies demonstrate the utility of using the P3 component as an index of task effort outside the laboratory.

Using outdoor landmarks, (Salvidegoitia et al., 2019) deployed a memory task on a university campus. They found increased memory recall associated with landmark features while outdoors. They also found differences in ERP components and EEG frequency spectra associated with better memory encoding around the landmarks participants walked around. In a MoBI study, (Pizzamiglio et al., 2017) compared participants' gait performance while self-paced walking, walking while chatting, and walking while texting. They found modulations in the theta and beta frequencies related to walking and conversing, while changes in beta power marked walking and texting. These changes were accompanied by a decrease in gait performance in dual-tasking. The authors concluded that changes in these EEG frequencies followed specific physical behaviors during walking.

In looking for markers of attention while outdoors, researchers have proposed an alternative approach using markers such as eyeblinks and saccades to investigate attentional mechanisms during motion. Using a task-free paradigm, investigators manipulated walking speed and lighting levels (Cao et al., 2020). They found that reductions of alpha power recorded over the occipital region were independent of visual stimulation during walking (Cao et al., 2020). These findings align with previous studies showing a decrease in alpha power during states of increased cortical excitability (Klimesch et al., 2007). Interestingly, Cao and colleagues (2020) concluded that during walking, the modulation in alpha power is not driven by visual sensory input per se but rather by the increased attentional demands of walking. This conclusion was drawn from their observations showing a similar decrease in alpha activity when participants walked in darkness without visual stimulation. Likewise, a previous study (Cao & Händel, 2019) observed that alpha suppression during walking might be due to an increase in sensitivity to peripheral stimuli. In other words, visual processing can be influenced by the state of motion/walking. In this study, the authors also found that walking increases the rate of saccades and eye blinks during the supporting phase of the gait cycle. This increase in eye movements was found to occur during the walking phase, where visual processing is decreased. The authors concluded that this walking phase-dependent modulation of eye movement could serve as a preparatory mechanism for the gait phase, where visual processing is most optimal. Notably, a previous walking study by (Ehinger et al., 2014) also found suppression of alpha power during turning movements. In this study, the authors reasoned that increases in visuo-attentional demands were marked by a decrease in alpha power. In a study where participants either stood still or walked at different speeds, (Lin et al., 2014) found that visually evoked potentials in the alpha frequency also decreased during walking relative to the standing condition. The authors argued that the observed alpha suppression could be attributed to increases in subject alertness during walking relative to standing. They also noted that visual distractions might have influenced the suppression of alpha activity during walking.

### *Cycling studies*

With increased hardware portability, researchers have employed cycling paradigms to explore attentional mechanisms in motion. For example, in an outdoor study using a three-class auditory oddball task, researchers were able to quantify the oddball P3 and alpha power while participants were either sitting still on a stationary bicycle, pedaling the stationary bicycle, or moving freely on the bike (Zink et al., 2016). Consistent with some walking studies cited previously, researchers found a decreased P3 amplitude and a decrease of alpha power during active cycling relative to stationary conditions. Crucially, this difference in resource allocation remained after researchers controlled for muscle artifacts. Both P3 and alpha reductions were interpreted as the result of an increase in cognitive demands and task difficulty. For example, the authors argued that increases in mental workload, task difficulty, or physical engagement might have led to the observed decrease in alpha power during the moving. Additionally, a study comparing cortical power modulations between bicycling and walking (Storzer et al., 2016) found that walking is associated with a larger decrease in alpha power. In this study, the decrease in alpha power was interpreted to be the result of increased motor planning and sensory processing during walking.

In a series of cycling studies, Scanlon and colleagues have shown that relative to indoor sitting, outdoor cycling is associated with a more negative P3 and a reduction of alpha power (Scanlon, Townsend, et al., 2019). The authors suggested that the decrease in P3 amplitude outdoors reflects the reallocation of cognitive resources between the cognitive task and the busier outdoor cycling. Additionally, they found decreases in alpha power during outdoor cycling relative to the indoor condition. As with the P3 finding, the authors attributed the decrease in alpha power to the sensory overload that characterized the busy outdoor environment. Interestingly, the authors found an unexpected increase in the N1 amplitude, a measure of early stimulus encoding, during the outdoor cycling condition. This increase in N1 amplitude was interpreted to be a potential auditory filtering mechanism required to maintain good performance in the auditory oddball while outdoors. In a control experiment where subjects listened to various types of sounds in the EEG chamber, (Scanlon, Cormier, et al., 2019) further replicated the N1 finding by showing a significant increase in N1 amplitude towards the outdoor sounds and white noise relative to silence. Again, the authors concluded that the increase in N1 amplitude to noise could represent higher sensory filtering of background noise. In a follow-up study, (Scanlon et al., 2020) deployed the cycling paradigm to different outdoor environments differing in auditory noise levels (quiet park vs busy roadway). Consistent with (Scanlon, Cormier, et al., 2019; Scanlon, Townsend, et al., 2019), it was found that relative to the park, the N1 ERP amplitude was increased when participants rode the busy roadway. Having replicated their initial findings, it was concluded that this N1 modulation by environmental noise represents an enhancement in sensory processes during loud environments to maintain task performance. The authors did not report any differences in alpha power in this paradigm.

### 1.3 Environmental complexity or movement complexity? Disentangling ongoing challenges in mobile attention research.

As the previous section illustrates, there is not a clear consensus regarding the mechanisms responsible for decreases in attention during motion. For example, (Sanctis et al., 2014) attributed the differences in P3 and N2 amplitude to increased task effort in the moving condition. This study found that higher task demands also led to adaptations in motor response (longer strides), to better respond to the cognitive task. Other studies argue that the cognitive demands from the external environment led to reductions in P3 amplitude during walking (De Vos et al., 2014; Debener et al., 2012). Meanwhile, (Reiser et al., 2019) concluded that differences in P3 amplitude were due to increases in movement complexity, therefore, supporting the notion that there are shared motor and cognitive resources. However, Ladouce et al. (2019) argued that during walking, processing demands from visual and inertial stimulation are responsible for the reduction in the P3.

A similar pattern was found in the above mobile studies that measured alpha power during motion. For example, (Zink et al., 2016) argued that relative to a still/stationary pedaling condition, reductions in alpha power during bicycle riding were driven by increases in cognitive demands due to the “real-life” aspect of being in motion. In a study comparing walking to cycling, (Storzer et al., 2016) concluded that decreases in alpha power were associated with enhanced sensory and attentional demands. However, (Lin et al., 2014) concluded that decreases in alpha power during motion could be attributed to increases in visual distractors and participant alertness. Interestingly, (Cao et al., 2020) suggested that the observed decreases in alpha power during walking are independent of visual processing. The authors suggested that the decrease in alpha power could be due to increases in attentional demands during walking. Notably, this paradigm involved a condition where participants walked in darkness, therefore reducing potential contributions from visual sensory processing.

While the reviewed studies provide different explanations for the reduction of attentional resources during motion (e.g., increases in visual sensory processing, motor demands, distractors), one important consideration is that there are no established guidelines in methodology for mobile research. Due to the early stage of mobile EEG, the differences in methodology and settings used can influence the interpretability of the results (Oliveira et al., 2016b). Meanwhile, since the publication of the first MoBI papers, there have been contrasting views regarding the electrode set of choice. While some have advocated for high-density, dry electrodes (Makeig et al., 2009), others have shown that active-wet electrodes deliver good results in outdoor environments (Scanlon et al., 2020; Scanlon, Townsend, et al., 2019). Meanwhile, Oliveira and colleagues (2016) published a set of proposed methodological guidelines for mobile EEG studies. Taken together, differences in methodology might influence the data acquisition and interpretation of results in mobile EEG studies.

As shown in Figure 1.2 and Table 1, due to the identical task parameters and setup used by our workgroup (Scanlon, Townsend, et al., 2019; Scanlon et al., 2020; Robles et al., 2021), we propose an analysis to compare how changes in environmental complexity and movement complexity affect alpha power in these studies. A fourth unpublished study (Robles et al., 2022) has been included in the analysis plans. While these studies have shown comparable results regarding some ERP components (an N1 auditory modulation found in (Scanlon, Townsend, et al., 2019) and in the study in Chapter 2), spectral analyses measuring alpha power have yielded mixed results. An alternative approach is to use a differing analysis called event-related spectral perturbations (ERSP). This technique measures temporal variations in EEG spectral power that are time-locked to experimental events (Makeig, 1993). ERSP analyses have the advantage that, unlike ERPs, they can provide information in the frequency domain, and relative to power analyses in the spectral domain, ERSPs can provide information about the temporal course of oscillatory activity (Grandchamp & Delorme, 2011). To test for statistical significance, we are using a permutation-based Fmax statistic (Blair & Karniski, 1993). This test was chosen for the proposed analysis because it allows for multiple comparisons while controlling for type I errors (Fields & Kuperberg, 2020; Guan et al., 2018). The Fmax permutation can prove useful for this analysis because we are interested in measuring changes in alpha power over the temporal window. The proposed analysis is a modified version of the Factorial Mass Univariate Toolbox (FMUT)

| **Study** | **task** | **Conditions** | **Environment/movement focus** |
|---|---|---|---|
| 1 - (Scanlon, Townsend, et al., 2019) | Auditory oddball | Cycling - Sitting still vs outdoor riding | environment + movement |
| 2 - (Scanlon et al., 2020) | Auditory oddball | Cycling - Quiet park vs busy road | environment<br>(movement complexity held constant between conditions) |
| 3 - Robles et al., 2022) | Auditory oddball | Cycling - low traffic vs intermediate vs heavy traffic | environment<br>(movement is held constant between conditions) |
| 4 - (Robles et al., 2021) | Auditory oddball | E-skateboarding - Preferred stance vs unpreferred stance | movement<br>(environment is held constant between conditions) |

**Table 1.** Mobile studies for ERSP analyses.

The studies summarized in the table above can help us explore the role of ongoing alpha activity while focusing on environmental complexity, movement complexity, or both. It is important to note that the four studies selected for the analysis all employed the same methodology, including the EEG hardware, software, electrodes, backpack, and oddball task settings (e.g., the stimulus intertrial periods), but that they are not collected on the same subjects so within subject based comparisons will not be possible. In study #1, participants completed the oddball task while sitting inside a laboratory and while cycling outside. This allows for the direct comparison of ongoing alpha activity between a sample of participants sitting still in a laboratory vs outdoor cycling. For this analysis, we predict a greater decrease of alpha activity in the outdoor cycling condition due to increases in environmental and motor complexity. In study #2, participants rode a bicycle at constant speed in a quiet park vs a busy road. And in study #3, participants rode a bicycle at constant speed in three urban lanes varying in traffic intensity (low, intermediate, high). Because riding speed was held constant in these studies respectively, these studies allow us to measure the effect of increased environmental demands on alpha power while holding movement complexity constant between conditions. For these studies, we predict a greater decrease of alpha power in conditions where environmental demands increase. Finally, in study 4, participants rode a Bluetooth-operated skateboard on an indoor running track. The experimental conditions included riding the skateboard using one's preferred stance vs their unpreferred stance. In this paradigm, we measure increased demands in motor behaviors (riding in an unpreferred stance) while keeping indoor environment conditions constant. For this study, we hypothesize that relative to a preferred stance, there is going to be a larger decrease in alpha power during the non-preferred stance, where motor demands are increased. Given the similarities between the study listed below, we can ask whether alpha ERSP power is a consistent measure of increased cognitive processing in the context of increased environmental demands, motor demands, or both.

### *1.4 Summary*

To understand the allocation of cognitive resources during naturalistic behaviors, we conducted a series of mobile experiments designed to explore the role of physical and environmental demands in several EEG markers of attention. For the first experiment (chapter 2), using an auditory oddball task, we asked what happens to classic indices of attention, such as the P3 and alpha power, when movement is almost completely minimized during navigation. For this question, we used a novel, Bluetooth-based e-skateboard system where participants can navigate freely in a large indoor environment. Furthermore, we manipulated physical complexity by comparing the EEG measures of attention during two conditions: when participants rode in their preferred stance vs a more challenging, non-preferred stance. In a second experiment (chapter 3), we present a study where participants rode a bicycle in three real-world scenarios varying in traffic noises. In this work, participants completed an auditory oddball task while riding a bicycle in three different urban environments in the south-central Edmonton streets. In this experiment, the cycling speed and pedaling were held constant across the three conditions. The goal of this manipulation was to test the effect of increased environmental demands on the N1 ERP and alpha power. Finally, for Chapter 4, we selected four studies that employed the same mobile methodology (the two studies described above plus two previously published studies from our workgroup). For this analysis, we compare ERSP alpha power in two domains: environmental and motor complexity. The analysis is aimed to determine whether ERSP alpha power accurately reflects changes in cognitive processing in the motor and environmental domains. For this analysis, we propose a mass univariate approach to measure changes in the alpha frequency over time, followed by a comparison of the pattern of results grouped by the amount of movement and environmental noise to investigate the role of alpha in resource allocation.

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# Chapter 2 - EEG in Motion: Using an oddball task to explore motor interference in active skateboarding

## 2.1 Introduction

For decades, the study of cognitive electrophysiology using Electroencephalography (EEG) has taken place inside highly controlled research facilities as EEG signals are easily contaminated by a myriad of environmental factors (Luck, 2014). EEG research has informed our understanding of human attention, yet, this knowledge generally comes from paradigms that isolate participants in Faraday cages to avoid electromagnetic fields and other sources of noise that can compromise data quality (Puce & Hämäläinen, 2017). Over recent years, developments in minicomputers such as the Raspberry Pi (https://www.raspberrypi.org/) and mobile phones have allowed such studies to move outside the lab and into the real world, resulting in a growth of mobile EEG studies within ecologically rich environments (Askamp & van Putten, 2014; Cruz-Garza et al., 2017; Kontson et al., 2015; Kuziek et al., 2017).

Mobile EEG research allows us to further understand attention and brain function by exploring cognitive functions using classic paradigms in real-world scenarios. For example, an oddball task in which participants respond to rare stimuli and ignore frequent distractors has classically been used to study attentional allocation. The ERP (event-related potential) known as the P3, a positive voltage increase associated with stimulus novelty in the oddball task (Polich & Comerchero, 2003) has been widely reported in EEG studies for decades since its amplitude is modulated by increases in task effort (Luck, 2014). This robust ERP is ideal to explore brain responses in more complex real-world environments due to its large signal-to-noise ratio and replicability in the oddball task (Zamrini et al., 1991)

Furthermore, the oddball paradigm allows for a dual-task approach where a primary task is presented concurrently with the oddball stimuli. These paradigms assume that resources needed to perform a primary task increase with task difficulty and compete with cognitive resources simultaneously devoted to the oddball task, leading to measurable reductions in P3 amplitude (Kok, 2001). There is a long history of using the P3 as a measure of resource allocation in realistic tasks such as studies of pilots (Sirevaag et al., 1993), as well as video game training studies showing that P3 magnitude to a secondary task increases as a function of training in a difficult primary task (Maclin et al., 2011; Mathewson et al., 2012).

In paradigms involving motion (walking etc.), resource allocation has been investigated via cognitive-motor interference (CMI). CMI refers to the costs in cognitive and/or motor performance during dual-tasking due to the allocation of limited brain resources (Leone et al., 2017). CMI paradigms allow measuring the markers of cognitive resource allocation or motor performance during increased dual-task demands. One important assumption in dual-task paradigms is the potential involvement of common neural processes in cognitive and motor function (Sanctis et al., 2014). PET studies have shown that activation of the lateral and superior parietal cortices, as well as prefrontal regions, is associated with the executive processes of updating, shifting, and inhibition that facilitates dual-tasking (Collette et al., 2005).

Changes in the motor domain have been previously associated with increased dual-task demands during walking. Gait speed, a general index of functional performance, has been shown to decrease during dual-task interference and such a decrease is considered an adaptation mechanism to maintain dual-task performance (Al-Yahya et al., 2011). For instance, De Sanctis et al. (2014) showed that increases in task load are accompanied by increases in stride length. The authors argued that this adjustment in motor performance can be seen as a strategic mechanism to slow down walking while participants are engaged in a concurrent task. With recent advancements in wearable technology, researchers can design specialized experimental paradigms to explore the relationship between the cognitive and motor domains during increased task load.

The past decade has seen an increased interest in Mobile brain/body imaging (MoBI) studies linking brain activity to naturalistic behaviors in 3D spaces (Gramann et al., 2014; Jungnickel & Gramann, 2016; Makeig et al., 2009). This integrative approach collects EEG, motor behavior, and environmental events to study action and participant/environment interactions (Ojeda et al., 2014). This is critical for cognitive neuroscience given the views that human cognition has evolved to maximize behavioral success within our complex environments (Makeig et al., 2009). Furthermore, researchers have recognized that even though traditional stationary studies have advanced our knowledge about cognitive processes, that approach itself is reductionist as it takes place in artificial settings (Ladouce et al., 2017). More critically, evidence from single-cell recording studies in animals suggests that there are differences in information processing during motion as opposed to a static or resting state (Gramann et al., 2011). MoBI studies involving naturalistic behaviors such as walking and running often use high-density recordings while applying independent component analysis (ICA) to systematically separate the sources of movement artifacts from the EEG signal (Gwin et al., 2010). Having mobile flexibility in EEG research design allows for higher ecological validity than traditional laboratory studies. This opens new avenues to study cognition under naturalistic settings where participant experience matches everyday situations more than an isolated and highly controlled environment.

Previous studies from our research group have successfully recorded ERP components during active physical performance and in real-world scenarios. For example, using an auditory oddball paradigm, (Scanlon et al., 2017)Scanlon et al. (2017) reliably recorded the P3 and MMN/N2b components, as well as a frontal alpha peak, during stationary cycling. Furthermore, it has been shown that differences in the experimental environment influence the morphology of the ERP component being recorded: In a follow-up study where participants completed the oddball task while cycling outdoors, Scanlon et al. (2019) showed that the P3 and MMN/N2b are present during outside cycling. Crucially, it was found that relative to indoor cycling, there is a more negative ERP amplitude in the oddball P3 and P2 components and a decrease of spectral power in the alpha range when cycling outside. This difference in P3 amplitude at electrode Pz was interpreted as an increase in cognitive processing due to being outdoors, where participants are continuously processing complex, external auditory and visual stimuli that compete with resources devoted to the oddball task while focusing on bicycle riding and direction.

Additionally, relative to indoors, Scanlon et al. (2019) found that cycling outside was associated with an increase of N1 amplitude for standard and target tones over mid frontal and parietal regions. The authors concluded that such an increase in N1 amplitude could reflect an increase in auditory filtering required to complete the oddball task in the noisier outdoor environment. These cycling studies suggest that certain ERP components show a different morphology outdoors, likely due to the influence of external stimuli bombarding the brain while being outside. Other studies comparing indoor vs outdoor cycling have also found a more negative P3 peak while participants cycle outside compared to indoors (Zink et al., 2016). In the context of dual-task interference, the decrease in P3 amplitude over parietal regions reported in these studies reflects the cognitive costs related to resource allocation during performance previously established in the literature (Nenna et al., 2020)

MoBI studies exploring CMI have also identified the P3 as one neural mechanism involved in resource allocation during task completion (Nenna et al., 2020). For example, Liebherr et al. (2018) demonstrated that increases in both motor task and cognitive difficulty lead to a more negative amplitude in the P3 time window in a cognitive task with a maximal difference over centro-parietal regions. The increase in motor difficulty was manipulated by having participants stand on one leg while completing the task. In accordance with these results, Reiser et al. (2019) employed an oddball paradigm outdoors to measure the influence of movement complexity in P3 amplitude. They showed that movement complexity was associated with increases in cognitive load followed by a more negative voltage over the P3 time window to the target tones over parietal regions.

Recently, Ladouce et al. (2019) used an oddball task to show that, relative to standing, walking is associated with a more negative P3 voltage over occipital areas to target tones. Critically, the P3 amplitude reduction in the walking condition was found to be due to visual and inertial processing during the task, and not the act of walking per se. The authors concluded that resource allocation during motion is independently modulated by inertial and visual processing. The observed modulations of P3 amplitude in these studies further show that mobile paradigms can be suitable for the study of resource allocation while in action. Taken together, these mobile studies demonstrate that the mechanism of CMI can be successfully captured using mobile designs. In the current study, we introduce the novel electric-skateboarding (e-skateboarding; operating a self-propelling skateboard with a wireless Bluetooth handheld controller) EEG approach to testing for cognitive interference in an attempt to expand the previous findings beyond the walking and cycling domains.

In addition to ERPs, oscillatory electrical brain activity has also been shown to vary with resource allocation and cognitive engagement in experimental tasks. For example, power in the alpha range (8-12 Hz) has been measured in studies of active visuospatial biasing and suppression (Kelly et al., 2006), selective inhibition, and other anticipatory mechanisms (Foxe et al., 1998; Rihs et al., 2007). Previous studies involving motor behaviors, such as walking and cycling, have found differences in alpha power based on attentional demands in these movement tasks. For example, Storzer et al., (2016) found that walking is associated with a stronger alpha decrease than stationary cycling due to an increase in sensory processing and motor planning in the walking condition. Wagner et al., (2014) have found decreases in alpha power in walking when motor planning and motor intention are required. Cycling was associated with decreases in alpha power when participants completed an oddball task riding a bicycle relative to a sitting position indoors (Scanlon, Townsend, et al., 2019). This decrease in power was attributed to increased stimulus processing from doing the task in an outdoor environment.

The results from the mobile EEG studies reviewed so far highlight the importance of outdoor paradigms for several reasons. First, replicating classic findings under less controlled scenarios (e.g., a busy road) is important for the field of cognitive electrophysiology since, ultimately, we want to understand and predict brain functioning in everyday situations outside laboratories. Second, it allows for exploratory and novel paradigms to be developed for research questions about complex naturalistic behaviors while maintaining higher ecological validity than stationary studies. This offers new and exciting avenues for mobile research that could validate the findings from stationary/laboratory studies (Ladouce et al., 2017). Third, mobile EEG is a promising tool that can offer affordable and flexible medical diagnosis (Krigolson et al., 2017), and can offer flexibility in measuring cognitive performance (e.g., fatigue/cognitive load) in real-life tasks (Darari et al., 2017).

In the current experiment, we used an active task of e-skateboarding on an indoor 200-meter track as a primary task while participants simultaneously completed an auditory oddball task and had their EEG recorded. We adopted a skateboard paradigm because it allows participants to be in active interaction with the environment while greatly minimizing body movements that lower the signal-to-noise ratio in EEG recordings (Oliveira et al., 2016b). We employed the portable EEG methodology previously used by our research group in cycling paradigms (e.g., see Scanlon et al., 2019) where participants could freely move while wearing the EEG system in a backpack (Figure 1). Using skateboarding as the primary task, our focus was to use an auditory oddball paradigm to test whether we could record a reliable P3 and MMN effect between standard and target tones.

We also wanted to investigate whether an increase in primary task difficulty (an increase in skateboarding difficulty) would produce measurable changes in P3 amplitude. E-skateboarding difficulty can be increased by manipulating stance preference: since skateboarding requires individuals to move laterally, it is common for learners to develop a stance preference while learning the task. Preference is reflected in which foot goes forward on the board or which shoulder they look over while riding. Right-handed skateboarders generally ride with their left leg forward; however, some right-handed skaters generally prefer to ride with their right foot forward. The former riding style is generally called “regular” whereas the latter is referred to as “goofy”. Due to the stability and safety of the e-skateboard, participants can be asked to switch their stance preference to increase riding difficulty without turning the task into a falling hazard.

In this context, riding in the non-preferred stance implies an increase in primary task difficulty, which has been previously associated with a decrease in P3 amplitude in the secondary oddball task (Kida et al., 2012; Kramer & Strayer, 1988).We tested the robustness of the oddball P3 effect while participants rode the skateboard in four different conditions (preferred stance clockwise direction, preferred stance counterclockwise direction, non-preferred stance clockwise direction, and non-preferred stance counterclockwise direction). For the ERP analysis, since dual-task processes modulate P3 amplitude, we predicted a decrease in P3 amplitude in the non-preferred stance due to increases in riding difficulty while completing the task.

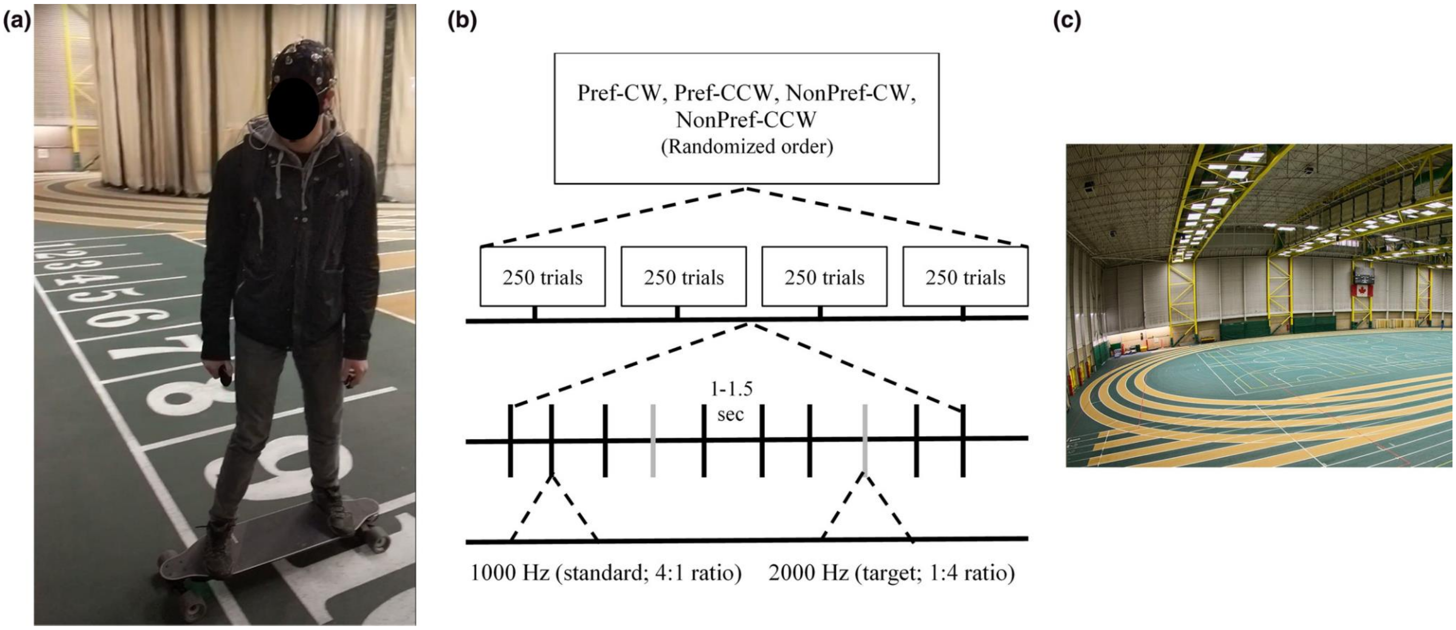


Figure 2.1. Setup task and location. A: Mobile EEG setup. B: Task diagram. C: Experiment location

Using the skateboard paradigm, we tested whether an increase in task difficulty (by having participants e-skateboard in their non-preferred stance) would be reflected in tonic alpha power decreases during the completion of the oddball task in the non-preferred condition. We also recorded participant’s resting-state EEG with their eyes both open and closed to test whether we could measure a typical alpha peak (an increase of spectra power in the 8-12 Hz range) right by the running track before completing the skateboard task. Decreases in resting-state alpha peak are associated with increased cognitive arousal (Barry et al., 2011). Since the experiment was taking place in a busy environment, we were motivated to assess resting alpha levels prior to the start of the task. Additionally, we computed the averaged alpha power between the left and right electrodes to conduct an exploratory analysis on alpha lateralization during skateboarding. Spatial attention paradigms (Ikkai et al., 2016; Kelly et al., 2006; Sauseng et al., 2005). demonstrated that alpha power increases over areas to be ignored. Such a shift in alpha power, with increased power in the hemisphere contralateral to the distractors, has been identified as a mechanism of sensory inhibition (Mathewson et al., 2011)

In the current paradigm, participants rode an e-skateboard around a running track clockwise and counterclockwise. This allows us to spatially separate the source of incoming distractors based on the direction participants ride. In the clockwise condition (regardless of riding preference) the largest source of distractors (joggers, walkers, and track users) come from the right side of space while in the counterclockwise condition, the source of distraction is always located on the left visual field of the participant. This is because participants were set to only ride in the outermost track during the task. We conducted exploratory analyses to test whether we could get an increase of alpha power over the parieto-occipital region contralateral to the source of distractors in the clockwise and counterclockwise riding directions.

## 2.2 Methods

### *Participants*

A total of 29 individuals from the university community completed the study (mean age = 20.96, age-range = 18-27, goofy-footed proportion: 41.37%, right-handed proportion: 87.5% female proportion = 37.93%). Participants received either an honorarium of $20 or credits towards Research Participation in an undergraduate psychology class. All participants had normal or corrected-to-normal vision and did not have neurological antecedents. Each participant was comfortable with basic skateboarding in both preferred and non-preferred stances. This study was approved by the Internal Research Ethics Board at the University of Alberta (Pro00050069) and participants gave informed consent before completing the study. This study conforms with the World Medical Association Declaration of Helsinki.

### *Materials and procedure*

The experiment was completed in the Universiade Pavilion (aka Butterdome) on a 200-meter indoor track at the University of Alberta during drop-in hours (pavilion users were performing leisure sports around the track during sessions). Participants first completed two, three-minute, resting-state tasks (beginning with either eyes closed or eyes open) to measure a baseline level of resting spectral activity while they were seated in the bleachers of the track. Participants were instructed to breathe calmly and either keep their eyes closed or fixated on a nearby object. Following both baseline tasks, participants were given a basic tutorial on using the Boosted V3 Stealth Electric Board (Palo Alto, California, United States; https://boostedboards.com/ca/) before starting the main skateboard experiment. The Boosted skateboard is a two-motor electric skateboard controlled by a joystick held in the right hand, with throttle and clutch controls on the thumb and trigger finger respectively. The joystick was held in the right hand while a response button was held in the left hand.

Participants began the task by standing on the skateboard and pressing the response button, starting a 10-second countdown. Participants were expected to be in motion around the Universiade Pavilion track when the countdown finished. To ensure clean data, participants were instructed to remain as still as possible, blink only when necessary, and keep their gaze directed forward. A sound cue was used to instruct the participants when the task was completed. Participants rode the skateboard using a limited acceleration mode with a maximum speed of 17 kph. Participants were trained to ride at a speed at which they felt most comfortable around the track for safety purposes. On average, the total participation time was 1 hour and 50 minutes. The average riding distance was approximately 1.92 km.

Based on the participant's preferred skateboarding stance and the direction the participant traveled around the Pavilion track, four conditions were generated: 'preferred clockwise', 'preferred counterclockwise', 'non-preferred clockwise', and 'non-preferred counterclockwise'. Condition order was randomly determined and counter balanced. In each condition, participants completed an auditory oddball task where two tones were consistently presented through headphones (either a 1000 Hz or 1500 Hz tone played at 65 dB). Participants were instructed to press the response button each time the 1500 Hz tone was played (target tone) and to withhold a response following the 1000 Hz tone (standard tone). There were no reports of issues with the task volume from any of the participants. A delay, randomly selected from a distribution between 1000 and 1500 ms, followed each tone. Response times were collected during this delay period. In all, 20% of trials contained a target tone and 80% contained a standard tone, with 250 trials in each condition. Each condition was approximately six minutes long. Between conditions, the participant returned to the starting position, the computers were reset, and the participant was given a small break.

The tones and response button task were programmed and administered using a Raspberry Pi 2 Model B computer (Raspberry Pi Foundation, Cambridge, UK) running version 9 of the Raspbian Stretch operating system and version 2.7.13 of Python. The Raspberry Pi 2 was powered via a micro-USB cable connected to a Microsoft Surface Pro 3 laptop. Audio output was via Sony earbuds connected to the 3.5mm audio connector on the Raspberry Pi 2. Coincident in time with tone onset, 8-bit TTL pulses were sent to the EEG amplifier via a cable connected to the GPIO pins of the Raspberry Pi 2. These TTL pulses were used to mark the EEG data for ERP averaging. EEG data was collected from participants using active, wet, low-impedance electrodes (actiCAP active electrodes kept below 5 kΩ). Inter-electrode impedances were measured at the start of the experiment. The following 15 electrode locations were used, arranged in the typical 10-20 electrode positions (F3, F4, T7, T8, C3, C4, P7, P8, P3, P4, O1, O2, Fz, Cz, Pz). A ground electrode was used, positioned at AFz. Ag/AgCl disk electrodes with SuperVisc electrolyte gel and mild abrasion with a blunted syringe tip were used to lower impedances. EEG data was recorded online, referenced to an electrode attached to the left mastoid. Offline, the data was re-referenced to the arithmetically derived average of the left and right mastoid electrodes.

EEG data was recorded with a Brain Products V-Amp 16-channel amplifier (Brain Products GmbH), connected to the same Microsoft Surface Pro 3 laptop powering the Raspberry Pi, running BrainVision Recorder software (Brain Products GmbH, Gilching, Germany). In addition to the 15 EEG sensors, two reference electrodes, and the ground electrode, vertical and horizontal bipolar EOG was recorded from passive Ag/AgCl easycap disks using Bip2Aux adapters connected to the auxiliary ports of the amplifier. EOG electrodes were affixed vertically above and below the left eye and affixed horizontally 1 cm lateral from the outer canthus of each eye. The participant’s skin was cleaned using Nuprep (an exfoliating cleansing gel) (Weaver & Co, Aurora, Colorado USA) before the placement of the electrodes, electrolyte gel was used to lower the impedance of these electrodes to under 5 kΩ in the same manner as previously mentioned. Data was digitized at 1000 Hz with a resolution of 24 bits and hardware filtered online between 0.1 Hz and 30 Hz, with a time constant of 1.5155 s and a notch filter at 60 Hz. All aforementioned equipment was held within a 2-pocket backpack worn by the participant, as shown in Figure 1. The total weight of the backpack containing the Raspberry Pi, V-vamp, and laptop was 4.55 lbs.

### *EEG analysis*

Analyses were computed in MATLAB R2018a (Mathworks, Natick, Massachusetts, USA) using EEGLAB (Delorme & Makeig, 2004) and custom scripts (https://github.com/kylemath/MathewsonMatlabTools). Statistical analyses were computed on JASP (JASP Team, Amsterdam, Netherlands). The EEG markers were used to construct 1200 ms epochs (200 ms pre-stimulus baseline + 1000 ms post-stimulus) time-locked to the onset of standard and target tones, with the average voltage in the first 200 ms baseline period subtracted from the data for each electrode and trial. To remove artifacts due to amplifier blocking and other non-physiological factors, any trials with a voltage difference from baseline larger than +/-1000 µV on any channel (including eyes) were removed from further analysis. At this time, a regression-based eye-movement correction procedure was used to estimate and remove the artifact-based variance in the EEG due to blinks as well as horizontal and vertical eye movements (Gratton et al., 1983). After identifying blinks with a template-based approach, this technique computes propagation factors as regression coefficients predicting the vertical and horizontal eye channel data from the signals at each electrode. The eye channel data is then subtracted from each channel, weighted by these propagation factors, removing any variance in the EEG predicted by eye movements.

Artifact rejection was again performed, using a voltage threshold of +/- 500μV. These artifact rejection thresholds were chosen to be relatively lenient, similar to other mobile EEG studies we have done (see Scanlon et al., 2017; Scanlon et al., 2019; Scanlon et al., 2020), to quantify how much noise (electrical, muscle, or otherwise) was present in the ERP data and to ensure an adequate number of trials were available for analysis. Baseline correction was performed again following the second artifact rejection. Table 1 shows the mean trial count for target and standard tones used for each condition after artifact rejection. The rejected number of trials for targets and standards respectively was similar for all conditions($F(3,112) = 0.84$, $p = 0.48$).

**Table 1:** Trial count information for targets and standards in each condition.

| Condition | Stimulus Type | Mean Trial Count | Standard Deviation | Trial Count Range (Minimum:Maximum) |
|---|---|---|---|---|
| **Preferred Clockwise** | Targets | 46.90 | 4.87 | 29:50 |
| | Standards | 185.83 | 21.61 | 104:200 |
| **Preferred Counterclockwise** | Targets | 47.79 | 5.06 | 26:50 |
| | Standards | 191.52 | 17.35 | 115:200 |
| **Non-preferred Clockwise** | Targets | 47.90 | 4.47 | 30:50 |
| | Standards | 190.34 | 17.59 | 131:200 |
| **Non-preferred Counterclockwise** | Targets | 47.76 | 4.56 | 29:50 |
| | Standards | 189.79 | 20.75 | 92:200 |

### *ERP Analysis*

Appropriate time window cut-offs for the MMN/N2b and P3 waveforms were determined by creating grand-average ERP waveforms, averaged across all participants and conditions, to create a single ERP waveform for electrodes Fz and Pz (Figure 2). We selected the peak within the grand average waveform as the center of the component of interest and used a window of 150 ms for the P3 analysis and a window of 100 ms for the MMN/N2b. These grand-average waveforms were used to avoid biasing the selected time windows towards any one condition.

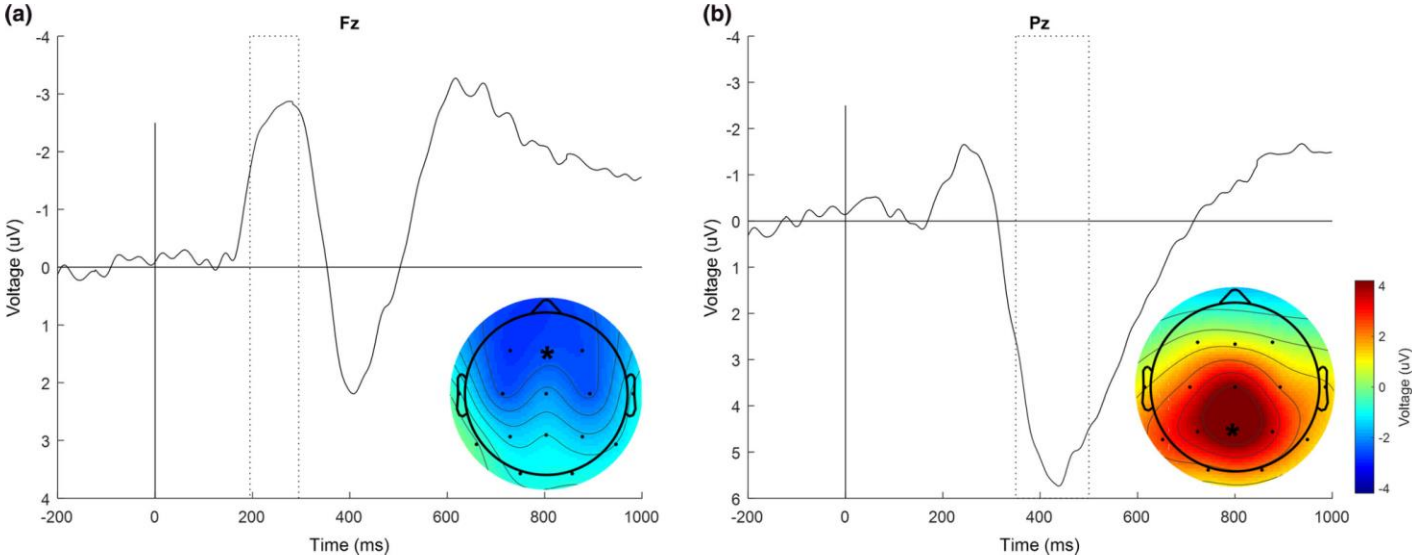


Figure 2.2. Grand-averaged ERP across conditions used to select time windows for analyses.

The negative deflection between 195-295 ms for electrode Fz was used for the MMN/N2b time window while the large positive deflection between 375-525 ms for electrode Pz was used for the P3 time window. Trial-averaged ERPs were derived in each of the four conditions (‘preferred clockwise’, ‘preferred counterclockwise’, ‘non-preferred clockwise’, and ‘non-preferred counterclockwise’) and waveforms were compared. A 2x2x2 ANOVA was run to compare tone type (standard and target), stance preference (preferred and non-preferred), and clock orientation (clockwise and counterclockwise) during the MMN/N2b and P3 time windows, at electrodes Fz and Pz respectively. Two-way repeated-measures ANOVAs were also conducted on the difference waveforms for the MMN/N2b and P3 time windows at electrode Fz and Pz respectively. Stance preference and clock orientation were the factors used for these analyses. These waveforms were derived by subtracting the standard ERP waveforms from the target ERP waveforms for both the preferred/non-preferred and clockwise-counterclockwise conditions, with $\alpha$ set to 0.05 for all analyses.

### *Spectral Analysis*

Average frequency spectra across the baseline and oddball epochs were also computed using the wavelet routine from the Better Oscillation Method (BOSC; Whitten et al., 2011) with a 6-cycle wavelet transform across a frequency range of 0.1 Hz to 30 Hz, increasing in 0.5 Hz steps. We chose this wavelet cycle parameter because we were interested in the overall sustained alpha power instead of the differences in power between target and standard tones. Spectral data was further analyzed using the "Fitting Oscillations & One Over F" (FOOOF) algorithm (Haller et al., 2018) to represent the data as two distinct components; the aperiodic background $1/f$ and periodic oscillations which may contain greater spectral power than the aperiodic component. This analysis was performed using version 0.1.1 of the FOOOF Matlab wrapper with the following settings: peak width limits = [0.5,12]; max number of peaks = Inf; minimum peak amplitude = 0.0; peak threshold = 2.0; background mode = fixed; verbose = true; frequency range = 0.5-30 Hz. The background $1/f$ spectra were then subtracted from the periodic component to better compare changes in spectral power between 0.5 Hz and 30 Hz across our conditions. All spectral analyses were done using this calculated FOOOF spectral data (Figure 6 C-D).

For the baseline task, spectra were computed for each participant by first dividing the data into 3000 ms segments. Spectra were calculated for each chunk, which was then averaged across the 3000 ms duration for each chunk. Then each averaged-chunk was combined within each participant and finally averaged across participants to generate grand-averaged spectra for both eyes open and eyes closed conditions. For the oddball task, we generated 3000 ms epochs around the onset of each standard trial (1000 ms pre and 2000 ms post standard onset) for each participant. Spectra were calculated for each epoch, then averaged across time and number of standard trials to generate spectra for each participant. These spectra were then averaged across participants to create grand-average spectra for each condition in the oddball task. Spectra were calculated using electrodes Fz and Pz. Resting-state EEG was not recorded from two participants and therefore their data was excluded from this main spectral analysis. Furthermore, to explore the role of left-right visual field distractors in hemispheric alpha, power was computed by combining the following parieto-occipital electrodes: left hemisphere (P7, P3, O1), right hemisphere (P8, P4, O2).

## 2.3 Results

### *Behavioral Results*

Figure 3A shows the mean accuracy in response to target tones across all four task conditions and by global stance preference (collapsed over direction of travel). Results from a two-way repeated measures ANOVA on behavioral accuracy show no significant main effect for either preference, (*F*(1, 28) = 0.74, *p* = 0.40, $\eta^2_p$ = 0.03), or clock orientation (F(1, 28) = 0.85, p = 0.36, $\eta^2_p$ = 0.03) and no significant interaction (*F*(1, 28) = 0.01, *p* = 0.91, $\eta^2_p$ = 4.61e-4).

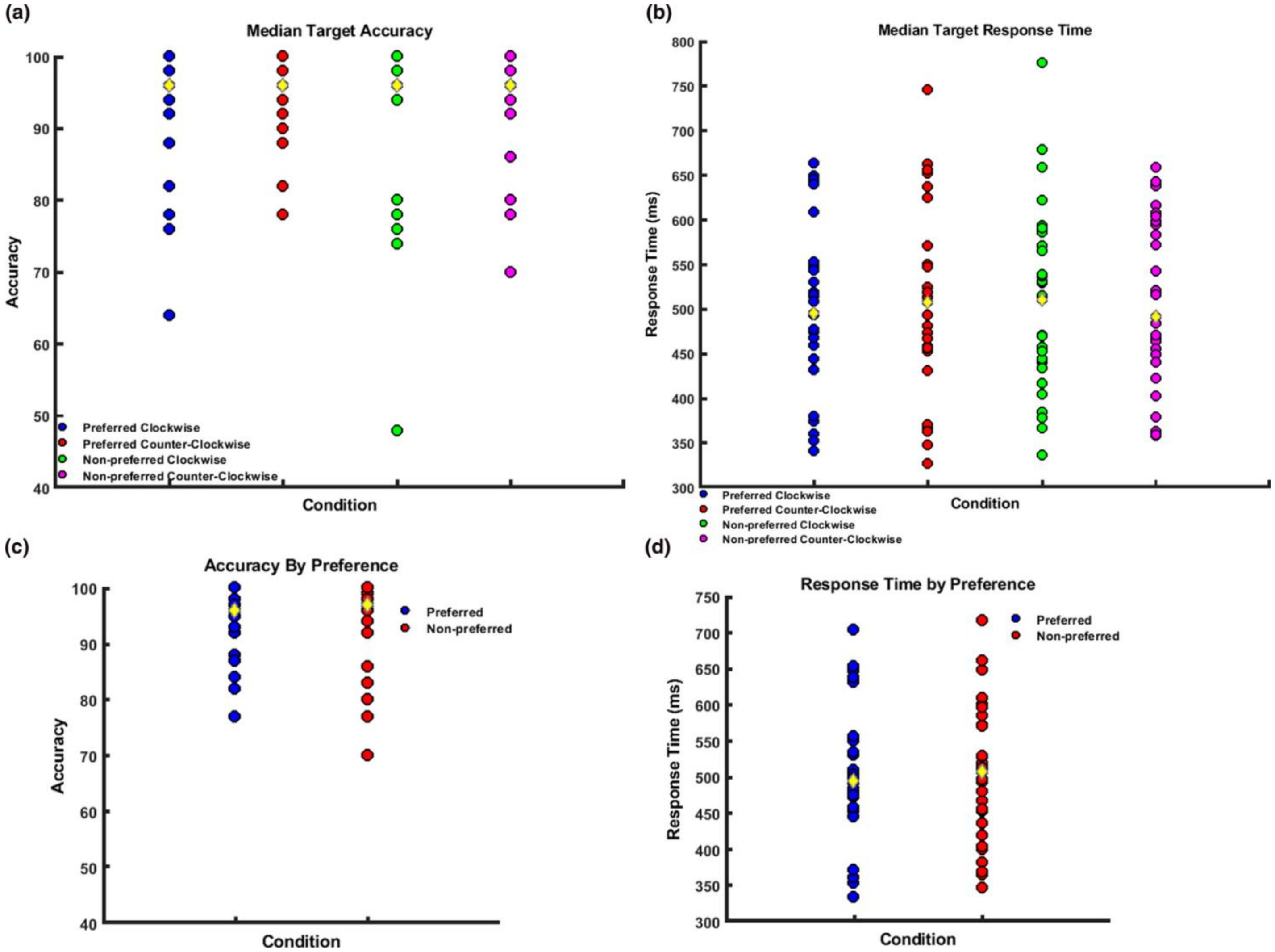


Figure 2.3. Behavioral task results. A: Mean target accuracy. B: Median target reaction time. C: Target accuracy by grand preference. Target reaction time by grand preference

Figure 3B shows mean reaction times in milliseconds for all four task conditions and by global stance preference. A two-way repeated measures ANOVA on reaction times show no significant main effect for either preference, ($F(1, 28) = 2.56\text{e-}4$, $p = .99$, $\eta^2_p = 9.15\text{e-}6$), or clock orientation ($F(1, 28) = .03$, $p = 0.87$, $\eta^2_p = 9.29\text{e-}4$), and no significant interaction ($F(1, 28) = 0.27$, $p = 0.61$, $\eta^2_p = 0.01$).

### *ERP Morphology and Topography*

Figure 4A shows the grand average ERPs for target and standard tones at electrode Fz for all study conditions. Target tones are depicted in colored lines while standard tones are depicted in black lines. Standard errors at each time point are depicted by the shaded regions. Compared to standard tones, there is an increase in negative voltage for the MMN/N2 time window between 195 and 295 ms following target tones. Figure 4C shows the grand average ERP at electrode Pz for all conditions, showing a clear positive increase in voltage in the P3 window (350 and 550 ms) following target tone onset. Additionally, topographies of the target-standard difference were computed for the MMN/N2b and P3 time windows across conditions to show the overall scalp activation distribution for both time windows. Based on the time window chosen for these topographies, one can observe a more anterior distribution for the MMN/N2b time window and a more posterior distribution for the P3 time window.

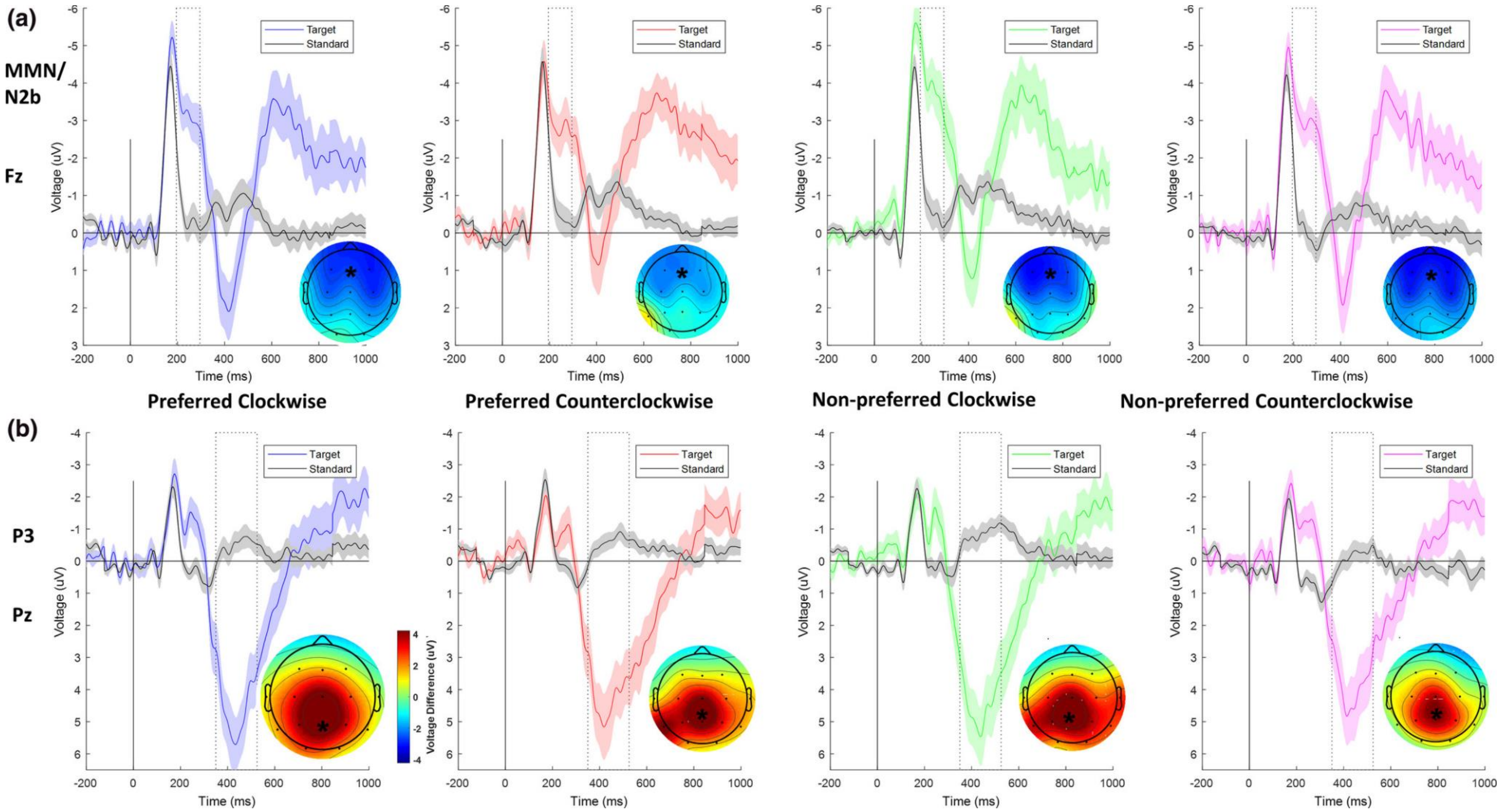


Figure 2.4. (a) ERPs at electrode Fz. Conditions (left to right): preferred clockwise, preferred counterclockwise, non-preferred clockwise, non-preferred counterclockwise. Target tones: colored lines. Standard tones: black lines. Shaded regions represent standard errors. Topographies for MMN/N2 window. (b) ERPs at Electrode Pz and topographies for P3 time windows

We conducted a 2x2x2 repeated measures ANOVA to understand the relationship between target/standard tones in all four conditions and whether the MMN/N2b and P3 are influenced by riding condition. For the MMN/N2b time window at electrode Fz, there was a significant main effect for tone type ($F(1, 28) = 87.72$, $p < .001$, $\eta^2_p = 0.76$). There was no significant effect of preference type ($F(1, 28) = 0.63$, $p = 0.43$ , $\eta^2_p = 0.02$) or orientation ($F(1, 28) = 2.78$, $p = 0.11$, $\eta^2_p = 0.09$), and there were no significant interactions: tone type*preference ($F(1, 28) = 2.04$, $p = 0.17$, $\eta^2_p = 0.07$), tone type*orientation ($F(1, 28) = 0.92$, $p = 0.35$, $\eta^2_p =$

0.03), preference*orientation (*F*(1, 28) = 1.87, p = 0.18, $\eta^2_p = 0.06$), tone type*preference*orientation (*F*(1, 28) = 0.01, p = 0.91, $\eta^2_p = 4.77e\text{-}4$). Table 2 shows the significant pairwise comparisons where it can be seen that the target-standard difference at the MMN/N2b window was reliable in all four conditions. All p-values for the pairwise comparisons were adjusted for multiple comparisons using Bonferroni correction.

**Table 2:** Pairwise results comparing target and standard ERP waveforms in each condition.

| **Comparison** | **Electrode/ Time Window** | **Mean Voltages (µV) (Targets:Standards)** | ***t*(28)** | ***p*** | **Confidence Interval** | **Effect Size (Cohen's d)** |
|---|---|---|---|---|---|---|
| **Preferred Clockwise** | Fz/MMN-N2b | -3.23:-0.58 | 5.43 | <0.001 | -4.23:-1.09 | -1.23 |
| | Pz/P3 | 4.71:-0.47 | 5.98 | <0.001 | 2.36:8.01 | 1.32 |
| **Preferred Counterclockwise** | Fz/MMN-N2b | -2.86:-0.72 | -4.37 | <0.001 | -3.71:-0.57 | -0.90 |
| | Pz/P3 | 4.35:-0.54 | 5.64 | <0.001 | 2.07:7.71 | 0.94 |
| **Non-preferred Clockwise** | Fz/MMN-N2b | -3.96:-0.75 | -6.56 | <0.001 | -4.78:-1.64 | -0.97 |
| | Pz/P3 | 4.59:-0.78 | 6.20 | <0.001 | 2.55:8.20 | 1.18 |
| **Non-preferred Counterclockwise** | Fz/MMN-N2b | -3.10:-0.30 | -5.71 | <0.001 | -4.37:-1.23 | -1.10 |
| | Pz/P3 | 3.95:-0.05 | 4.61 | <0.001 | 1.17:6.82 | 0.82 |

For the P3 window at electrode Pz, there was a significant main effect for tone type (*F*(1, 28) = 50.86, $p < .001$, $\eta^2_p = 0.65$), no significant effect of preference type (*F*(1, 28) = 0.08, p = 0.78 , $\eta^2_p = 3e\text{-}3$) or orientation (*F*(1, 28) = 0.11, p = 0.74, $\eta^2_p = 4e\text{-}3$), and there were no significant interactions: tone type*preference (*F*(1, 28) = 0.41, p = 0.53, $\eta^2_p = 0.01$), tone type*orientation (*F*(1, 28) = 1.42, p = 0.24, $\eta^2_p = 0.05$), preference*orientation (*F*(1, 28) = 0.17, p = 0.68, $\eta^2_p = 6e\text{-}3$), tone type*preference*orientation (*F*(1, 28) = 0.83, p = 0.37, $\eta^2_p = 0.03$). Table 2 shows the pairwise comparisons at electrode Pz where, across all conditions, the oddball P3 difference between targets and standards was highly reliable across all combinations of orientation and preference.

We also analyzed the difference waveforms of our ERPs across the preference and orientation conditions. These waveforms were calculated by subtracting standard trial ERPs from target trial ERPs, allowing us to better understand the differences in evoked activity between our two-tone types. Figure 5A shows the difference-wave ERP for the preferred and non-preferred stance in the MMN/N2b time window. Figure 5B shows the difference-wave ERP for the clockwise and counterclockwise conditions in the MMN/N2b time window. A 2x2 repeated measures ANOVA was calculated for electrodes Fz and Pz and their respective time windows, as described previously. Our results at electrode Fz show no significant effect of preference ($F(1, 28) = 2.04$, $p = 0.17$, $\eta^2_p = 0.07$) or orientation ($F(1, 28) = 0.92$, $p = 0.35$, $\eta^2_p = 0.03$), and no significant interaction ($F(1, 28) = 0.01$, $p = 0.91$, $\eta^2_p = 4.78e\text{-}4$).

Figure 5C shows the difference-wave ERP by preference conditions at electrode Pz for the P3 time window. Figure 5D shows the difference-wave ERP for the clockwise and counterclockwise conditions in the P3 time window. Similar results also occur for electrode Pz, with no significant effect of preference ($F(1, 28) = 0.41$, $p = 0.53$, $\eta^2_p = 0.02$), or orientation ($F(1, 28) = 1.42$, $p = 0.24$, $\eta^2_p = 0.05$), and no significant interaction ($F(1, 28) = 0.83$, $p = 0.37$, $\eta^2_p = 0.03$).

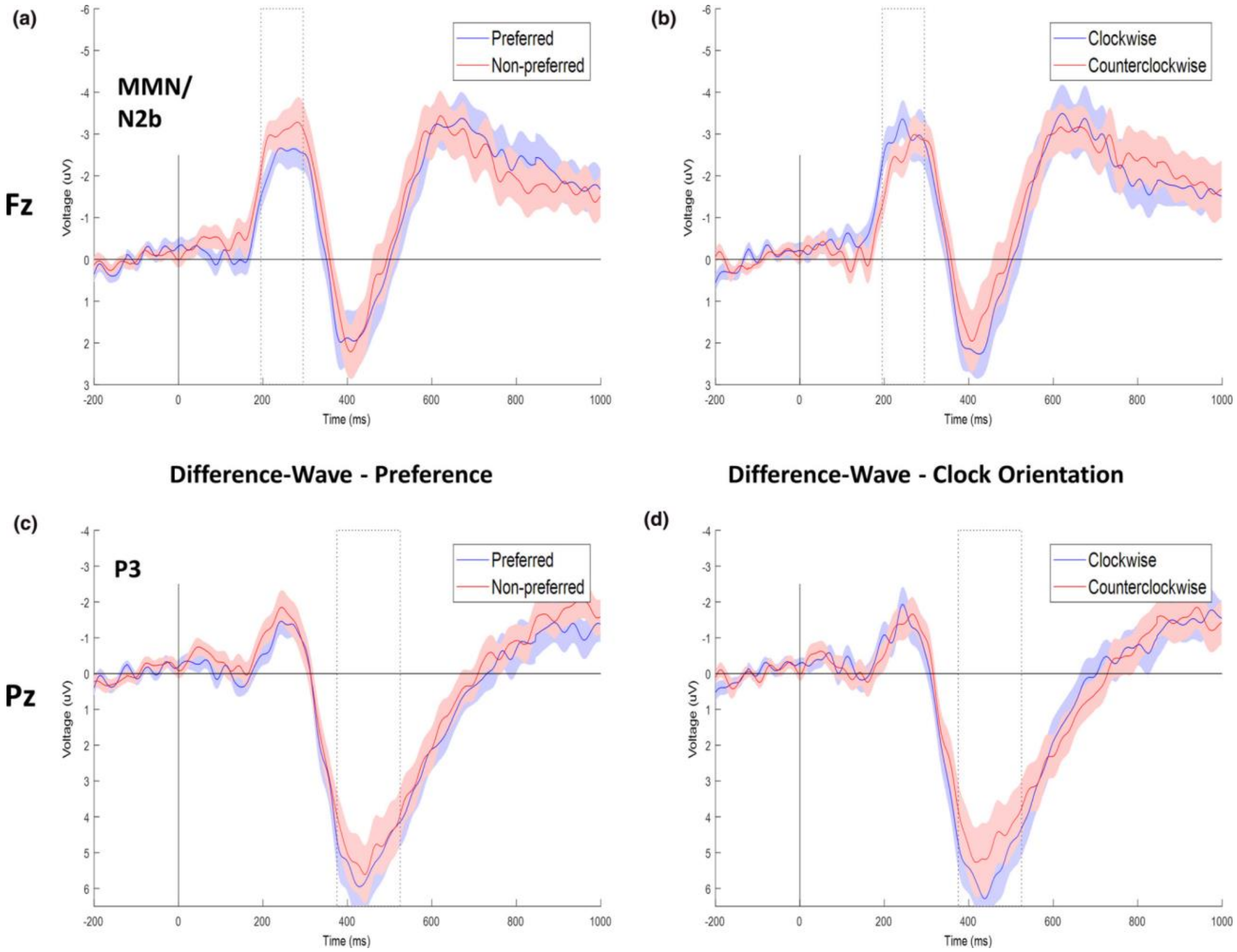


Figure 2.5. Difference-wave ERPs by (a) grand preference for the MMN/N2b time window at electrode Fz. (b) grand clock orientation for the MMN/N2b time window at electrode Fz. (c) grand preference for the P3 time window at electrode Pz. (d) grand clock orientation for the P3 time window at electrode Pz

### *Spectral Results*

Figure 6A shows the power spectra plots for all four conditions for the frequency range 1-30 Hz at electrode Fz. Resting-state baseline spectra for eyes open-close conditions is also depicted. These resting-state power spectra show a predominant peak within the alpha frequency range (8-12 Hz) which is larger during the eyes-closed condition. Power topographies for the preferred and non-preferred clockwise conditions (upper region) and preferred and non-preferred counterclockwise conditions (lower region) were generated for the alpha frequency range.

Topographies show higher power distribution across central parietal-occipital regions, particularly in the non-preferred conditions. Figure 6B shows the power spectra for all conditions and baseline at electrode Pz. Figures 6C-D depict the FOOOF- background EEG spectra used for statistical analysis. This spectra plot shows a clear peak in the alpha frequency in the resting state condition that is more predominant in the eyes-closed condition. These spectra plots also reveal an increase in the Beta activity (13-30 Hz) in all the riding conditions relative to the eyes open spectra at electrodes Fz and Pz likely due to muscle activity.

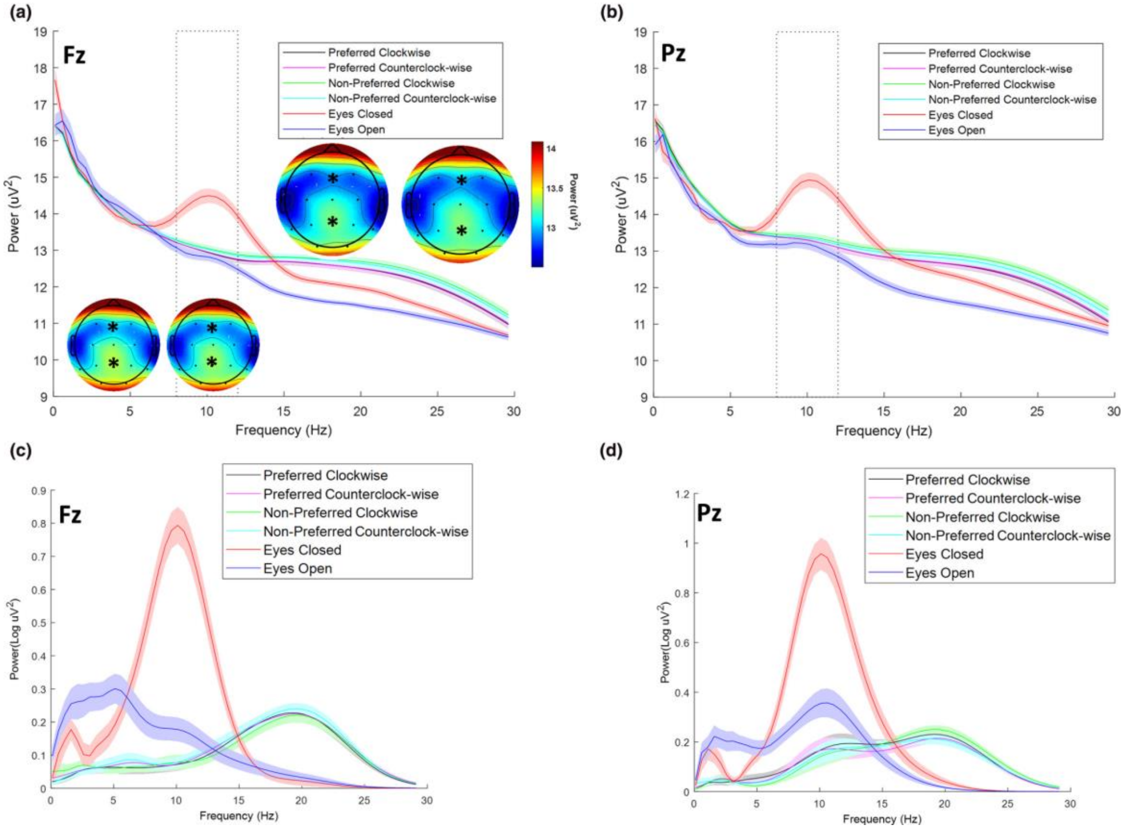


Figure 2.6. (a) Power spectra at electrode Fz for all conditions plus resting-state baseline (eyes opened/closed). Shaded regions represent standard errors for all conditions. Power topographies for alpha band range (8–12 Hz) for preferred clockwise and counterclockwise conditions (upper region) and non-preferred clockwise and counterclockwise conditions (lower region). (b) Power spectra at electrode Pz for all conditions. (c) FOOOF-background data used for statistical analysis at electrode Fz. (d) FOOOF- background data used for statistical analysis at electrode Pz

Relative to the resting state, there is a general decrease of alpha power in the riding conditions. A one-way repeated measures ANOVA was conducted to assess the differences in alpha peak for all conditions at electrodes Fz and Pz. A Greenhouse-Geisser correction of sphericity was applied to the analysis ($\varepsilon_{Fz} = 0.38$, $\varepsilon_{Pz} = 0.44$). Significant effects of condition type were observed for electrode Fz ($F(1.91, 49.66) = 84.84$, $p < 0.001$, $\eta^2_p = 0.76$) and electrode Pz ($F(2.12, 57.50) = 58.01$, $p < 0.001$, $\eta^2_p = 0.69$). Table 3 shows the significant pairwise comparisons. All p-values were adjusted for multiple comparisons using Bonferroni correction. This analysis shows that both resting-state conditions (eyes open and eyes closed) are significantly different from all skateboard conditions at electrode Pz and marginally significant at electrode Fz. There are no further significant differences between conditions. We conducted a two-way repeated-measures ANOVA using preference and clock orientation as factors at electrodes Fz and Pz. We did not find a main effect for either riding preference ($F(1, 26) = 0.38$, $p = 0.57$, $\eta^2_p = 0.01$) or riding orientation ($F(1, 26) = 3.46$, $p = 0.07$, $\eta^2_p = 0.009$). No significant main effects were found at electrode Pz for preference ($F(1, 26) = 1.65$, $p = 0.20$, $\eta^2_p = 0.060$) or riding orientation ($F(1, 26) = 0.2$, $p = 0.603$, $\eta^2_p = 0.01$).

**Table 3:** Pairwise results comparing A) Baseline Eyes Closed and B) Baseline Eyes Open spectra to each of the other five conditions.

**A**

| Comparison | Electrode | Mean Spectra Difference ($\mu V^2$) | | *p* | Confidence Interval | Effect Size (Cohen's d) |
|---|---|---|---|---|---|---|
| **Baseline Eyes Open** | Fz | -0.51 | -13.46 | <0.001 | -0.62:-0.39 | 2.59 |
| | Pz | -0.50 | -9.79 | <0.001 | -0.22:-0.32 | 1.88 |
| **Preferred Clockwise** | Fz | 0.62 | 16.39 | <0.001 | 0.50:0.73 | 3.15 |
| | Pz | 0.67 | 13.20 | <0.001 | 0.52:0.83 | 2.54 |
| **Preferred Counterclockwise** | Fz | 0.61 | 16.39 | <0.001 | 0.50:0.73 | 3.13 |
| | Pz | 0.68 | 13.23 | <0.001 | 0.52:0.83 | 2.54 |
| **Non-preferred Clockwise** | Fz | 0.61 | 16.26 | <0.001 | 0.50:0.73 | 3.12 |
| | Pz | 0.70 | 13.72 | <0.001 | 0.55:0.85 | 2.64 |
| **Non-preferred Counterclockwise** | Fz | 0.61 | 16.16 | <0.001 | 0.50:0.72 | 3.11 |
| | Pz | 0.69 | 13.52 | <0.001 | 0.54:0.84 | 2.60 |

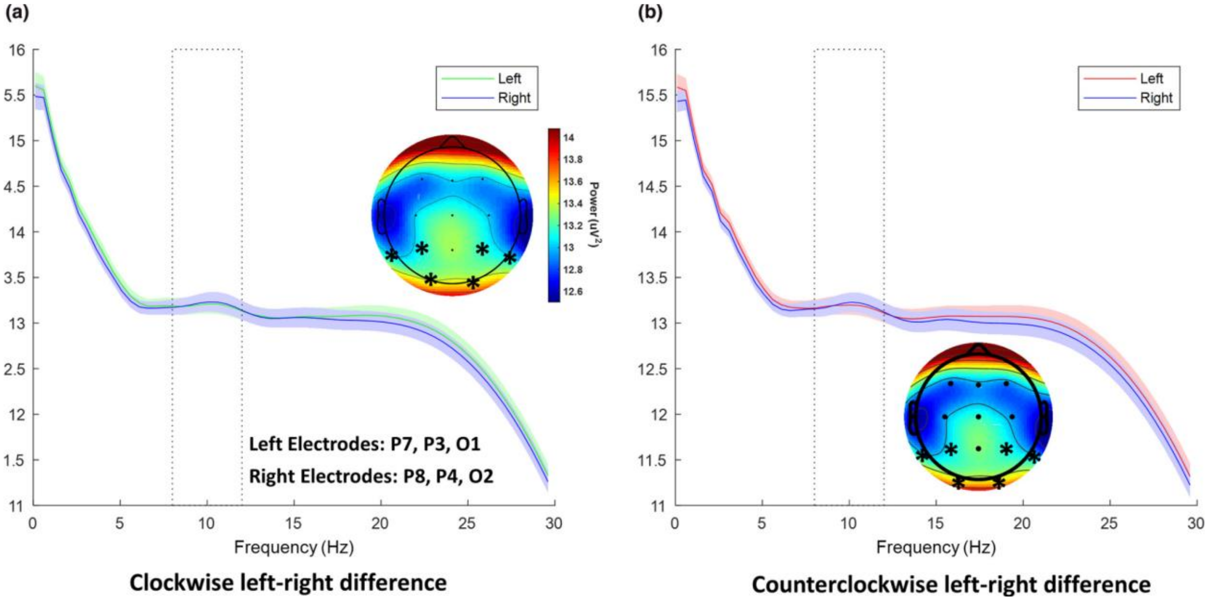
**B**

| Comparison | Electrode | Mean Spectra Difference ($\mu V^2$) | *t*(26) | *p* | Confidence Interval | Effect Size (Cohen's d) |
|---|---|---|---|---|---|---|
| **Baseline Eyes Closed** | Fz | -0.51 | -13.46 | <0.001 | -0.62:-0.39 | -2.59 |
| | Pz | -0.50 | -9.79 | <0.001 | -0.65:-0.35 | -1.88 |
| **Preferred Clockwise** | Fz | 0.11 | 2.93 | 0.060 | -0.002:0.22 | 0.56 |
| | Pz | 0.17 | 3.41 | 0.013 | 0.02:0.32 | 0.65 |
| **Preferred Counterclockwise** | Fz | 0.10 | 2.82 | 0.083 | -0.006:0.22 | 0.54 |
| | Pz | 0.17 | 3.90 | 0.012 | 0.02:0.33 | 0.66 |
| **Non-preferred Clockwise** | Fz | 0.10 | 2.80 | 0.088 | -0.007:0.22 | 0.53 |
| | Pz | 0.20 | 3.93 | 0.002 | 0.04:0.35 | 0.75 |
| **Non-preferred Counterclockwise** | Fz | 0.10 | 2.70 | 0.11 | -0.011:0.21 | 0.52 |
| | Pz | 0.19 | 3.72 | 0.004 | 0.03:0.34 | 0.71 |

*Left-right hemispheric alpha by preference and riding orientation*

We conducted an additional exploratory analysis to measure whether peripheral distractors influence alpha lateralization (due to the role of alpha synchronization in suppressing irrelevant areas of the visual field), we compared the left minus right hemisphere difference in alpha band power based on riding orientation (clockwise vs counterclockwise).

Figure 7 shows the left and right parieto-occipital alpha power by riding direction in the clockwise (left side panel) and counterclockwise (right panel) conditions. We conducted a t-test of the power difference between left-right hemispheres in the clockwise and counterclockwise conditions. Such t-test revealed no differences in hemispheric alpha power between conditions ($t(28) = 0.12$, $p = .90$ d = 0.02).



**Left Electrodes: P7, P3, O1**

**Right Electrodes: P8, P4, O2**

**Clockwise left-right difference**

**Counterclockwise left-right difference**

Figure 2.7. Power spectra for left and right parieto-occipital hemispheres for clockwise direction (left) and counterclockwise direction (right)

## 2.4 Discussion

The present study employed a mobile EEG paradigm to successfully record ERP components and oscillatory activity from participants moving on an e-skateboard. Participants responded to an auditory oddball task while riding around a complex scenario in their preferred and non-preferred stances. We introduced a higher degree of motor interference in the non-preferred condition to evaluate whether there was a change in resource allocation measured by the posterior P3 amplitude. To our knowledge, this is the first portable EEG experiment using skateboarding. We chose to use a skateboarding paradigm for several reasons: We wanted to deploy the mobile EEG methodology previously developed by our research group (Kuziek et al., 2017; Scanlon et al., 2017) to a novel scenario using a new task, as it is important to demonstrate that this mobile EEG methodology can help researchers design and test attentional paradigms away from the laboratory. Our study further demonstrates the robustness of the oddball-P3 effect under a novel skateboard task, providing further evidence that classic attentional paradigms can be replicated under less controlled environments and complementing a long history of laboratory research using this task (Kok, 2001).

The implementation of the e-skateboards (and e-scooters) offers a simple solution to the problem of excessive motion artifacts during EEG data collection while allowing participants to freely move in space. Considerable efforts have been made to ensure that the contribution of motion artifacts in the EEG data is managed effectively, such as the integration of portable EEG in experiments involving movement and action. For example, the MoBI approach  (see Makeig et al., 2009; Gramann et al., 2010; Gwin et al,.2010) simultaneously records EEG, muscle movements, and environmental events to study cognitive processes away from the traditional EEG approach that requires substantial restrictions in human behavior.

The groundbreaking MoBI approach has adopted multi-data streaming that includes electromyographic sensors and relies on advanced decomposition techniques to achieve the ultimate goal of exploring human cognition under natural and unconstrained behavior. According to Gramann (2014) “new techniques are now required for studying cognition under a more general range of conditions that include natural motor behavior” (p. 1). The present skateboarding approach is a simple but highly effective tool that can help mobile researchers accomplish that goal of conducting research while subjects can perform unconstrained navigation. As it was pointed out by Nenna and colleagues (2020), many MoBI studies have used artificial setups (e.g., treadmills in walking studies) where motor behaviors are not captured as they would occur in everyday fashion. We deployed the skateboard paradigm to a running track, but future studies can make use of different environments (parks, roads, etc.) to achieve great ecological validity while exploring cognition. Given that balance during e-skateboarding can be easily accomplished by maintaining a proper center of gravity (e.g., keeping one’s legs spread well enough), this new paradigm can be a great tool for mobile EEG researchers who want to adopt a naturalistic task that does not introduce excessive motion artifacts during recording.

### *Behavioral results*

In the current study, participants responded to target tones by pressing a button with their left hand. We calculated response accuracy and reaction time based on the four experimental conditions (preferred-clockwise, preferred-counterclockwise, non-preferred-clockwise, and non-preferred-counterclockwise) and by the grand averaged preferred and non-preferred conditions. We found no significant differences in accuracy or reaction time across conditions, even though accuracy was marginally higher in the preferred stance condition. Additionally, there was a larger standard deviation in the non-preferred condition for both accuracy and reaction time, suggesting that participants performed more uniformly in the preferred stance. These results contrast previous findings, such as Reiser et al. (2019), where increases in motor task difficulty in an oddball paradigm were associated with poorer task performance. It is possible that behavioral effects could not be achieved by our oddball task due to a ceiling effect since mean accuracy was quite high in all conditions.

### *P3 & MMN/N2b results*

We hypothesized that the target-related P3 would be larger in the preferred stance condition due to differences in riding difficulty. Previous research shows that an increase in task difficulty (i.e., riding in one's least comfortable stance) should be reflected in a more negative amplitude voltage in the P3 time window (Kok, 2001; De Sanctis et al., 2014). While we were able to measure significant, and expected, differences between ERPs following standard and target tones (we were able to detect a P3 response following rare stimuli as shown in Figure 2B and Table 2) we found no significant P3 differences between our conditions. Previous mobile EEG studies in naturalistic environments have shown a P3 amplitude decrease during increased task load in walking (Ladouce et al., 2019) and cycling (Scanlon et al., 2020; Scanlon, Townsend, et al., 2019; Zink et al., 2016).

We expected that the increase in difficulty in the non-preferred riding condition was going to be marked by a more negative voltage within the P3 time window. However, we failed to find differences in our current paradigm. Similar results were reported by Gramann et al. (2010), where they show no differences in P3 amplitude based on increases in motor demands in a visual oddball task. Interestingly, previous findings from Ladouce and colleagues (2019) show that the P3 amplitude reduction seen during cognitive interference is not modulated by motor demands from the act of walking itself. These results go against the view that increases in task load in the motor domain lead to a reduction of cognitive resources (Leone et al., 2017). Additionally, Ladouce has shown that resource allocation during movement is modulated by both inertial and visual stimulation at the sensory level. It could be possible the similarity in visual and inertial stimulation during the preferred and non-preferred conditions might have modulated the parietal P3 amplitude in the same magnitude regardless of riding difficulty. If this is the case, one can expect a similar level of reduction in P3 amplitude during e-skateboarding regardless of a possible increase in riding difficulty. Considering that no behavioral differences in accuracy and reaction time were found by increasing riding difficulty, it is possible that the change in stance preference did not interfere with the cognitive resources employed by the oddball task. Future paradigms should consider increasing the oddball task difficulty (e.g., manipulating tone frequency), or the non-preferred task difficulty (e.g. wobbly skateboards).

We also found an MMN/N2b difference between target-standard tones in all our experimental conditions. These results replicate previous EEG findings from other cycling studies by our research group (Scanlon et al., 2017; Scanlon, Townsend, et al., 2019). This ERP component is elicited by sudden changes or deviations following the repeated presentation of a stimulus, such as the change from target to standard tones (S. H. Patel & Azzam, 2005). While the standard-target amplitude difference is present in all our conditions, we did not find differences in this component based on riding preference. The lack of differences in MMN/N2b amplitude is likely due to the environmental noise being the same in all task conditions for participants, reflected in similar ERP amplitudes across conditions.

*Spectral Results*

We recorded each participant's eyes open/close baseline spectra before completing the oddball task. We found an expected and significant increase in power within the alpha range (8-12 Hz) at electrodes Fz and Pz for the eyes-closed condition compared to the eyes-open, as shown in Table 3. Additionally, we found a complete attenuation of alpha power during the skateboard task relative to both baseline conditions at electrode Pz. At electrode Fz, this general reduction of alpha power between resting state and riding was found to be overall marginally significant at electrode Fz (table 3). These results support the findings of previous studies showing a decrease in alpha during complex behaviors such as walking (Beurskens et al., 2016; Storzer et al., 2016) and bicycle riding (Zink et al., 2016; Scanlon et al., 2020). However, it is important to note that this reduction in alpha power should not be taken as evidence that the experimental manipulation leads to quantifiable reductions in alpha since participants did not complete the oddball task during the resting conditions.

One of the goals of the present study was to assess whether increases in riding difficulty would be reflected in a reduction in the alpha band, based on our understanding that alpha power is modulated by increases in task demand (Foxe, et al., 2011). However, there were no significant differences in alpha power based on riding preference. Since we found an overall decrease in power during the task relative to their resting state power, it is possible that the desynchronization in alpha power we found is likely due to an overload of incoming stimuli from the task and environment that would induce a general state of cortical excitability (Klimesch et al., 2011). We found an unexpected increase of power in the beta band (13-30 Hz) in the skateboarding conditions relative to the resting spectra (Figure 6). We attribute this increase of power to increased muscle movements. Similar results were reported by Scanlon et al., (2019), showing an overall increase in beta power during outdoor cycling. This beta increase during the riding conditions contradicts previous findings linking beta desynchronization to active movements (Jain et al., 2013).

An exploratory goal in the present study was to measure the potential influence of peripheral distractors in alpha lateralization suppression. Generally speaking, participants consistently experienced a higher number of distractors in the inner tracks of the running pavilion due to joggers and track users present while participants completed the experimental task. Based on previous findings showing shifts in hemispheric alpha based on the location of spatial distractors (Sauseng et al., 2005; Kelly et al, 2006; Ikkai et al., 2016), we were motivated to compare parieto-occipital alpha power across hemispheres to measure whether we could get an effect in overall lateralization without systematically manipulating distractor location. We found no significant differences in mean alpha power in parieto-occipital regions. In a study by Malcolm et al., (2018) exposure to optic flow was found to attenuate parietal alpha power during walking. It might be possible that the state of motion experienced by the skateboarders led to a consistent suppression of induced alpha power between conditions. We did not find any reliable effects in terms of alpha lateralization, but more suitable cueing paradigms that fully isolate distractor location could help in answering whether alpha lateralization to visual distractors during active motion occurs.

### *ERSP plans*

We should acknowledge that we did not look at task-evoked activity in this, or in any previous study from our research group. This is an important avenue for future mobile studies interested in exploring short-term changes in cortical excitability evoked by task events. Changes in evoked power within certain frequencies (e.g., decreases in alpha/increases in beta) following periods of interest reflect the allocation of attentional resources that facilitate task performance (Mathewson et al., 2011). For instance, authors have previously shown event-related desynchronizations in the alpha band during the P3 period in an oddball task (Bernat et al., 2007). Since desynchronization in alpha power has been associated with increases in excitability and information processing (Klimesch et al., 2007), it would be relevant to explore evoked changes in alpha power during motion in the current paradigm. Additionally, increases in frontal theta power have been previously associated with increases in cognitive load (Flumeri et al., 2018), and during periods of response inhibition thereby reflecting increases in executive control (Nigbur et al., 2011). Exploring the temporal dynamics of frontal theta activity during preferred and non-preferred riding could be an interesting avenue to pursue since changes in mean theta activity have been linked to levels of mental effort devoted to task completion (Onton et al., 2005).

### *Limitations to generalizability*

While this research was able to successfully elicit the expected effects related to the ERP and spectral differences for the oddball and baseline tasks respectively, there are still several limitations of this study that must be further discussed. One such limitation is that we failed to quantify the participants’ perceived riding difficulty between the preferred and non-preferred conditions. This could have informed us about the degree of riding interference experienced by participants in the non-preferred condition and the relationship between subjective riding difficulty and overall ERP amplitude. Interestingly, Nenna et al. (2020) reported that even when participants do not experience subjective mental load in dual tasks when compared to a single task, it is still possible to obtain differences in neural responses. It could be possible that the expected increase in difficulty between the preferred and non-preferred conditions is being nullified by the electric skateboard in a way that participants can easily adapt to riding in their non-preferred stance since the board is self-propelling and very stable.

We also did not measure torso muscle activity and acceleration on the body. Skateboarding has little overt movement but relies on balance using the torso and proximal muscles of the legs and arms. Further research could correlate changes in these muscle groups during different riding conditions with brain activity and sensory input to objectively quantify muscle involvement and motor task interference. More critically, by failing to record the acceleration between preferred and non-preferred conditions we could not record whether a hypothetical increase in task difficulty led to motor adjustments (e.g., slowing down) as a mechanism to enhance task performance (see Al-Yahya et al., 2011; De Sanctis et al., 2014). Additionally, while this skateboard paradigm offers the opportunity to greatly minimize covert movements (in comparison to walking or bicycle riding paradigms), it does not eliminate muscle movements methodically. Another limitation in the present study is the lack of an experimental condition where participants complete the oddball task while not moving. Our initial motivation to conduct this study was to test whether a change in riding difficulty leads to measurable changes in the ERP and oscillatory domains. While the inclusion of a non-riding oddball condition would have improved the present results, we believe that the preferred vs non-preferred comparison is suitable for the present research question.

The auditory oddball task used did not result in significant behavioral, ERP, or spectral alpha power differences between conditions, contrary to our expectations. Given that the field of mobile EEG is developing, obtaining behavioral effects in line with ERP results is an important step in understanding brain processes in real-life scenarios. This limitation may be attributable to our sample size; however, given that we are able to measure the expected oddball and spectral alpha differences, with large effect sizes, we believe the lack of difference between our skateboarding conditions could be due to other limitations. The auditory oddball task we used may be too easy, with any behavioral or electrophysiological changes hitting a ceiling regardless of condition. A possible solution would be to utilize a more difficult auditory oddball task where the stimuli are more similar or introduce distractor stimuli throughout the task. Given that participants are on a constantly moving skateboard, with a constantly changing visual environment, a visual oddball task may be more appropriate and attentionally demanding.

## 2.5 Conclusion

In the current study, we developed a skateboard EEG paradigm and replicated the classic oddball P3 effect while participants freely skated through a busy running track. While we found consistent target-standard tone differences in the P3 and MMN/N2b in frontal and parietal regions, we did not observe a reduction in P3 amplitude following increases in riding difficulty. We also present evidence that the classic peak in resting-state alpha completely diminishes while skateboarding and this overall desynchronization is the result of an increased load of incoming stimuli from the environment and task. The results in the current study support the notion that EEG paradigms are suitable for the study of human cognition under high ecological validity.

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# Chapter 3 - Surrounding Traffic Matters: Increases in Traffic Volume Are Related to Changes in EEG Rhythms in Urban Cyclists

## 3.1 Introduction

### Breaking away from the laboratory

From the early days of scientific psychological research until now, most published research has occurred inside research laboratories. This traditional research has prioritized high experimental control during data collection (Bigdely-Shamlo et al., 2016). For instance, to maintain high internal validity, researchers have stressed the importance of controlling for extraneous factors such as light, noise, and temperature (Luck, 2014). When it comes to studying human attention, techniques such as electroencephalography (EEG) require high standards in experimental control due to its vulnerability to physical movement such as foot tapping, jaw clenching, and eye blinking. For example, it is commonly known that several sources of physical noise such as movement, and biological artifacts, such as heartbeat and respiration, can cause temporary distortions in EEG signals (Delorme et al., 2007). These artifacts are inherent to EEG and require proper collection techniques; training participants to blink less or in irregular intervals or applying correction/rejection techniques (Makeig et al., 2009). Virtually, most of what we know about human brain processes related to attention and cognition comes from laboratory paradigms. Not surprisingly, researchers have previously argued that the dynamic nature of brain processes should be studied under equally dynamic environments where subjects can walk, reach, and navigate (Gramann et al., 2014; Jungnickel et al., 2019; Ladouce et al., 2017; Reiser et al., 2019)

Fortunately, the evolution of modern technology has brought unprecedented computing power to portable devices such as phones and minicomputers. These advancements have directly enabled researchers to use EEG in naturalistic actions and environments (Scanlon, Townsend, et al., 2019). A powerful approach known as mobile brain/body imaging (MoBI) was developed to study movement and brain dynamics in three-dimensional environments (Makeig et al., 2009). These brain/body dynamics are captured by collecting data from several sources, including EEG and movement sensors and the timing of events in the environment. Ultimately, MoBI approach aims to understand the relationship between active behaviors (moving, touching, and pointing) and brain dynamics associated with these behaviors (Jungnickel & Gramann, 2016). Since artifacts and noise are known to affect EEG quality, mobile approaches rely on data-cleaning techniques such as independent component analyses for data cleaning and processing (Gwin et al., 2010).

Previous studies from our research group have focused on the development and use of mobile paradigms. This includes the validation of mini computers such as the Raspberry Pi minicomputer as a valid alternative for EEG data collection (Kuziek et al., 2017), using the Muse headband for stroke prediction in ambulance/ER settings (Wilkinson et al., 2020), and deploying the Muse headband for EEG data collection in rural communities in Malawi (Neto et al., 2021). In several studies, our workgroup used mobile settings to explore the role of several attentional mechanisms during active tasks. For example, we developed and validated an e-skateboard paradigm to study attentional allocation during active skateboarding (Robles et al., 2021). In that study, we manipulated task difficulty by having participants complete an auditory oddball task while riding a Bluetooth-operated e-skateboard around a busy running track. We found that increases in motor difficulty were not associated with changes in the P3 event-related potential (ERP), commonly linked to the reallocation of cognitive resources (Sanctis et al., 2014). We also found global reductions in alpha power during skateboarding relative to a resting condition. It was concluded that such a change in alpha power could be due to the skateboarding task inducing increased cortical excitability (Sauseng et al., 2009).

Several studies from our workgroup have used a cycling paradigm to study attention in naturalistic settings. Using an auditory oddball paradigm, the authors deployed a cycling EEG paradigm where subjects performed the task while cycling outside and sitting down in a Faraday chamber (Scanlon, Townsend, et al., 2019). They found a decrease in alpha power and P300 amplitude outdoors relative to the laboratory condition associated with the reallocation of cognitive resources while cycling. Notably, they found that cycling outdoors was associated with decreases in P2 and increases in N1 amplitude. The N1 is a negative early deflection in the ERP that is generally greater for the attended, as opposed to the ignored, stimuli (Woldorff & Hillyard, 1991). That effect was further replicated in a different study where participants rode a bicycle in a quiet park and next to a busy road (Scanlon et al., 2020). It was found a consistent increase in N1 amplitude alongside the busy road relative to the quiet indoor environment. Other studies concluded that the increase in N1 amplitude could serve as an auditory filtering mechanism to better process the tones in the noisier environment. In a laboratory experiment, (Scanlon, Cormier, et al., 2019) administered the auditory oddball task while participants listened to various sources of noise (white noise, silence, outdoor sounds). This study found an increase in N1 and a decrease in P2 amplitude when participants listened to a white noise mask and traffic sounds. It was concluded that the N1/P2 modulations could reflect sensory filtering of the background noise, particularly to ecologically valid sounds. By deploying a mobile EEG paradigm outdoors, these cycling studies suggest that different environmental conditions lead to predictable changes in early sensory ERP amplitude as a mechanism of auditory filtering.

Other EEG studies have explored similar indices of attention under naturalistic behaviors such as walking. Many of these studies have assessed resource allocation using various electrophysiological indices such as the P3 and EEG frequency spectra such as the alpha and beta bands. For instance, (Zink et al., 2016) also found that outdoor cycling was associated with a decrease in alpha power and P3 peak amplitude relative to indoors. The authors suggested that an increased cognitive workload outdoors could drive the differences in P3 and alpha amplitude. In a dual-task paradigm, (Liebherr et al., 2018) showed that increases in both cognitive difficulty and motor demands lead to a more negative P3 amplitude. (Ladouce et al., 2017) concluded that the observed reductions in P3 amplitude could be related to sensory inertial processing (during physical displacement through space) as opposed to the action of walking alone. Interestingly, (Storzer et al., 2016) found that, relative to cycling, walking is associated with a greater alpha power decrease. These authors argued that the sensory processing and motor planning associated with walking could lead to the decrease of alpha power observed.

## Different infrastructures, different attentional demands?

Cycling has been shown to improve individual physical health, including cardiovascular health (Oja et al., 2011). Furthermore, cycling can improve an individual’s mental well-being (Ma et al., 2021). Given these benefits, it would be important for governments to consider how to encourage cycling for residents. One study suggests that cyclists experience less physiological stress where cycling infrastructure exists (Teixeira et al., 2020). While many distractors can compromise cycling safety, our current study aimed to understand the influence of traffic volume noise in different cycling environments. Inspired by the findings from Scanlon and colleagues suggesting differences in auditory filtering in indoor vs outdoor cycling (2019) and in noisy roadways relative to quiet park areas (2020), the current study aimed to test the effects of traffic volume in different types of bicycle lanes. The current study explores the reallocation of cognitive resources (as measured by the N1/P2 and P300 ERPs and alpha power) during active bicycle riding. Participants completed an auditory oddball task while riding a bicycle in different cycling environments (heavy, intermediate, and low traffic). Using these differences in road types as the experimental conditions, we hypothesized that, relative to low traffic, heavy traffic riding should be associated with changes in auditory processing related to N1 and P2 amplitude. That is, riding during heavy traffic should increase attentional demands in the bicycle-oddball task. We also hypothesized that relative to a low traffic condition, riding in the heavy traffic condition should lead to decreases in positivity in the P3 ERP and alpha power alike.

## 3.2 Methods

### Participants

A total of 24 individuals from the university community were recruited (mean age = 20.96, age-range = 18 - 27). Participants received an honorarium of ten dollars/hr. or two credits towards Research Participation for courses in the Psychology department. Participants presented no history of physical or neurological disorders. Before the experiment, each participant verbally confirmed that he/she/they were comfortable riding a bicycle. This study was approved by the Internal Research Ethics Board at the University of Alberta (Pro00050069), and participants signed an informed consent form before completing the study.

### Materials and procedures

In this experiment, participants rode a Kona Mahuna bicycle (figure 1A). Participants selected the bicycle size (17” or 19”) based on height, while the saddle height was adjusted based on the rider’s preference and comfort. The bicycles were equipped with a response button for the auditory oddball task. This button was attached to the right side of the handlebar and adjusted to each participant to ensure that they could respond with their right thumb while riding. This location of the response button allowed for smooth handling and access to the brake lever while responding to the task without moving the hand out of its natural riding position. In line with the work of (Scanlon et al., 2020), the bicycle gear/resistance was kept constant for all participants (second gear in the crankset and half gear in the cassette) for consistency and to maintain the physical activity at sub-aerobic levels throughout trials.

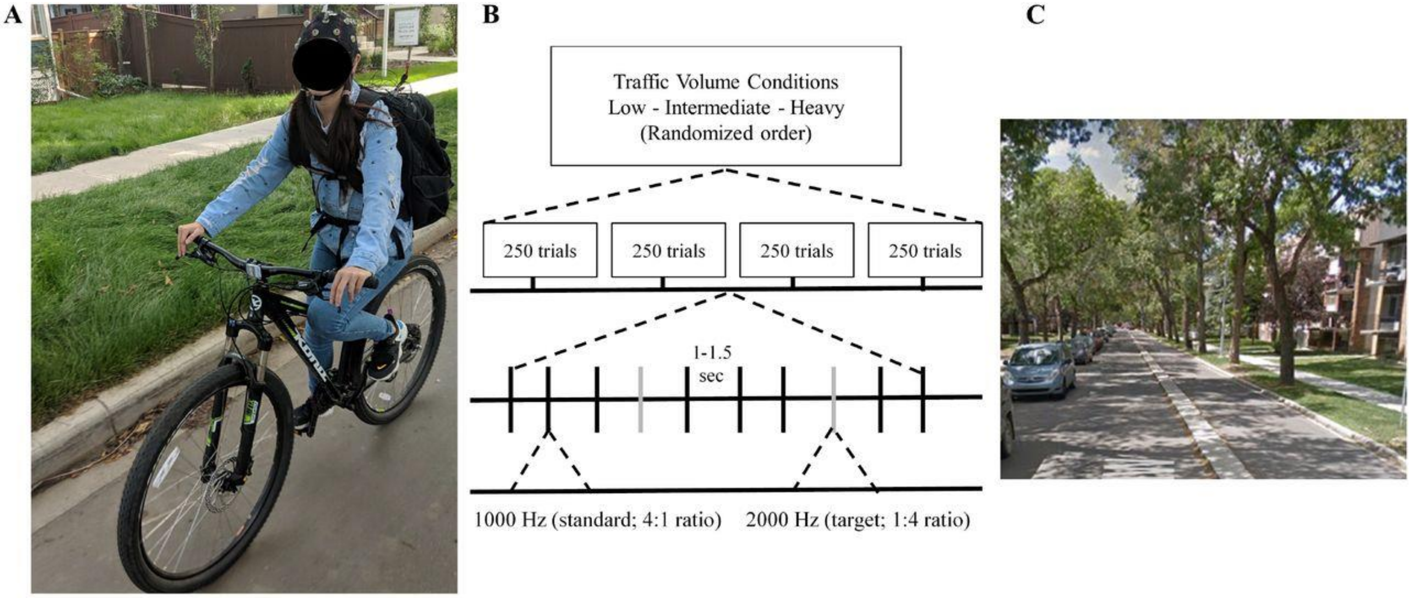
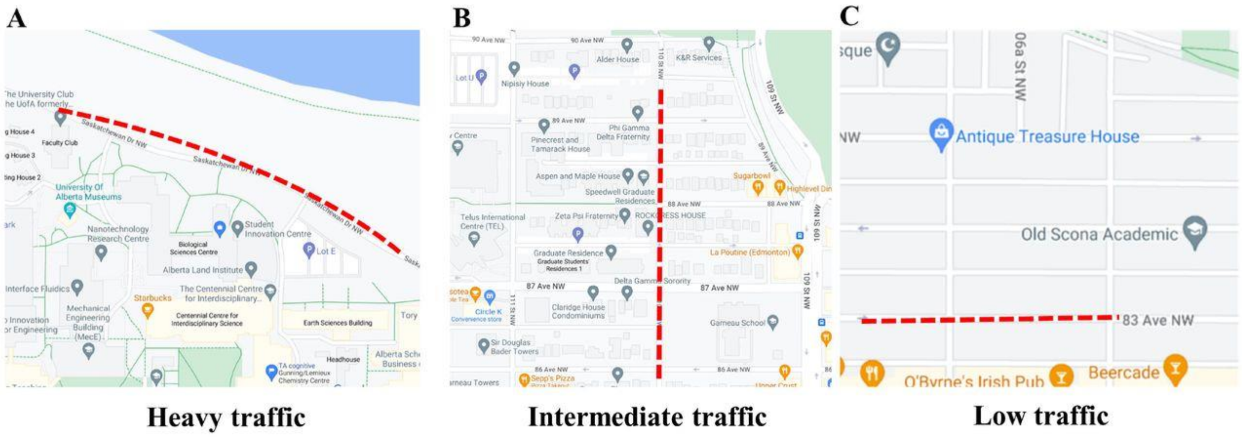


Figure 3.1. Setup and task. A: Bike EEG setup. B: Oddball task diagram. C: Experiment location sample.

Consistent with the methodology from our workgroup (Kuziek et al., 2017; Robles et al., 2021), the task was delivered via a Raspberry Pi 2 Model B computer using Version 9 of the Raspbian Stretch operating system and version 2.7.13 of Python. The Raspberry Pi was powered using a Microsoft Surface Pro 3 laptop. The task tones were delivered using Sony earbuds connected to a standard 3.5mm audio connector in the Pi computer. Using the GPIO pins in the Raspberry Pi 2, 8-bit TTL pulses were sent to the EEG amplifier through a wired connection.

The experiment was carried out in three different bicycle lanes nearby the north campus of the University of Alberta. During the time of data collection (August-October 2019), such lanes were characterized by different levels of traffic: (heavy traffic, intermediate traffic, and low traffic). Figure 1C shows a sample location of one of the experimental conditions. The heavy traffic condition (figure 2A) is located at the Saskatchewan Drive road lane (https://goo.gl/maps/BQG8ERJoEzcajz2WA). This lane is characterized as a multi-use path with a flow of fast traffic (50 km/hr) alongside the cycling space. Therefore, the ongoing sounds of the fast traffic should interfere with the participant's cognitive resources during the oddball-cycling task. This level of cognitive interference can be expected to be higher in heavy traffic and lower in quiet traffic. This lane is located in a designated multi-use path, and cyclists are protected from car traffic.

The next condition was the moderate traffic condition (Figure 2B). This lane was a painted bike lane located on 110 Street NW (https://goo.gl/maps/7v6y3UJUG3kPVm6v6). The traffic volume in this lane is lower than the heavy condition as it is located in a smaller, one-way street of local traffic. Importantly, this is a non-protected, striped bike lane. Therefore, since drivers pass close to the cyclists (> 2 meters), the sound of the passing cars is expected to interfere with the oddball task to a lesser degree than in heavy traffic. The low-traffic condition (Figure 2C), located at 83 Avenue NW (https://goo.gl/maps/RmKJCX97od5ARQE97), is a new protected-buffered bike lane characterized by the lowest traffic among all lanes. Given the characteristics of this lane, one can expect that cyclists will experience the least level of traffic noise interference in this condition. During the experimental conditions, participant speed/safety was enforced by a research assistant who rode in front of the participant at an average distance of 12 feet. The assistant was trained to slow down and come to a full stop if necessary (e.g., large incoming vehicles at intersections).



**Heavy traffic** **Intermediate traffic** **Low traffic**

Figure 3.2. Experimental Conditions. A: Heavy traffic. B: Intermediate traffic. C: Low traffic.

Participants completed an auditory oddball task (Squires et al., 1975). In this task, participants listened to a series of tones played consistently via headphones (1,000-Hz "standard" or 1,500-Hz "target" tone played at 65 dB). Participants were instructed to use the button to respond to the target tone and to withhold a button response to the standards. Participants responded to each target tone during a delay period (1,000-1,500 ms) that followed after each tone presentation during the experiment. Each experimental condition contained a set of 250 trials, with a total of 20% of these being the target tone (Figure 1B). Each condition lasted approximately 6 minutes. At the end of each condition, participants and research assistants rode the bicycles to the starting point of the following condition. Participants were given a small break between experimental conditions during which impedance levels were checked. The order of the conditions was randomized among participants.

## EEG Recording

The EEG signal was collected using active, wet, low-impedance electrodes (actiCAP active electrodes kept below 10 kΩ). At the start of the experiments and between conditions, impedance was lowered using a blunted syringe with SuperVisc electrolyte gel. Streamed data were visually inspected to ensure low levels of impedance. Using the 10-20 electrode system, we employed the following electrode set: F3, F4, T7, T8, C3, C4, P7, P8, P3, P4, O1, O2, Fz, Cz, Pz. Location AFz was used for the ground electrode. Ag/AgCl disk electrodes. Data were recorded online, referenced to the left mastoid, and re-referenced to the arithmetically derived average of the left and right mastoids offline.

A V-Amp 16-channel amplifier (Brain Products GmbH) was used to record the EEG data. The V-Amp was connected to the Microsoft Surface laptop, where the EEG was recorded using Brainvision Recorder software (Brain Products GmbH). Additionally, passive Ag/AgCl easy cap disk electrodes were used to record the vertical and horizontal bipolar electrooculography (EOG) via Bip2Aux adapters. EOG electrodes were affixed vertically above and below the left eye and affixed horizontally, 1 cm lateral from the outer canthus of each eye. Nuprep exfoliating cleansing gel (Weaver & Co) was used to clean the participant's skin before electrode placement. As previously mentioned, electrolyte gel was applied to each electrode to maintain inter-electrode impedance under 10 kΩ. EEG Data was digitized at 1,000 Hz with a resolution of 25 bits and hardware filtered online between 0.1 and 30 Hz, with a time constant of 1.5155 and a notch filter at 60 Hz. All the experimental equipment was carefully placed inside a Lululemon backpack. The Raspberry Pi, connection cables, headphones, and electrodes were strategically placed inside the backpack pockets and secured with Velcro bands to reduce cable sway and tension that could disconnect signals during data collection. The overall weight of the backpack was 4.55 lbs.

## EEG Processing

Analyses were computed in Matlab R2019a (MathWorks) using EEGLAB (Delorme & Makeig, 2004) and custom scripts (https://github.com/kylemath/MathewsonMatlabTools). Statistical analyses were computed on JASP (JASPTeam, Amsterdam, Netherlands). The EEG markers were used to construct 1200-ms epochs (200 ms pre-stimulus baseline) time-locked to the onset of standard and target tones, with the average voltage in the first 200-ms baseline period subtracted from the data for each electrode and trial. Variance in the data due to horizontal and vertical eye movements, as well as eye blinks were regressed out using the Eye Movement Correction Procedure (Gratton et al., 1983). An artifact rejection was applied and any trials with voltage differences from the baseline larger than +/- 500 µV were removed. The resulting number of rejected trials following procedures did not vary significantly across experimental conditions ($F(1.54,35.43) = 0.120$, $p = .83$).

## ERP Analysis

For the N1 and P2 analyses, time window cutoffs were chosen based on our workgroup's previous EEG cycling studies (Scanlon et al., 2020). The N1 time window was defined as the grand-average of the negative increase in amplitude between 118 and 218 ms, maximal at electrode Fz. This component showed a peak latency of 168 ms. The P2 time window was defined as the grand average of the positive increase in amplitude between 218 and 318 ms at electrodes Fz and Pz, with a latency peak of approximately 292 ms. The P3 time window was selected by computing a grand-averaged, difference-wave ERP across participants and conditions to avoid biasing the selected time window towards any condition). Using this grand-average waveform, we selected the peak of positive increase in amplitude between 355 and 505 ms. We selected the highest peak within this time window, resulting in a peak latency of 430 ms.

We conducted one-way, repeated-measures ANOVAs to test for ERP differences between the different bicycle lanes in the electrodes of interest. For instance, to test for the N1 and P2 differences across bike lanes, an ANOVA was run using the bike lane factor (Sask. Dr., 110 St., 83 Ave.) for the standard and target tones, respectively. For the P3 analysis, we conducted a one-way, repeated-measures ANOVA using the target-standard difference-wave ERP between the different bicycle lanes. The significance criteria $\alpha$ was set to 0.05 for all comparisons. Sphericity corrections were applied when necessary for the ERP and other ANOVAs in this manuscript.

### Spectral analysis

In addition to the ERP analysis, we were interested in investigating differences in overall sustained alpha power between bike lanes. We conducted an EEG frequency spectra analysis on the averaged EEG epochs using the wavelet routine from the Better Oscillation Method, BOSC (Hughes et al., 2012). The epochs consisted of a 1000 ms baseline and a 2000 ms post-stimulus period using the standard tones. We selected a 6-cycle wavelet transform across a frequency range of 0.1 Hz to 30 Hz, increasing in 0.5 Hz steps.

## 3.3 Results

### Behavioral results

Reaction times and accuracy were calculated for the three conditions. Figure 3.3A depicts the reaction times in participant response to the target oddball tone. For reaction time, using a Greenhouse-Geisser corrected one-way repeated measures ANOVA, we found a significant main effect for condition type ($F(1.455, 33.46) = 3.90$, $p = 0.042$, $\eta^2_p = 0.145$). A Holm adjusted post-hoc test revealed a significant increase in reaction time in the low traffic condition lane relative to heavy traffic. ($M_{diff} = -35.43$, $p = 0.01$). No further significant differences in reaction times were found among the different lanes. Figure 3B depicts participant accuracy to the target tones in the oddball task. A one-way repeated measures ANOVA found no significant differences in accuracy among the conditions ($F(2, 46) = 0.89$, $p = .415$, $\eta^2_p = 0.038$).

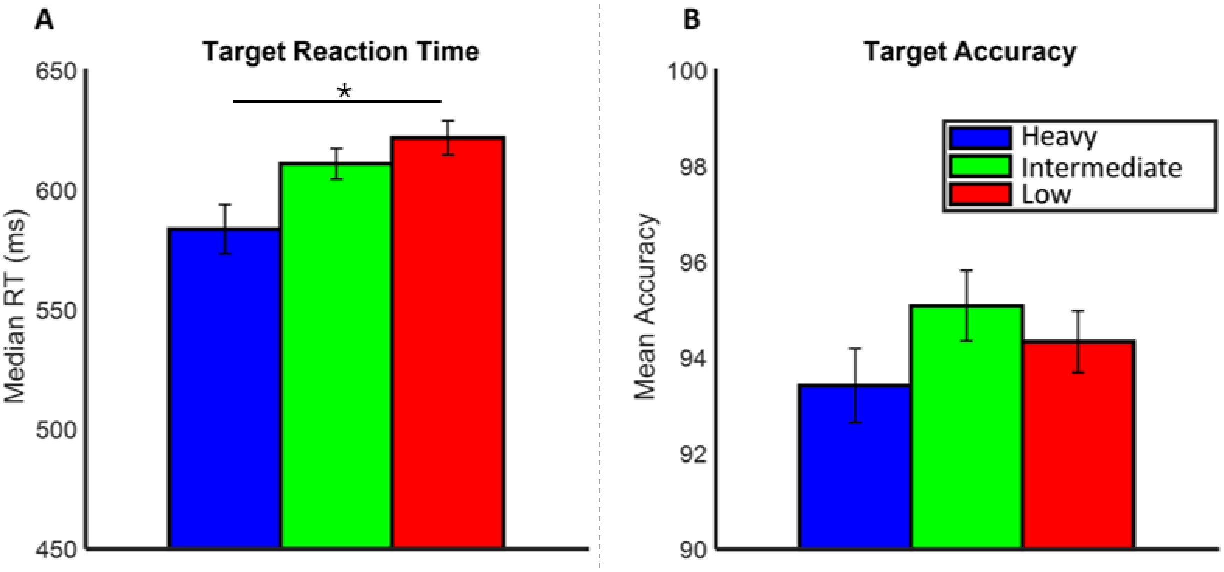


Figure 3.3. Behavioral results. A: Target accuracy. B: Target reaction time.

**ERP morphology and topography**

Figure 4 shows the grand average ERPs for standard and target tones at electrodes Fz and Pz for all traffic types. Standard tones are depicted in black, while target tones are depicted in colored lines. The shared regions depict the standard errors at each ERP line. A visual inspection of the grand-average ERPs shows an overall increase in negative voltage for the N1 time window (118-218 ms), followed by a positive increase at the P2 time window (218-318 ms) at all electrodes and in all conditions. Furthermore, there is an increase in positive voltage at the P3 time window for the target tones relative to the target tones showing a maximal difference at Pz.

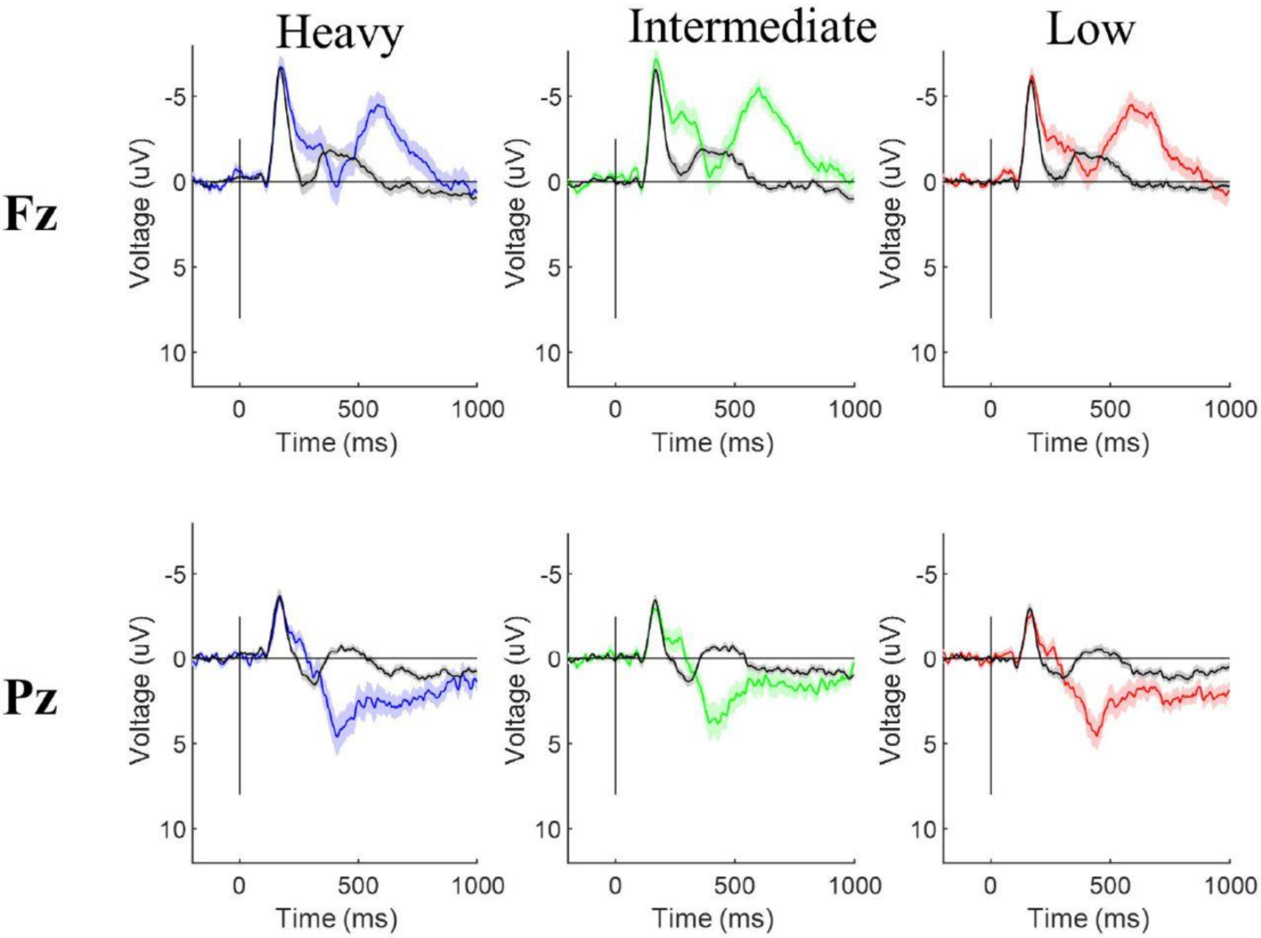


Figure 3.4: Grand-Average ERPs by traffic condition.

Figure 5A and 5B depict the topographies for the N1 and P2 time windows for the standard and target tones, respectively. The topographies for the chosen N1 time window show a fronto-central distribution. In contrast, the topographies for the P2 time window show a posterior distribution where the highest activity is located towards the parietal region and seen more prominently in the standard tones.

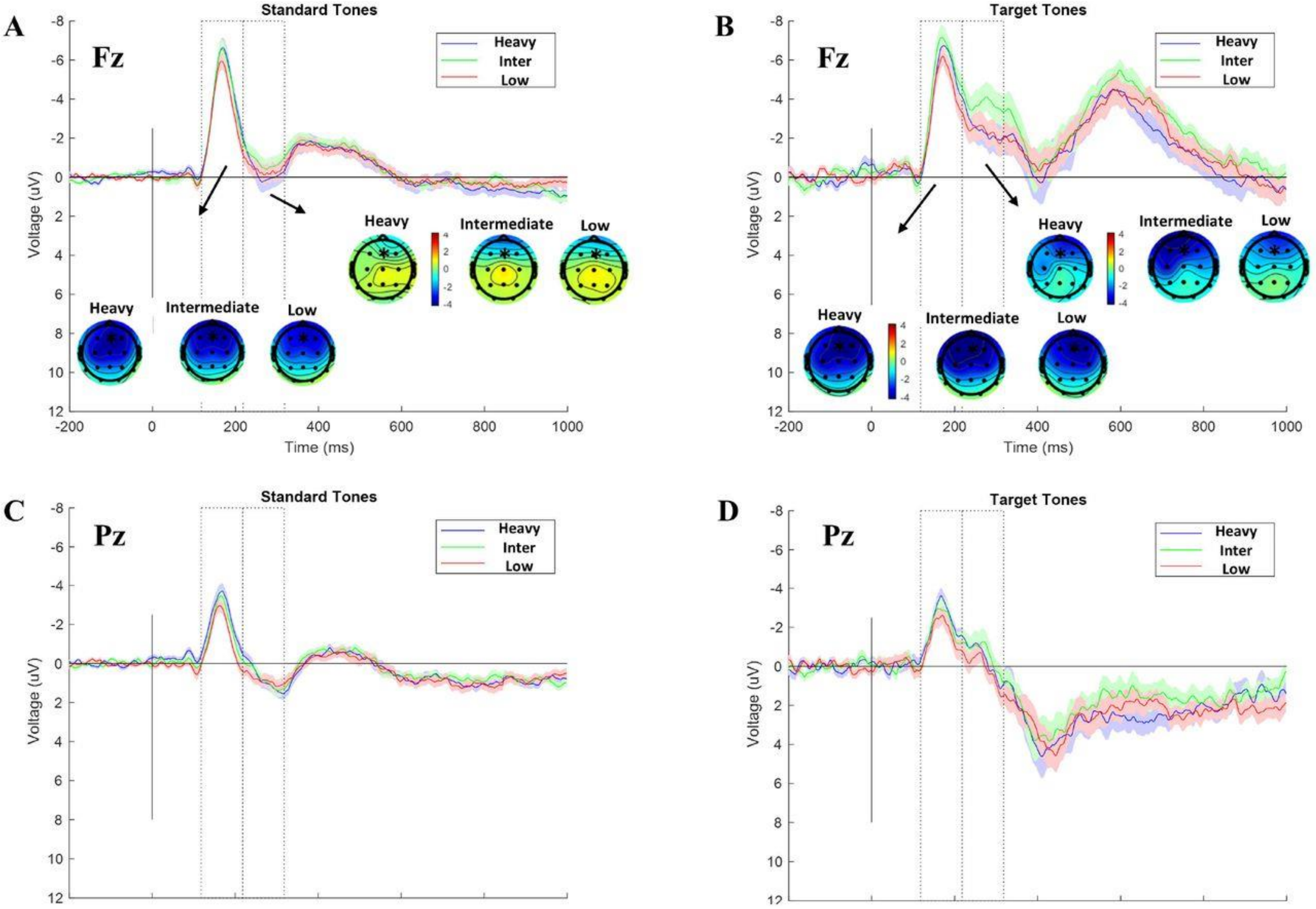


Figure 3.5: N1 and P2 ERPS. A: N1 and P2 ERP time windows for standard tones at electrode Fz. Topographies for the N1 & P2 by traffic condition for standard tones. B: N1 and P2 ERPs for target tones at electrode Fz. Topographies for the N1 & P2 by traffic condition for target tones. Shaded regions represent standard errors. C: N1 and P2 ERP time windows for standard tones at

electrode Pz. D: N1 and P2 ERP time windows for target tones at electrode Pz. Shaded regions represent standard errors.

### N1/P2 ERP results

We conducted a one-way repeated measures ANOVA to compare the mean in the N1/P2 ERP time window at electrodes Fz and Pz. Figure 3.5A shows the N1/P2 ERPs for standard tones at electrode Fz. We found a significant N1 main effect for the bike lane condition for standard tones ($F(1.45, 33.517) = 3.63$, $p = 0.05$, $\eta^2_p = 0.136$). A Holm adjusted post-hoc test revealed a significant decrease in N1 amplitude in the low traffic condition relative to heavy traffic ($M_{diff} = -0.61$, $p = 0.041$). No significant differences in the P2 ERP were found for standard tones at electrode Fz ($F(1.50, 43.63) = 1.49$, $p = 0.23$, $\eta^2_p = 0.049$).

Figure 5B shows the N1/P2 ERPs for target tones at electrode Fz. Regarding the N1 ERP, no differences in target tones were found between the bike lanes for electrode Fz, ($F(2,46) = 2.42$, $p = 0.10$). A repeated-measures ANOVA found a significant main effect for the traffic condition for the P2 time window for target tones ($F(1.70,49.48) = 3.75$, $p = 0.037$, $\eta^2_p = 0.115$). A post-hoc revealed a less positive amplitude during the P2 time window for intermediate traffic relative to the low traffic condition ($M_{diff} = -1.420$, $p = 0.032$).

Figure 5C shows the N1/P2 ERPs for standard tones at electrode Pz. We found a significant main effect for the traffic condition for standard tones in the N1 time window ($F(2, 46) = 7.42$, $p = 0.002$, $\eta^2_p = 0.244$). A Holm adjusted post-hoc test revealed a significant decrease in N1 amplitude in the low traffic relative to heavy traffic condition ($M_{diff} = -0.82$, $p = 0.001$). No statistically significant differences were found for the P2 ERP at electrode Pz for the standard tones ($F(1.40, 40.81) = 0.87$, $p = 0.39$, $\eta^2_p = 0.029$). Figure 5D shows the N1/P2 ERPs for target tones at electrode Pz**.** No significant differences in ERP amplitude were found for the N1 ($p$ = 0.34) or P2 ($p$ = 0.44) ERPs for target tones.

### P3 Results

Figure 6 shows the averaged difference-wave ERP for the target-standard tones at electrode Pz. The difference waveform shows an increase in positive power starting at approximately 300 ms that resembles the classic oddball-related P3 (Luck, 2014). A one-way repeated-measures ANOVA was conducted to test for differences in P3 amplitude between the bicycle lanes. The ANOVA found no statistically significant differences in P3 amplitude between the traffic conditions ($F(2,46) = 0.191$, $p = 0.82$).

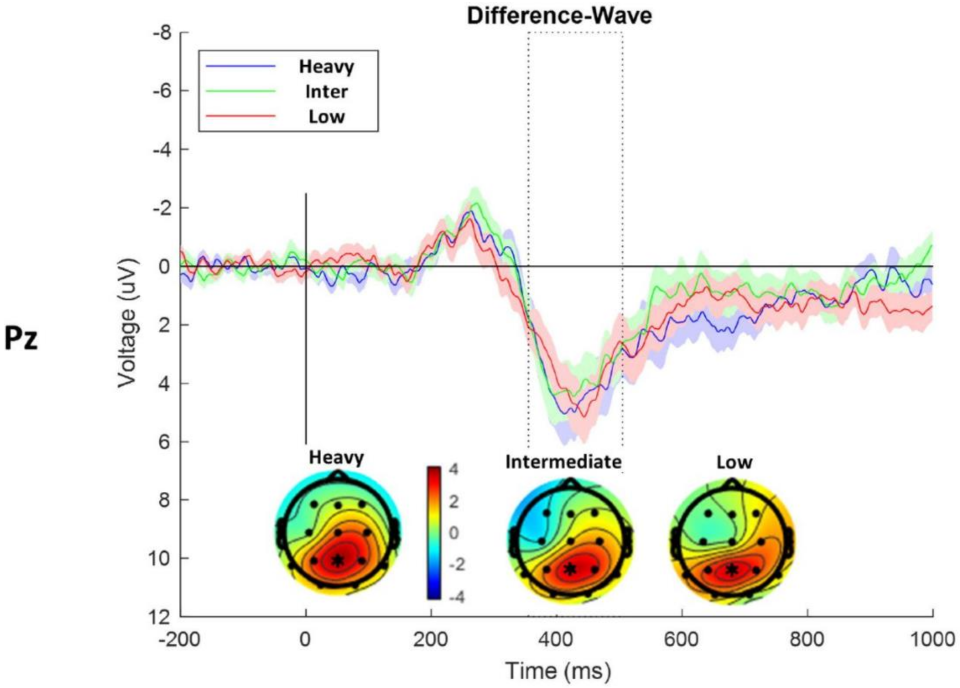


Figure 3.6: Difference-wave P3 ERPs at electrode Pz. Topographies for the P3 time window. Shaded regions represent standard errors.

### Spectral results

Figure 7 shows the EEG power spectra plots for the different lanes. The different color lines represent the different bike lanes. The shaded regions depict the standard error among each group. The 1/f EEG spectra plots show a slight increase in power within the alpha range (8-12 Hz) for all conditions. It also depicts the topographies in the alpha range by experimental conditions, which exhibit similar distributions in the parietal regions. Notably, the figure shows a decrease in alpha power in the low traffic condition relative to the other traffic conditions. We conducted a one-way repeated-measures ANOVA to test for differences in alpha power between the road types. The ANOVA revealed a significant main effect for the bike lane at electrode Pz ($F(2, 46) = 3.98$, $p = 0.02$, $\eta^2_p = 0.148$). A Holm-corrected post-hoc comparison shows a statistically significant difference in alpha power in the low traffic condition relative to the intermediate traffic ($p = 0.021$).

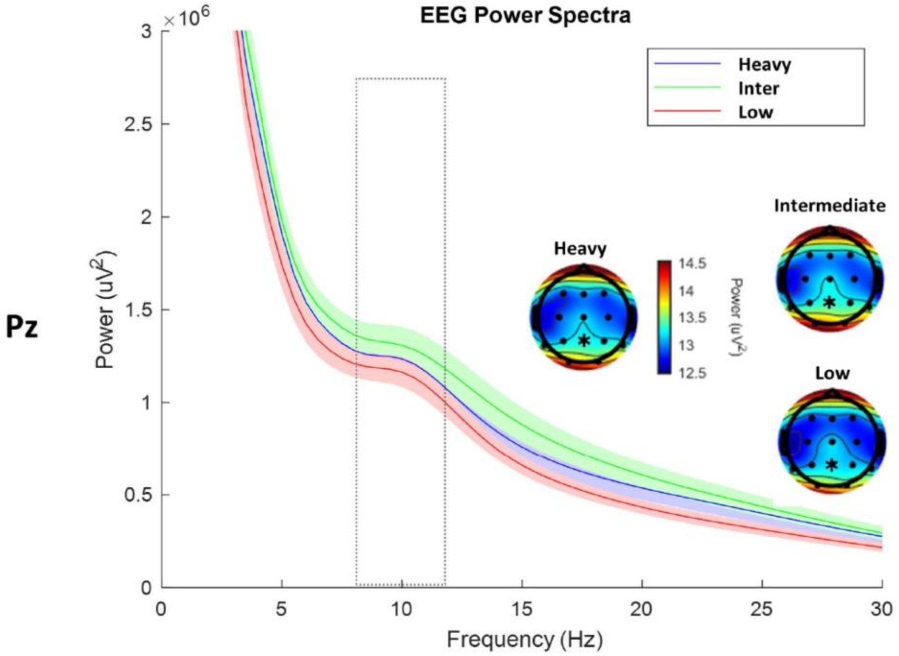


**Figure 3.7**: EEG power spectra at electrode Pz. The squared area depicts the alpha range of 8-12 Hz. Shaded regions represent standard errors.

## 3.4 Discussion

In this study, we measured EEG activity from individuals under different urban traffic conditions. Participants completed an auditory oddball task while riding a bicycle in three different cycling environments. The first condition (low traffic) was recorded in a separate cycling lane located next to a one-way, low-traffic road. The second condition involved completing the oddball task alongside a painted, intermediate traffic volume lane, and the final condition involved riding on a multi-use path alongside heavy/fast traffic. The task parameters, such as the riding speed, stimulus presentation, and recording methods, were chosen following previous mobile EEG work from our laboratory to ensure our methodology is replicable under new environments and for comparability. Overall, we found evidence suggesting that changes in urban traffic environments can be reflected in auditory mechanisms, such as the N1 increase under heavy traffic.

### Behavioral Results

In the present paradigm, participants responded to the target tones in the oddball task by pressing a button attached to the handlebar. We calculated button response accuracy and response times in each experimental condition. We found no significant differences in accuracy by traffic condition. We found no significant differences between accuracy scores. We found significant statistical differences in target reaction time between the traffic conditions. Interestingly, participant reaction time was statistically slower in the low traffic lane and faster under heavy traffic. While it is generally expected that fewer distractions lead to better performance (e.g. lower reaction time), it might be plausible that participants' arousal levels might influence the difference in reaction time. Given the relationship between reaction time and traffic volume, the faster/heavy traffic condition might have increased participants' subjective arousal, thus leading to faster button response (Kovacs & Bories, 2010; Nishisato, 2013). In other words, participants' reaction times might have slowed down under low traffic due to a more relaxed state than riding alongside heavy traffic.

## N1 and P2 differences by traffic volume

In this study, we hypothesized that, relative to low traffic, heavy traffic would elicit a more negative N1 amplitude during street cycling. Figure 8 shows a summary of the comparisons performed for this analysis. Consistent with previous work from our laboratory, the main finding in the current study is that increases in environmental noise were associated with increases in N1 amplitude (see Scanlon et al., 2017; Scanlon, Townsend, et al., 2019). Namely, we found that relative to low traffic, heavy traffic was associated with a significant increase in N1 to the standard tones at both electrodes, Fz and Pz. The significant differences in N1 amplitude found in the present study occurred between the heavy vs low traffic only. Interestingly, no significant differences were found between the intermediate and low traffic conditions. However, a visual inspection of the N1 shows a consistent pattern where the intermediate traffic amplitude falls between high and low traffic (Figure 8A). In other words, as the traffic volume goes from heavy > intermediate > low, the observed N1 amplitude follows the same order: higher amplitude in heavy traffic, medium amplitude in intermediate traffic, and lowest amplitude in low traffic. Due to this study's randomization of task orders, we attribute these differences to environmental conditions and not order effects.

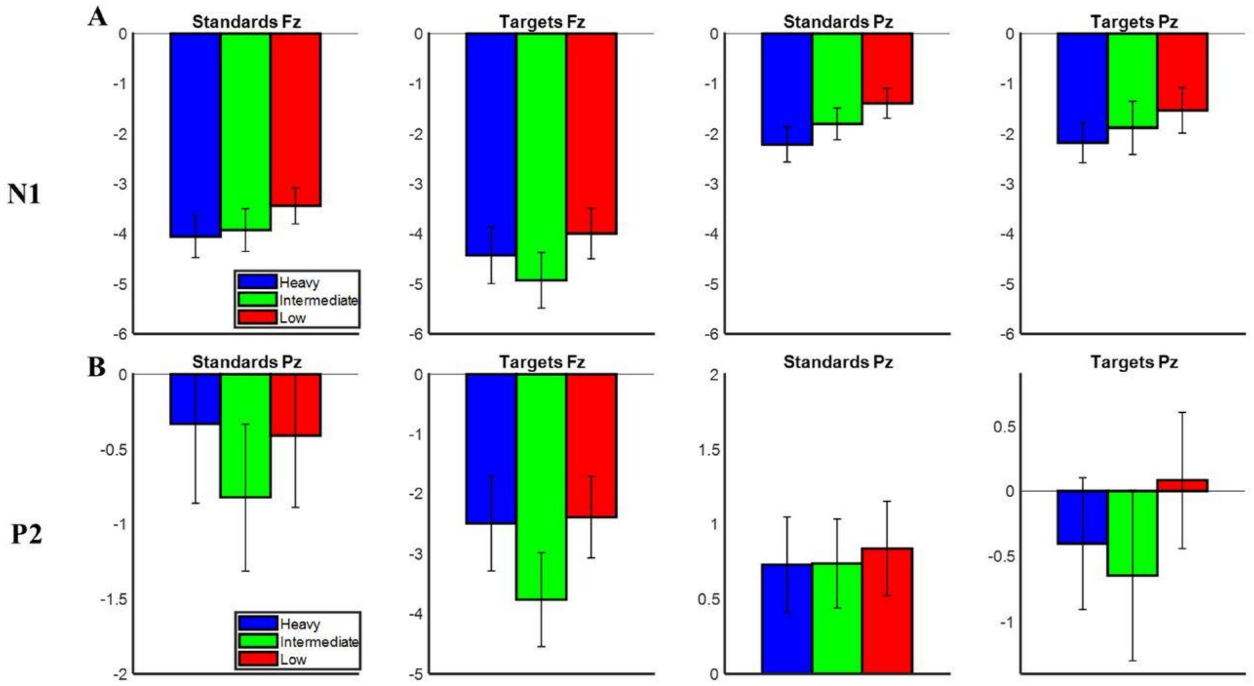


Figure 3.8: Bar graph summaries of the N1 and P2 ERP comparisons by electrode type and condition. A: N1. B: P2.

The role of the auditory N1 in stimulus processing has been established in previous literature. It is known that changes in the properties of auditory stimuli (e.g., intensity and frequency) modulate N1 amplitude (Näätänen & Picton, 1987). For instance, changes in the environment are followed by changes in N1 activity (Paiva et al., 2016). In the context of mobile EEG, our workgroup’s focus on the N1 started in a study by (Scanlon et al., 2017). Using an oddball task, the recorded subject’s EEG while sitting indoors and riding a bicycle outside. They found an unexpected increase in N1 and a decrease of P2 during outdoor cycling relative to sitting indoors. In a follow-up control experiment, we found that this N1/P2 effect was larger when subjects were listening to outdoor sounds and white noise relative to noises of silence. A follow-up experiment further showed that increases in traffic sounds, as indexed by the road type (quiet park vs noisy road) further showed the previously found N1 effect (Scanlon et al., 2020).

In these studies, the authors concluded that the observed modulation in N1 could serve as a filtering mechanism that should facilitate sound processing in louder environments.

In the present study, we were interested in exploring the influence of environmental conditions during active bicycle riding. By deploying our paradigm to different urban settings, we tested whether it was possible to obtain reliable N1 effects given the differences in traffic levels. The current results show that the N1 effect shown by our workgroup in parks vs roads is also sensitive enough to quantify differences in auditory processing in cycling environments. In other words, we showed that even in similar urban environments, differences in traffic conditions could influence auditory processes during the oddball task and while performing a motor task. These findings can inform city infrastructure and planning by showing that traffic noise modulates EEG activity associated with stimulus processing. This could provide a more objective measure of traffic noise impact on bike infrastructure.

Given the mixture of behavioral results and the consistency of the N1 effect, one must consider the behavioral implications of the observed N1 differences of the present study. Like in (Scanlon et al., 2020; Scanlon, Townsend, et al., 2019), we did not find significant differences in target accuracy. This could lead to the conclusion that a larger sample size might be necessary to quantify any statistical differences in target accuracy better. The difference in target reaction times between low and heavy traffic is of equal interest. We found slower reaction times in the low traffic condition and faster reaction times in heavy traffic. An important observation is that the N1 effect was not found in the target conditions. Whether the lack of significant target N1 differences is attributed to the sample size, ultimately, the present study cannot confirm whether the observed  N1 modulation is associated with behavioral accuracy as previously found (Hink et al., 1977).

We only found one significant difference in P2 amplitude between conditions, a less positive amplitude in the intermediate traffic relative to low traffic. Given the previous findings from our group showing a decrease in P2 amplitude outdoors relative to indoors (Scanlon, Townsend, et al., 2019), and a similar decrease in outdoor sounds vs silence noise (Scanlon, Cormier, et al., 2019), we expected to find a decrease in P2 amplitude in the heavy traffic relative to low traffic. The only significant P2 difference found in the present study was between intermediate and low traffic, where there was a decreased P2 amplitude in the intermediate condition. Interestingly, this effect was only significant in the target tones. While inconsistent with our initial expectations, the lack of P2 differences among the other comparisons might suggest a general role in P2, where even similar road conditions (regardless of noise intensity) can elicit an equal decrease in this ERP (Scanlon et al., 2020). An alternative explanation to these findings has to do with the consistency of traffic sounds. Because heavy traffic is characterized by consistently loud noises and low traffic by consistently quieter noises, it is possible that in the intermediate condition, participants were exposed to a switch between noisy and quiet. This would make the auditory filtering associated with the P2 harder to predict. In the context of other mobile research, other studies have observed decreases in P2 amplitude during increased task load (Reiser et al., 2021). Given the fact that P2 amplitude is generally associated with task difficulty (Sugimoto & Katayama, 2013), an important question for future mobile paradigms is to test whether the P2 effect reflects a filtering function that discriminates between outdoor and quiet sounds or whether increases in bike difficulty can elicit changes in P2 amplitude.

### P3 differences by traffic volume

Regarding the P3, it was hypothesized that riding in heavy traffic would be associated with decreases in P3 positivity. Given the well-established literature associating P3 amplitude to task effort (Kok, 2001; Polich & Comerchero, 2003) , we expected to test whether changes in traffic conditions alongside the bike lanes would be reflected in changes in P3 amplitude (e.g., a more negative amplitude during heavy traffic). There were no significant differences in P3 amplitude between the experimental conditions. This lack of a P3 difference using a free navigation paradigm brings several points to discuss when it comes to studying attentional demands using motion paradigms. First, the P3 effect is generally associated with task effort (Dinteren et al., 2014) and has been historically studied in stationary indoor laboratory settings. The present findings are consistent with a previous skateboarding study where we found that increases in task difficulty were not associated with changes in the P3 (Robles et al., 2021). A common factor between the current findings and the skateboard findings is that we compared several experimental conditions involving free navigation and similar motor and sensory demands. For example, in this study, the riding conditions did not vary in motor intensity (terrain incline and riding speed remained constant among the bicycle lanes), and all the conditions were carried out in unstructured outdoor environments where participants were exposed to outdoor stimuli. In terms of task interference, the lack of a P3 effect in our studies supports several mobile studies' findings that free unconstrained navigation appears to interact with attentional resources differently from stationary conditions and other conditions involving fixed movements. Some of these studies are discussed below.

Scanlon and colleagues (2017) found no differences in P3 amplitude between stationary pedaling and sitting on a stationary bike while participants completed an oddball task in an EEG chamber. These results suggest that an increase in motor demands alone did not modulate P3 amplitude. However, in a follow-up study, Scanlon and colleagues (2019) showed that relative to an indoor sitting condition, riding outdoors was associated with a significant P3 decrease. In a cycling study that also used an oddball paradigm, (Zink et al., 2016) found an increase in P3 amplitude in a free condition relative to a fixed bike. The authors concluded that, in the free biking conditions, participants were exposed to a greater cognitive load relative to fixed cycling. Notably, (Ladouce et al., 2019) used a series of oddball experiments to show that relative to standing still, walking is associated with a decrease in P3 amplitude. Crucially, they also found similar P3 amplitude decreases between walking and when participants were pushed while sitting in a wheelchair. The authors also found similar P3 amplitudes between treadmill walking and standing still, arguing that the combined effect from visual and inertial stimulation was a likely candidate to explain the findings in their experiment. Overall, the findings in the present study and the mobile studies discussed above suggest a stronger attenuation of P3 amplitude in paradigms when we consider the transition from stationary and fixed to free movement. This is particularly true in outdoor studies, where one can expect an increase in stimulus processing relative to traditional laboratory settings (Scanlon et al., 2019). Free navigation and outdoor paradigms are promising alternatives relative to traditional indoor research (Makeig et al., 2009). Researchers must continue to explore the role of attentional processes using naturalistic paradigms to understand human attention under higher ecological validity better.

## Alpha power differences by traffic volume

We hypothesized that, relative to low traffic, riding under heavy traffic would decrease alpha power during the oddball task. We found no differences in alpha power between the low and high traffic conditions. Interestingly, the only two conditions that yielded statistically different levels of alpha power were the low and intermediate, with a larger alpha power decrease in the low traffic. In a previous study (Robles et al., 2021), we were motivated to test alpha power during skateboarding because previous mobile research has shown that increases in cognitive and motor load during motion are associated with decreases in power (Storzer et al., 2016; Zink et al., 2016). We showed that relative to a resting baseline, alpha power was greatly diminished during skateboarding. In that study, we found no differences in alpha power during increased cognitive and motor inference. We concluded that the difficulty of the task (completing an oddball task while riding the skateboard) would draw enough cognitive resources to deplete alpha power during the task. In terms of the present study, it is also possible that the task (riding a bicycle outdoors) led to a global state of cortical excitation due to the external environment stimulation and task. In this sense, the constant exposure to external stimuli during the three experimental conditions might have resulted in similar levels of cortical excitation. This increased excitation might lead to equal decreases in alpha amplitude in this study (Sauseng et al., 2009).

### 3.5 Limitations and future directions

There are several limitations in this study that will be discussed in this section. We failed to obtain an objective measure of traffic volume of the road conditions during the experiment (pre-pandemic traffic). We could have correlated the N1 amplitude to the levels of traffic noise in dB during the time of the experiment. Future mobile experiments testing auditory paradigms outdoors can benefit from recording and quantifying the levels of street noise. For example, in tasks that involve auditory filtering, recording the outdoor noise levels can allow for the correlation analyses of ERP or spectral power to the decibels of the street sounds. We also did not record a baseline condition with no traffic sound. Given our interest in testing differences in

N1 in similar urban environments, we did not consider recording a condition without traffic sounds. Implementing a condition where participants ride in a busy environment (busy track or park) could have provided an important piece of information regarding the role of the N1. For instance, a busy park without traffic could serve as a suitable baseline condition where subjects are equally busy as in an urban track but without traffic sounds. In a previous cycling study, (Scanlon et al., 2020) showed marked differences in N1 amplitude between a quiet park and near a roadway. To further assess the degree to which the reported N1 effect is sensitive to environmental sounds, it could be helpful to integrate a condition equally busy as a street lane but without traffic.

Due to the real-world nature of our experiment, our three conditions had other differences between them besides just the amount of traffic. They faced different directions, had different scenery, different numbers of intersections, different lighting and trees, and different amount of other bike traffic, and these variables changed from day to day outside of our control. These degrees of freedom are an inevitable consequence of this realistic scenario research. We find it easier to consider the experimental manipulation as including all these variables together as a package, but this does make replication difficult. Further difficulties are present due to changing infrastructure. Our intermediate-style pathway has since been replaced with a fully separated bike lane more similar to the low-traffic lane since the time of data recording. Further work might use virtual reality or fully controlled outdoor scenarios to control these extraneous variables better.

An important consideration is how much we can manipulate the task difficulty in a real-world setting without compromising participant safety. While the lack of behavioral effects in the study can be considered a limitation, there is a limit to which we can increase task difficulty before it can turn into a falling hazard. For instance, using flashing LED glasses, we have tested a visual version of the current study on an indoor running track while subjects ride a Bluetooth-operated skateboard. A disadvantage of this design is that it can only be deployed to semi-controlled settings (e.g., using an empty running track) where any accidents can be minimized. For example, in the current study, we had a researcher riding in front of the participant to ensure participant safety at all times. While we had no forms of safety-related incidents or situations, it is possible that attending to a visual task might affect the participant's coordination, which is an undesirable outcome as we prioritize participant and equipment safety.

Another consideration for future designs is using a webcam to time and capture moments from the environment. In previous mobile studies, researchers have implemented the use of recording environmental events during driving, such as pedestrian crossing and cars driving nearby the participants (Flumeri et al., 2018). Other indices of attention, such as eye blinks, are now being implemented to record cognitive engagement during navigation (Wunderlich & Gramann, 2020). These events could be used for interesting analyses (such as evaluating EEG signals and reaction time at random times, such as during a change of traffic light or a sudden distractor). Furthermore, using a structured protocol to record outside conditions (weather conditions, infrastructure conditions, average environmental noise, average level of stops/nearby distractions) could provide rich details that could be used in conjunction with task performance and EEG recordings.

## 3.6 Conclusion

In the current study, we used an oddball EEG cycling paradigm to test the effects of environmental noise on auditory attention while participants rode in different urban lanes. We showed that levels of traffic volume were associated with changes in auditory attention. While showing the feasibility of deploying mobile paradigms into real-world environments, we demonstrated that traffic volume interacts with cognitive resources during multitasking.

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# Chapter 4 - Evaluating the role of evoked alpha power as a measure of selective attention under different levels of environmental and movement complexity.

## 4.1 Introduction

With the expansion of portable technology over the past two decades, imaging and recording of brain activity via mobile EEG is now an affordable reality that can aid the study of attention in creative ways (Gramann et al., 2011; Joshi et al., 2020; Lau-Zhu et al., 2019; Makeig et al., 2009). This ability to step outside the laboratory to study attention can help us bridge the gap between the body of knowledge produced inside isolated EEG chambers and the external world, previously inaccessible to researchers. Many factors can influence EEG recordings' accuracy and interpretability, including noise artifacts (Lai et al., 2018; Chen et al., 2019). This is because recorded EEG signals largely contain the true brain activity plus a myriad of other signals, such as low-frequency activity induced by neck tension and movements, and other signals internal and external to the body (Jackson & Bolger, 2014; Maddirala & Shaik, 2018; Usakli, 2010). Efforts to maintain a high signal-to-noise ratio have greatly determined the modality of EEG experiments for decades. For instance, usually, participants are not allowed to move or even blink when they complete EEG experiments (Luck, 2014).

While the traditional approach of restricting movement has been a necessary step in EEG experiments, many argue that this restriction in movement hinders our ability to translate lab-based findings into the real world (Gramann et al., 2014). For example, if one were interested in brain processes related to good sports performance, having the ability to record EEG signals during a real game would constitute a state-of-the-art methodology to understand processes under their true state (Hölle et al., 2021; Jungnickel et al., 2019; Jungnickel & Gramann, 2016; Thompson et al., 2008). Furthermore, some have argued that motionless laboratory experiments might in and of themselves be considered a restrictive approach to understanding brain processes that are shaped to interact with complex environments (Ladouce et al., 2017; Mathewson et al., 2012). Fortunately, the past decade has seen an increase in published mobile studies. This includes proof of concept papers (Blum et al., 2017; Debener et al., 2012, 2015; Dikker et al., 2017; Kuziek et al., 2017) and other mobile studies aimed at the understanding of attention while outdoors or during motion (Ladouce et al., 2019; Reiser et al., 2019, 2021; Salvidegoitia et al., 2019; Scanlon, Townsend, et al., 2019; Zink et al., 2016). Mobile paradigms can be a promising tool in the field of attention as it offers affordable hardware that makes research paradigms easy to deploy to many environments. One of the main goals of the mobile/portable EEG field is to transition cognitive neuroscience from highly controlled and restrictive environments into real-world paradigms where subjects behave naturally (Gramann et al., 2014). A key component of this transition is the validation of research paradigms that include portable hardware and data-cleaning methods tailored to studying cognition during active behaviors. Given the early stage of mobile EEG, it is important to stress the importance of discussing research methods for better replicability and further understanding of brain mechanisms in motion.

Given the variety of equipment currently available for mobile research, it is important to provide transparent results and methodologies for reproducibility (Pernet et al., 2020; Styles et al., 2021; Meyer et al., 2021), but also to test matching paradigms across different environments and conditions. This practice could advance our knowledge about attentional processes during motion and outside the laboratory.

### *Attention under dynamic conditions*

Changes in cognitive demands are generally measured using EEG techniques such as event-related potentials (ERPs) or analyses of spectral activity. The amplitude of ERP waves has been long associated with cognitive and mental processes related to attention (Kok, 2001; Korzyukov et al., 2012; Luck, 2014). For instance, changes in activity around 300 ms post-stimulus, i.e., the P300 or P3 are linked to the task effort or difficulty (Polich & Comerchero, 2003; Linden, 2005). Analyzing the spectral activity of the EEG allows for the analysis of the power spectra, which measures the amount of EEG activity within a frequency range (Xiao et al., 2018). The activity within various frequencies such as alpha has been previously associated with cognitive processes (Bazanova & Vernon, 2014), inhibitory control and timing of cortical activity (Klimesch et al., 2007), attention, and memory (Klimesch, 1997, 1999; Mathewson et al., 2011). Using these indices of attention, several mobile studies have manipulated dual paradigms during motion.

Several indoor studies have focused on studying attention during states of motion to understand the profile of attentional reallocation during movement. These studies have employed dual-task paradigms that combine attentional tasks while the subject is in motion. These dual task paradigms often refer to the concept of cognitive-motor interference (CMI) (P. Patel et al., 2014). CMI relies on the assumption that there are shared neural processes that govern cognitive and motor functions (Al-Yahya et al., 2011; Sanctis et al., 2014). During a mobile task, CMI occurs with increases in either cognitive load or motor complexity (Al-Yahya et al., 2011; Leone et al., 2017). The assumption for CMI is that these dual-task paradigms require subjects to adjust their motor behavior and/or cognitive strategy to perform a dual task (Cockburn et al., 2003; Dennis et al., 2009; Plummer-D’Amato et al., 2012). Motor behavior adjustments include slowing down the pace or adjusting the gait speed (Cockburn et al., 2003; Al-Yahya et al., 2011; Wagner et al., 2014).

Cognitive markers of increased CMI include EEG changes in the P3 ERP (Cortney Bradford et al., 2019; Reiser et al., 2019) and alpha power (Beurskens et al., 2016; Bohle et al., 2019; Leone et al., 2017; Reiser et al., 2021). For instance, increases in movement complexity have been associated with decreases in P3 amplitude and alpha power (De Vos et al., 2014; Sanctis et al., 2014; Liebherr et al., 2018; Reiser et al., 2019; Scanlon et al., 2021). Interestingly, previous work by (Ladouce et al., 2019) showed that increases in visual and inertial processing induce the observed P3 amplitude decrease during motion. In this study, the authors employed a wheelchair to achieve movement without motor involvement and concluded that movement itself might not be driving the resource allocation indexed by P3 amplitude.

While faraday chambers provide an ideal setting to minimize external noise and improve internal validity (Luck, 2014; Suwandi et al., 2022), outdoor experiments encounter an inevitable problem that emerges in complex environments. Relative to traditional EEG chambers, complex and outdoor environments are characterized by a plethora of ongoing stimuli that individuals process at all times while in these environments. This results in a reduction of available cognitive resources that can be measured in the EEG signal (Reiser et al., 2019). Examples of this phenomenon have been observed when participants complete an oddball task between indoor and outdoor conditions. In several mobile studies, a reduction of P3 amplitude has been found outdoors relative to indoor environments (Debener et al., 2012; De Vos et al., 2014). Notably, (Scanlon, Townsend, et al., 2019) found that relative to an indoor sitting condition, riding a bicycle outdoors is associated with a decrease in P3 amplitude. A trend towards reduced alpha power outdoors was also found. The authors suggested that an increase in sensory processing outdoors was associated with the changes in P3 and alpha power.

### *Alpha power and cortical inhibition-excitation. Implications for mobile research.*

EEG activity can be recorded at various frequencies. The magnitude of the EEG signal within a frequency, or power (Park et al., 2020), is a measure of EEG activity within different frequency ranges such as delta (0.2 ~ 3.99 Hz) or theta (4 ~ 7.99 Hz). EEG activity contained within the alpha frequency band (~8-12 Hz) is often associated with memory and cognitive performance (Klimesch, 1999), alertness, and expectancy (Klimesch et al., 1998), suppression of distracting information (Foxe & Snyder, 2011) among other functions. Generally, decreases in alpha power are associated with increased cortical excitability (Sauseng et al., 2005; Rihs et al., 2007; Thut et al., 2006). Within the context of this research, a decrease in alpha power constitutes an enhancement of sensory processing. A very influential framework involving the dynamics of alpha power was put forward by (Klimesch et al., 2007). They proposed that under certain conditions, increases in alpha power, or event-related synchronization (ERS) reflect a process of inhibitory control. These include instances where participants encode information and ignore irrelevant stimuli. On the other hand, event-related desynchronization (i.e., decreases in alpha power) is inversely related to cortical activation during sensory and cognitive processing (Pfurtscheller & Lopes da Silva, 1999). For example, low alpha power before stimulus onset is associated with greater target detection (Ergenoglu et al., 2004), whereas increased prestimulus alpha power has been associated with increased inhibition (Kelly et al., 2006; Klimesch et al., 2007; Mathewson et al., 2009). This phenomenon can be seen in other tasks requiring cortical inhibition. For example, during visual processing, areas that are currently unattended are associated with increases in alpha power (Worden et al., 2000; Rihs et al., 2007). Because alpha oscillations are a prominent marker of brain activity and excitability (Başar et al., 1997;

Mathewson et al., 2011; Palva & Palva, 2007), investigating alpha dynamics via mobile EEG can help us gain insight into resource allocation under dynamic environments.

Mobile EEG studies measuring changes in alpha power have also found significant alpha-band modulations driven by increases in motor complexity. For example, (Zink et al., 2016) compared subjects' EEG alpha power riding a bicycle outdoors vs pedaling a stationary bike outdoors. In addition to a decrease in P3 amplitude during the free riding, the authors found a decrease in alpha power during the free moving condition. These authors attributed the decrease in alpha power to the increase in task complexity during the riding condition. Interestingly, (Storzer et al., 2016) found that relative to cycling, walking was associated with a significant decrease in alpha activity. Such a decrease in alpha activity during walking was attributed to increases in sensory and motor demands. As with previous ERP studies, there is a mixture of explanations regarding the factors that decrease alpha activity. While the studies above suggest that increases in motor demands can explain the decreases in alpha power, other factors such as increases in visual processing and participant alertness, have been previously proposed as the mechanisms responsible for alpha power decreases (Lin et al., 2014). Other literature such as (Cao et al., 2020) argued that alpha power is independent of visual processing by showing alpha modulation when participants walk in darkness.

With mobile EEG, changes in attentional markers become difficult to explain due to the introduction of motion, which sometimes happens in complex and outdoor environments. For example, a change in alpha power induced by a dual task could be attributed to an increase in visuo-attentional demands (Ehinger et al., 2014; Cao & Händel, 2019) or by a combination of competing factors such as the attention devoted to the task while focusing outdoors (Scanlon, Townsend, et al., 2019). Crucially, (Ladouce et al., 2019) found that watching a video of a hallway traversal led to a larger reduction of the P3 relative to walking with obstructed vision. While this could suggest that visual and inertial processing decrease attentional resources without motor involvement, (Cao et al., 2020) showed that alpha power decreases during walking in total darkness. Taken together, these outdoor changes in the EEG are likely a combination of increases in visuo-attentional demands, motor complexity, or environmental complexity. Ideally, by testing a valid and reliable mobile EEG methodology across a variety of settings, one can gain more insight into the dynamics of outdoor EEG.

### *The present analysis*

While the above section addressed several methodological considerations relevant to the quality of mobile studies, it is important to acknowledge that achieving gold standard parameters in the field of mobile EEG is a distant reality. Even when mobile EEG collection hardware achieves laboratory-based quality, the variety of methods and choices that are used along different research steps could be contributing to the replication crisis in our field (Conrad & Bailey, 2020; Rodrigues et al., 2021). For years, our research workgroup has adopted flexible mobile paradigms that can be used indoors or outdoors (Mathewson et al., 2012; Kuziek et al., 2017; Scanlon, Cormier, et al., 2019; Scanlon, Townsend, et al., 2019; Robles et al., 2021). Figure 4.1 shows an example of the matching methodologies from our workgroup with the skateboard paradigm used by (Robles et al., 2021), which was developed following the cycling paradigm by (Scanlon et al., 2017; Scanlon, Townsend, et al., 2019; Scanlon et al., 2020). A clear advantage of matching methodologies across studies is that analyses can be tailored to investigate the same phenomena across studies. Furthermore, this can help us understand how specific EEG oscillations change across experimental conditions.

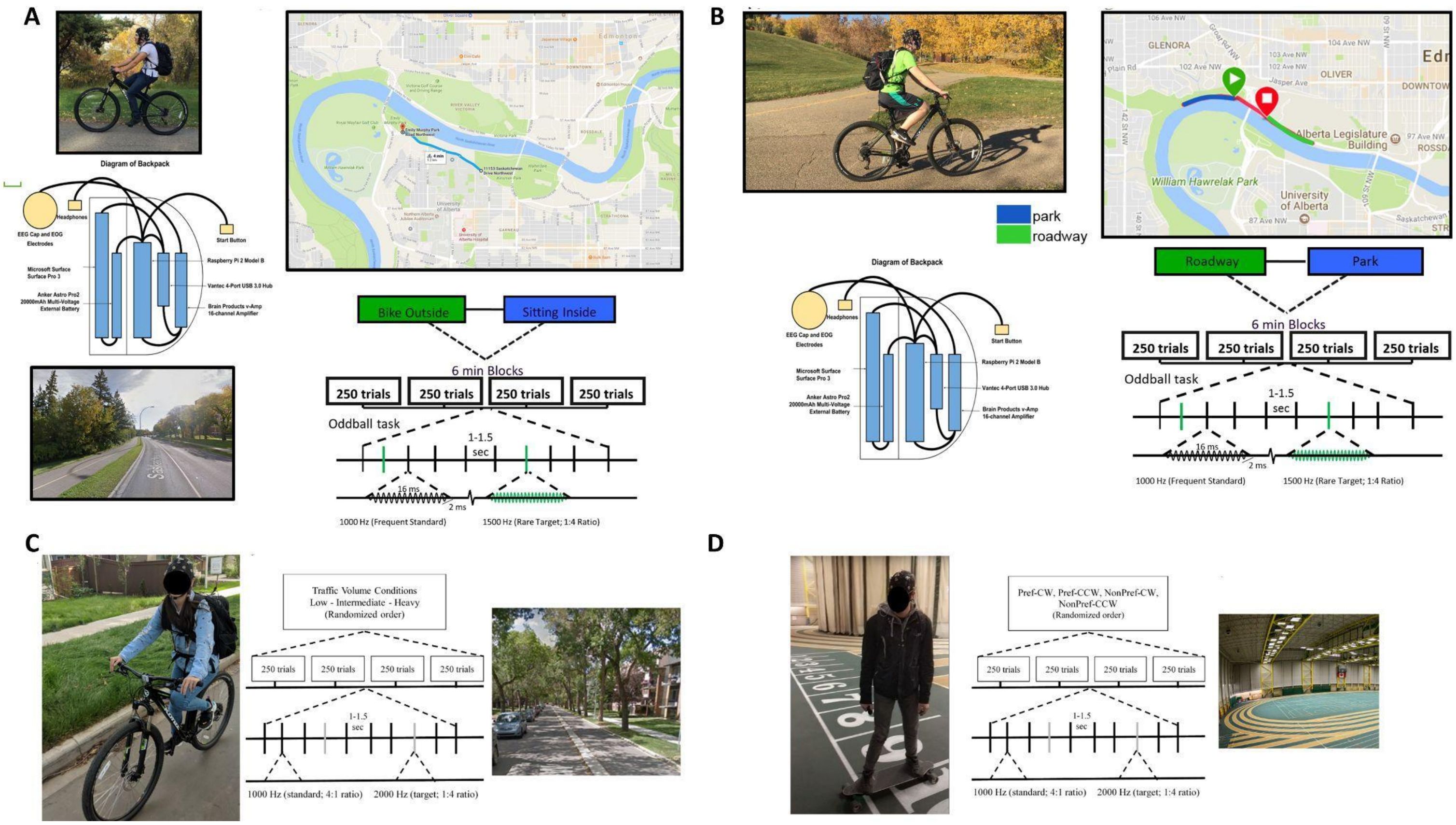

**Figure 4.1.** Applab Mobile EEG setup. (top): E-Skateboard Paradigm. (bottom): Cycling paradigm.

Figure 4.1 shows four experiments from our workgroup using identical experimental parameters. In these experiments, participants freely navigated different environments while completing an auditory oddball task. Study #1 (Scanlon, Cormier, et al., 2019) used an oddball paradigm in an indoor sitting vs an outdoor bicycle riding paradigm to compare several EEG markers of attention between these conditions. Study # 2 (Scanlon et al., 2020) deployed the same methodology to compare subjects' EEG between a quiet park vs a busy roadway. To further investigate how different urban environments interact with subjects' resource allocation, study #3,(Robles et al., 2022) deployed the same cycling paradigm shown in studies #1-2 to three local bicycle lanes varying in traffic noises (low, intermediate, high). Finally, study #4 (Robles et al., 2021) deployed the mobile paradigm developed by Scanlon and colleagues, but instead of using the bicycle for navigation, we tested a low-movement, Bluetooth-operated e-skateboard modality.

**Table 4.1. Mobile studies for analyses.**

| **Study** | **task** | **Conditions** | **Environment/movement focus** |
|---|---|---|---|
| 1 - (Scanlon, Townsend, et al., 2019) | Auditory oddball | Cycling - Sitting still vs outdoor riding | environment + movement |
| 2 - (Scanlon et al., 2020) | Auditory oddball | Cycling - Quiet park vs busy road | environment<br>(movement complexity held constant between conditions) |
| 3 - (Robles et al., 2021) | Auditory oddball | E-skateboarding - Preferred stance vs unpreferred stance | movement<br>(environment is held constant between conditions) |
| 4 - (Robles et al., 2022) | Auditory oddball | Cycling - low traffic vs intermediate vs heavy traffic | environment<br>(movement is held constant between conditions) |

### *Summary of main findings*

Initially observed by study #1 (Scanlon, Townsend, et al., 2019), relative to the indoor condition, riding outdoors was associated with an increase in the N1 ERP amplitude. The authors suggested that the unexpected increase in the N1 amplitude could represent an auditory filtering mechanism, as the participants were exposed to outdoor noises. Another notable finding was a decrease in alpha power in the outdoor environment relative to an indoor-sitting condition. Given the inhibitory function of alpha, the authors concluded that the decrease in alpha power outdoors was attributed to an overload of external stimulus processing. Interestingly, the N1 effect was replicated in a follow-up, indoor study, where (Scanlon, Cormier, et al., 2019) found significant increases in the N1 amplitude following traffic sounds and white noise relative to silence.

Study # 2, (Scanlon et al., 2020) replicated the N1 effect originally found in study #1. In this study, she found an increase in N1 amplitude in the busy roadway condition relative to the quiet park. These findings further supported the initial observations made by (Scanlon, Townsend, et al., 2019), which proposed that the increase in N1 amplitude might serve as a mechanism for auditory filtering in busier environments. Unlike study # 1, this paradigm did not find any statistical differences in alpha power between the quiet park and the busy roadway environments.

Notably, in study #3 (Robles et al., 2022) we replicated the N1 effect observed in the two previous cycling studies. We found significant increases in N1 amplitude when participants rode a bicycle in heavy traffic relative to low traffic. While this study hypothesized a decrease of alpha power towards the busier environments (as found in study #1), we found a decrease in alpha power in the low condition relative to the intermediate traffic condition.

In study #4, (Robles et al., 2021) deployed the oddball task paradigm using an e-skateboard to manipulate the subject's riding difficulty. We found no differences in the N1 or P3 ERPs when comparing the preferred (low motor complexity) vs the unpreferred riding stance (high motor complexity). We also failed to observe a significant difference in alpha power between participants' preferred skateboarding stance and non-preferred stance.

As the summary of these studies shows, we found a reliable N1 ERP effect in the cycling paradigms when participants were exposed to various levels of traffic sounds. The consistency of the N1 effect in various environments is an example of good replicability using mobile EEG.

Due to the mixed effects regarding the dynamics of alpha activity during motion, the goal of this chapter is to re-analyze the EEG spectral activity of the 4 studies using a different approach. First, to keep the parameters standards, the data is preprocessed using identical settings. This approach is feasible, given that the oddball task parameters are identical in the four studies. Second, we are re-testing for global alpha differences in each individual study by fitting it into an algorithm called Fitting Oscillations & One Over F, or FOOOF (Donoghue et al., 2020). This technique allows the removal of aperiodic oscillatory activity from periodic oscillatory activity. Aperiodic activity, or 1/f 'background noise' differs from periodic activity in that it lacks a predominant temporal frequency (He, 2014). It has been previously argued that by removing the aperiodic information from the periodic spectral information, power estimates become less biased to the influence of aperiodic oscillatory activity (Gerster et al., 2022; Merkin et al., 2023; Pathania et al., 2021; Tröndle et al., 2022).

Finally, to further understand how alpha power reallocates in outdoor environments and under motion, we are using an event-related spectral perturbations (ERSP) analysis (Makeig, 1993). This analysis allows us to visualize the temporal changes in oscillatory activity in relation to stimulus onset. Even-related changes in the EEG spectra are identified as the changes in power within a given frequency band. Event-related synchronization (ERS) refers to an increase in power within a frequency, whereas a decrease in power is referred to as event-related desynchronization (ERD) (Pfurtscheller, 1997; Pfurtscheller & Andrew, 1999; Pfurtscheller & Lopes da Silva, 1999). In the alpha literature, ERS is generally associated with cortical inhibition (Klimesch et al., 2007; Pfurtscheller et al., 1996), whereas ERD is associated with increases in excitability (Klimesch et al., 2007; Mathewson et al., 2011; Steriade & Llinás, 1988; Takemi et al., 2013). We believe that by applying an identical preprocessing treatment to the data and more sophisticated spectral analysis, we can better address the lack of replicability of alpha results between our studies.

Using the FOOOF and ERSP analyses, we can measure differences in alpha power of the four studies while focusing on increases in environmental complexity, movement complexity, or both. Because study #1 measured the subject's EEG indoors sitting vs outdoors riding, we are comparing the alpha power in the environmental spectrum (isolated vs outdoors) and in the movement spectrum (sitting vs cycling). For this data set, we predict that alpha power is decreased outdoors, due to heightened sensory and cognitive processing. Study # 2 offers a setting where cycling speed and cadence level are kept constant between conditions. Therefore, it provides an opportunity to focus on the environmental spectrum as we test for alpha power differences between the quiet park and busy road conditions. For this analysis, we predict finding lower alpha power in the busy condition due to higher sensory processing. Study #3 also focuses on the environment spectrum as participants rode a bicycle at constant speed between three urban lanes varying in traffic levels. For this study, we predict finding lower alpha power in the heavy traffic condition relative to low traffic. In study # 4, the environmental conditions are held constant as participants rode the skateboard on an indoor running, where experimental conditions were homogenous during the experimental sessions. For this study, we expect to find lower alpha power during the preferred stance, where motor demands are greater.

For the ERSP analysis, following previous literature showing that desynchronization of alpha is an index of cortical activation (Sutoh et al., 2000; Klimesch et al., 2007; Peng et al., 2015), we predict a larger alpha desynchronization following target tones for the low environmental and movement complexity relative to the high environmental and movement complexities across all studies.

## 4.2 Methods

### *Selection of studies for analysis*

The current analysis is set to investigate the dynamics of alpha power under dynamic motion. This analysis focused on the profile of event-related spectral alpha activity when participants are exposed to various environmental and movement complexity levels. To accomplish this goal, four mobile studies from our workgroup were selected. As stated previously, there are two reasons these studies are suitable for a cross-study alpha analysis. First, these studies employed the same hardware, task, minicomputer, electrode type, button press, task (including stimulus presentation and ITI), backpack, and (Figure 4.1). Additionally, these experiments took place on the University of Alberta campus, usually under similar weather and environments. The consistency of these settings should present a methodological advantage for replication but also to compare and contrast results. Second, as figure 4.1 shows, the movement modality and environmental settings of these studies allow the comparison of alpha dynamics by environmental and movement complexity. In the context of this analysis, an increase in environmental complexity is categorized as a change from an indoor to an outdoor location or also a change from a quiet environment to a busy urban environment. A key assumption is that, relative to laboratory or indoor settings, outdoor environments contain a plethora of stimuli that constantly bombard our senses.

Movement complexity is framed as the relative physical demand accompanying a motor task. In this analysis, an increase in motor complexity is defined as a condition when a participant goes from a simple motor task (stationary pedaling) to a more demanding physical task (outdoor bicycle riding). Additionally, due to the variety of environmental and physical conditions in these experiments, some of these allow us to focus on environmental complexity while keeping movement constant (Robles et al., 2022; Scanlon et al., 2020). For example, in these studies, participants rode the same bicycle in busy vs quiet areas. However, (Robles et al., 2021) focus on movement complexity (skateboarding in one's preferred stance vs their unpreferred stance) while keeping the environment constant at an indoor running track. Yet, (Scanlon, Townsend, et al., 2019) manipulated both the level of environmental complexity (indoor lab chamber vs outdoors) and motor complexity (sitting still vs bike riding outdoors). Using these changes in environmental/movement complexity as references, we can frame any systematic changes in the EEG as being drawn by increases in environmental or movement complexity. Since analyses of oscillatory activity allow for the visualization of power over experimental conditions, we can measure the extent to which environmental or physical increases influence ongoing alpha power.

### *Participants*

The first study included in this analysis, (Scanlon, Townsend, et al., 2019) had 12 participants from the university community (M = 22.9 years, range = 20-31; 4 female). The second study, (Scanlon et al., 2020) included 15 participants from the university community (M = 23.4 years, range = 20-31, 4 female). The study (Robles et al., 2021) included 29 participants from the psychology department (M= 20.96 years, range = 18-27, female proportion = 37.93%). Lastly, (Robles et al., 2022) included 24 participants (M = 20.96 years, age range = 18-27). Participants received an honorarium of $10 CAD or participation credits towards the psychology department research pool. All these studies were approved by the Internal Research Ethics Board at the University of Alberta (Pro00050069), and participants signed an informed consent form before completing the study.

*Study selection criteria*

Figure 4.1 shows that the four studies included in the present analysis were selected for the following criteria. First, studies share the same settings in the behavioral task, electrode map, EEG software, and hardware. A fifth study was originally selected for analysis (Scanlon et al., 2017) but was later discarded due to a shorter intertrial interval period, making it less suitable for this analysis. Second, to be selected for the analysis, the conditions of each experiment should have focused on either a change in environmental complexity or movement complexity. As stated previously, (Scanlon, Townsend, et al., 2019) compared participants' EEG in an oddball sitting still vs riding a bicycle outdoors. Therefore, we focus on the dynamics of alpha power between indoor vs outdoor environments (i.e., the increase in environmental complexity) and between sitting still vs outdoor riding (i.e., the increase in movement complexity). The second study (Scanlon et al., 2020) measured participants' EEG while they rode in a quiet park vs a busy road. These conditions allow for the testing of alpha dynamics between a low environmental vs a high environmental complexity place. Since (Robles et al., 2022) deployed the oddball paradigm to three different urban environments varying in traffic noise (low vs intermediate vs heavy traffic), this allows for another comparison of alpha dynamics, but in this study, we considered three different urban environments. Because the physical task in both experiments remained constant between conditions (i.e., participants rode at sub-aerobic levels at comparable speeds and pedaling cadence between all conditions), this study, as well as the study by Scanlon and colleagues (2020) described above, are suitable to explore alpha power in terms of environmental complexity. In (Robles et al., 2021), participants rode a skateboard on an indoor running track where the environmental conditions (light, temperature, volume of concurring track users) remained constant throughout the testing period. Because this experiment manipulated the riding difficulty (preferred vs unpreferred stance), this paradigm makes it suitable to study the dynamics of alpha power between low and high movement complexity.

### *EEG preprocessing*

EEG data were analyzed with custom scripts (https://github.com/d-robles/mobile_ersp) with MATLAB and EEGLAB (Delorme & Makeig, 2004). Due to the matching stimulus intertrial times between the four studies, the EEG data were preprocessed using identical settings. The EEG data were bandpass filtered with a high-pass threshold of 0.1 Hz and a low-pass filter of 30 Hz. An Eye Movement Correction Procedure (Gratton et al., 1983) was used to correct eye movements. Artifacts surpassing a voltage difference larger than +/− 500 µV of the baseline were removed. The data were epoched around the onset of the standard and target tones of the oddball task. Additionally, the data from studies #3 and 4 were downsampled to 500 Hz to match the recording settings of studies #1 and #2.

### *FOOOF analysis*

To compare differences in global alpha power between conditions, we compared the average induced alpha power in the standard trials of the oddball task. The FOOOF analysis is a recently developed oscillatory analysis developed by Donoghue and colleagues (2020), that separates the periodic and aperiodic properties contained within the EEG recordings. By separating the periodic from the aperiodic properties, this algorithm allows for a less biased visualization of frequency peaks. Stats were computed on the grand-averaged periodic-aperiodic spectra by selecting a frequency range bin of interest [7 13 Hz] at electrode Pz. The spectra were computed for the standard tones, averaged across the whole epoch [-1000 2000 ms]. For this analysis, we used a wavelet routine from the better oscillation method, BOSC (Hughes et al., 2012). A 6-cycle wavelet transform was applied to a frequency range between .1 to 30 Hz, with increasing 0.5 Hz steps. The analysis was performed using version 0.1.1 of the FOOOF Matlab wrapper with the following settings: peak width limits = [0.5,12]; max number of peaks = Inf; minimum peak amplitude = 0.0; peak threshold = 2.0; background mode = fixed; verbose = true; frequency range = 0.5–30 Hz. The background 1/f spectra were then subtracted from the periodic component to better compare changes in spectral power between 0.5 and 30 Hz across our conditions. All spectral analyses were done using this calculated FOOOF spectral data (Figure 2).

### *ERSP analysis*

A Morlet Wavelet analysis was computed to extract the evoked frequency spectra. The analysis was performed with the 'newtimef()' EEGLAB function (Delorme & Makeig, 2004). Following recommended guidelines for time-frequency analyses, because the time period of interest in the alpha activity is from 0 to 1000, epochs were 3,000 ms long, centered 1000 ms prior to the stimulus onset, and 2000 ms after onset (Cohen, 2014). A Morlet wavelet was used, with a cycle of 1 Hz at the lowest frequency, increasing in 0.5 steps towards the highest frequency. The wavelet was zero-padded with a ratio of 2 to improve the frequency resolution. The frequency range used for this analysis was 1 to 30 Hz. This resulted in a 698 ms wide window, containing 200 samples ranging from -651.0 to 1551.0 ms centered around the stimuli onset.

### *Statistical analysis*

To test for alpha power differences between the experimental conditions in the four studies, the FOOOF and ERSP data were analyzed using repeated-measures ANOVAs using the permutation-based *Fmax* statistic (Blair & Karniski, 1993). This method was designed to test for the statistical significance of waveform data where no underlying statistical assumptions are required. Another advantage of this approach is that it allows for the comparison of multiple time points while controlling for type 1 errors (Fields & Kuperberg, 2020). The MATLAB scripts used for these analyses were adapted from the Factorial Mass Univariate Toolbox (FMUT: Fields, 2017). The toolbox can be accessed at https://github.com/ericcfields/FMUT. The scripts used for this analysis can be accessed at https://github.com/d-robles/mobile_ersp. For the FOOOF analysis, the Fmut permutation test was computed on each frequency bin within the alpha range averaged over the whole epoch. For the ERSP analysis, the permutation analysis was carried out using a time window between 300 and 700 ms post-stimulus. A subset of successive time window bins ranging from the 300-700 time range was submitted to the analysis. We tested for a main effect in the condition type for each of the experiments selected. For all permutation analyses, the familywise alpha (α) was set to 0.05, and 10,000 random within-participant permutations were used to estimate the distribution of the null hypothesis.

## 4.3 Results

### *Behavioral results*

Behavioral results have been reported previously and are shown below. Study #1 did not record the participant's responses to the oddball task tones, hence no behavioral results are reported for this analysis. For study #2, behavioral plots are shown in figure 4.4d. No differences in accuracy (Mdiff = −1.60; SDdiff = 2.49; t(9) = −2.03; p = 0.0729 or reaction times (Mdiff = 4.10; SDdiff = 26.2; t(9) = 0.495; p = 0.633, were found. For study # 3, behavioral plots are shown in figure 4.5d. We found a significant difference in reaction times between the traffic lanes (F(1.455, 33.46) = 3.90, p = 0.042, η2p = 0.145). A post-hoc revealed an increase in RT in the low traffic relative to heavy traffic (Mdiff = −35.43, p = 0.01). For study #4, behavioral plots are shown in figure 4.6d. No significant differences in either accuracy or reaction times were found between the preferred and non-preferred riding stances.

### *Grand-average spectral results*

FOOOF plots are shown in figure 4.2. Panel D shows the periodic minus aperiodic components of the EEG signal. As the plot shows, overall, the indoor sitting condition shows the largest peak within the alpha range.

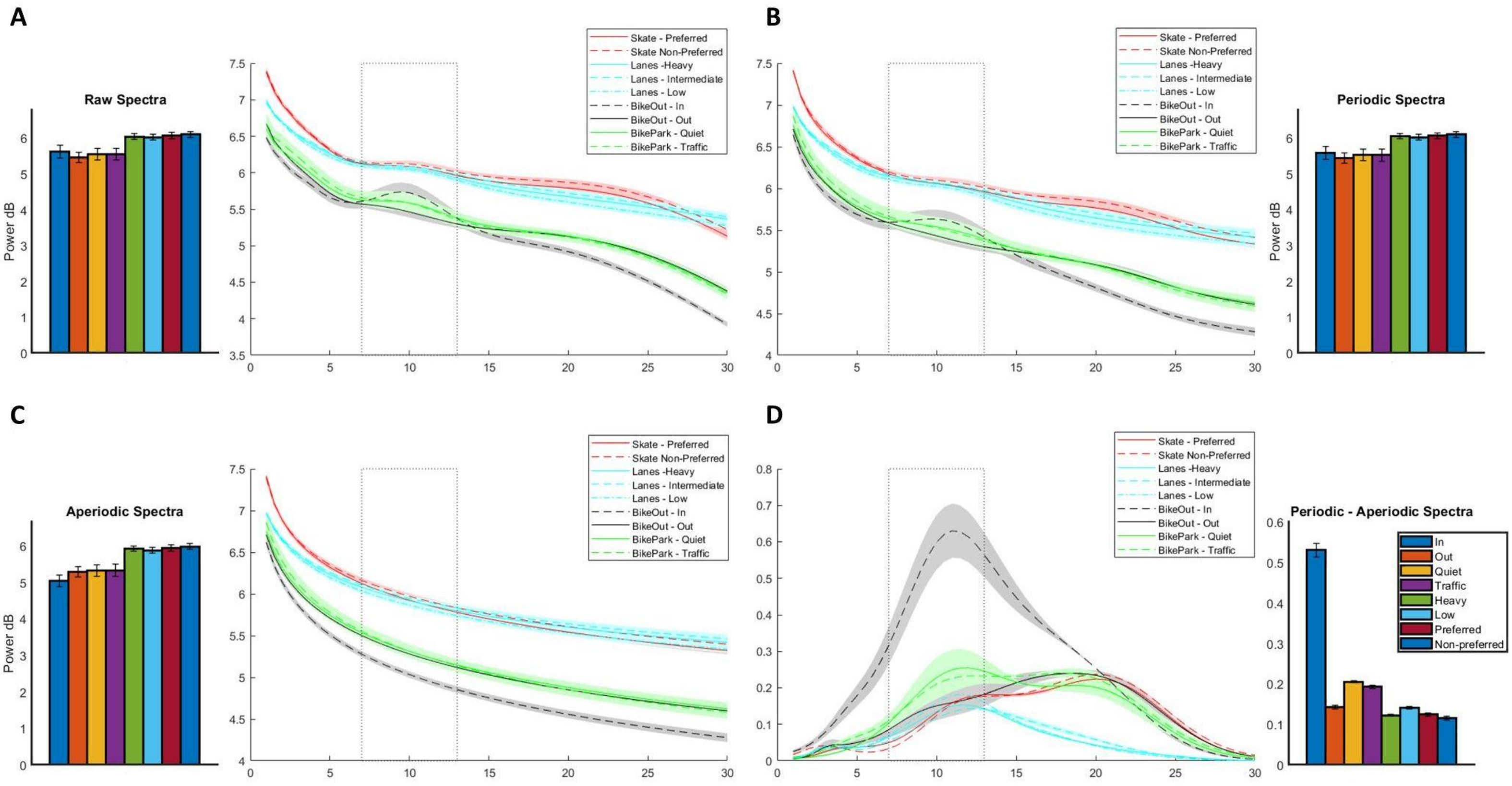

**Figure 4.2.** Summary of EEG Grand-average Spectra. (A): Raw EEG Spectra. (B): Periodic Spectra. (C): Aperiodic Spectra. (D): Aperiodic spectra after background subtraction.

For study # 1, alpha power was significantly higher in the inside condition relative to the outdoor condition at each alpha frequency bin, *Fmax* (1,11) = 6.23, $p<0.00$. For study #2, no significant differences in alpha power were found between the quiet park and busy roadway conditions. *Fmax* (1,9) = 5.82, $p > 0.05$. For study #3, we found a significant difference between conditions at the alpha range. The frequency bin at 10 Hz was statistically significant in the permutation-based Fmax analysis, *Fmax*(2, 46) = 4.27, $p < 0.05$, whereas surrounding frequencies had a marginally significant effect. Interestingly, the periodic plot above shows the highest alpha peak for the low traffic condition, suggesting an alpha power decrease towards the loudest traffic conditions. Finally, we found no significant differences in alpha power between the preferred and the non-preferred riding stances in study #4, *Fmax*(3,84) = 3.73, $p>0.05$.

### *ERSP results*

To better understand the dynamics of alpha activity during motion, we performed an ERSP analysis on the stimulus-evoked alpha activity for the target and standard tones. We compared the averaged alpha activity over the 300-700 ms post-stimulus time window. We performed the permutation-based Fmax analysis of the time bins containing 24 successive time points between 300 and 700 ms. Figure 4.3 shows the ERSP activity for the inside and outside conditions. For study #1, we found a significant interaction between the tone and condition types during the post-stimulus activity between inside and outside *Fmax*(1,11) = 9.48, $p <0.05$. The bar plot in figure 4.3d shows that there is an event-related alpha power desynchronization to the target tones that only occurs in the inside condition.

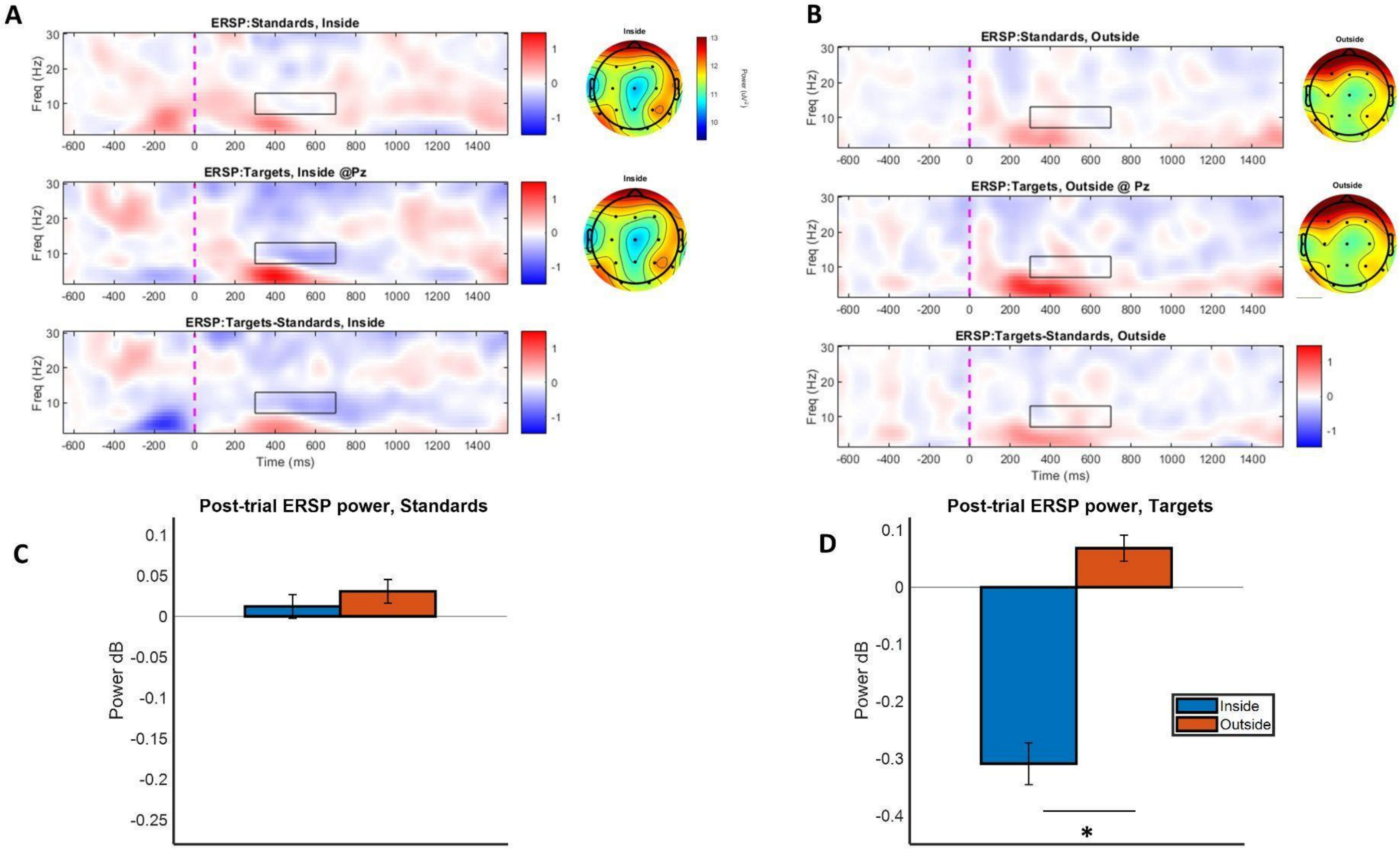

**Figure 4.3.** Study #1 EEG Spectra. (A): Inside ERSP. (B): Outside ERSP. (C): Averaged Post-stimulus alpha power for standard tones. (D): Averaged Post-stimulus alpha power for Target tones.

Figure 4.4 shows the spectral activity for the quiet park vs busy road in study #2. We found a significant main effect for the condition type at the post-stimulus window between the park and the roadway *Fmax*(1,9) = 15.02, p <0.05. As the bar plot in figure 4.4c shows, there we found a significant desynchronization of alpha power to the target tone in the quiet conditions relative to traffic in the post-stimulus window.

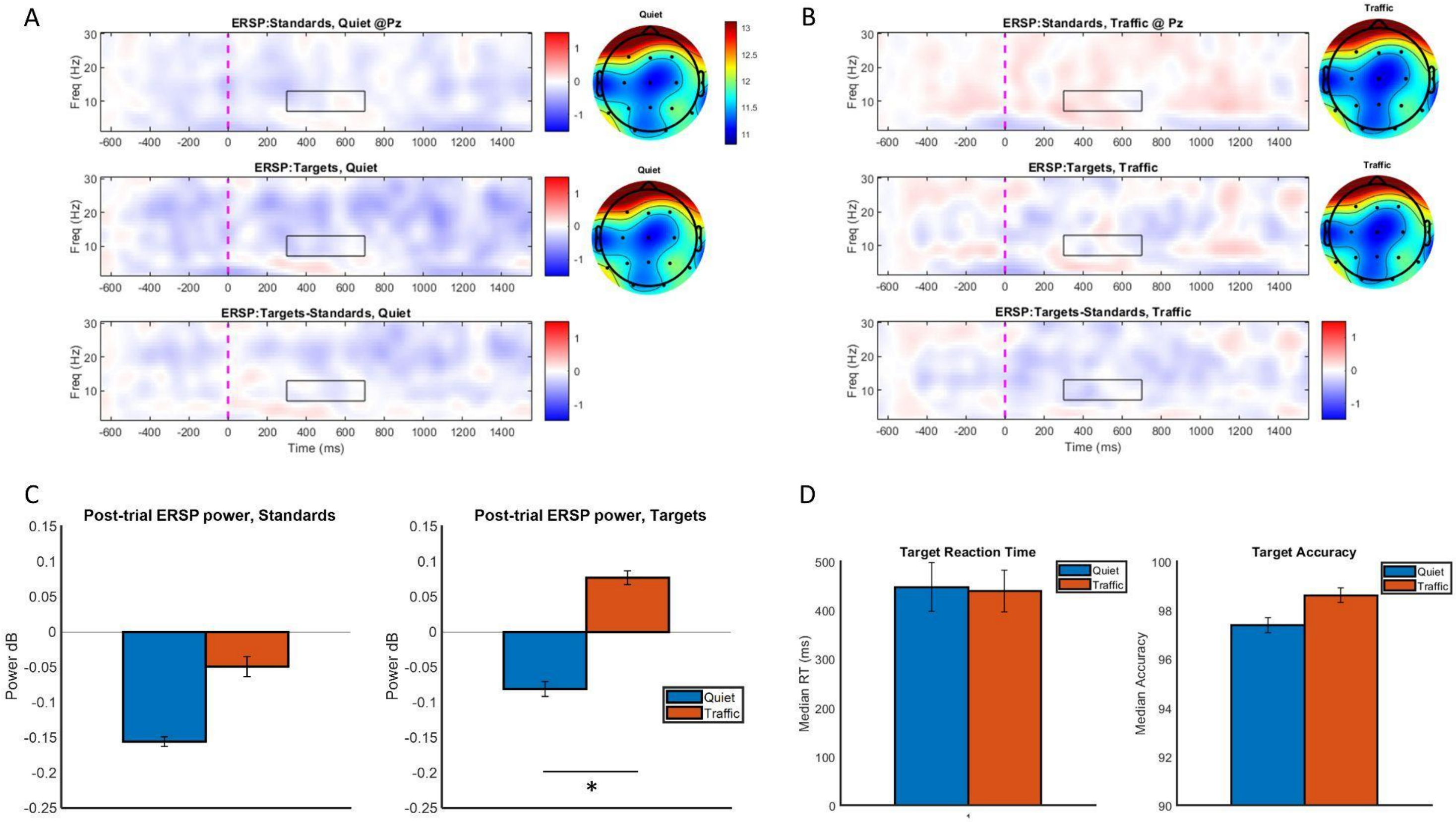

**Figure 4.4.** Study #2 EEG Spectra. (A): Park ERSP. (B): Roadway ERSP. (C): Averaged Post-stimulus alpha power for standard tones. (D): Averaged Post-stimulus alpha power for Target tones. Study #2 Behavioral results. (A): Response Accuracy. (B): Response Reaction Times.

Figures 4.5 and 4.6 show the spectral activity for studies #3 and 4 respectively. No significant differences in evoked alpha power were observed for study #3, *Fmax* (2,46) = 5.46, p > 0.05. Likewise, study #4 showed no further significant differences in evoked alpha power *Fmax* (3,84) = 3.73, p > 0.05

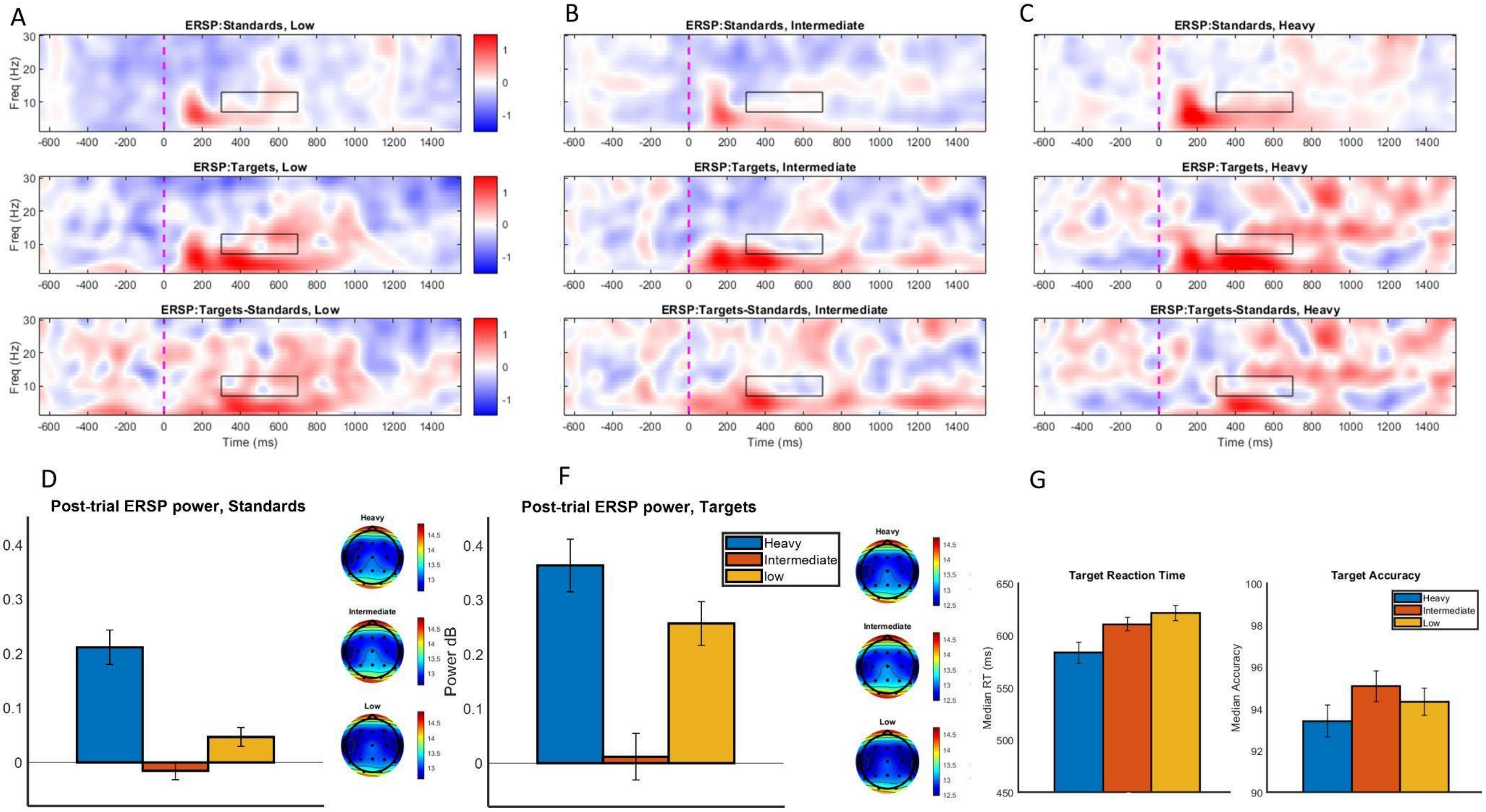

**Figure 4.5.** Study #3 EEG Spectra. (A): Low Traffic ERSP. (B): Intermediate ERSP. (C): Intermediate traffic ERSP. (D): Averaged Post-stimulus alpha power for standard tones. (F): Averaged Post-stimulus alpha power for Target tones. Study #3 Behavioral results. (A): Response Accuracy. (B): Response Reaction Times.

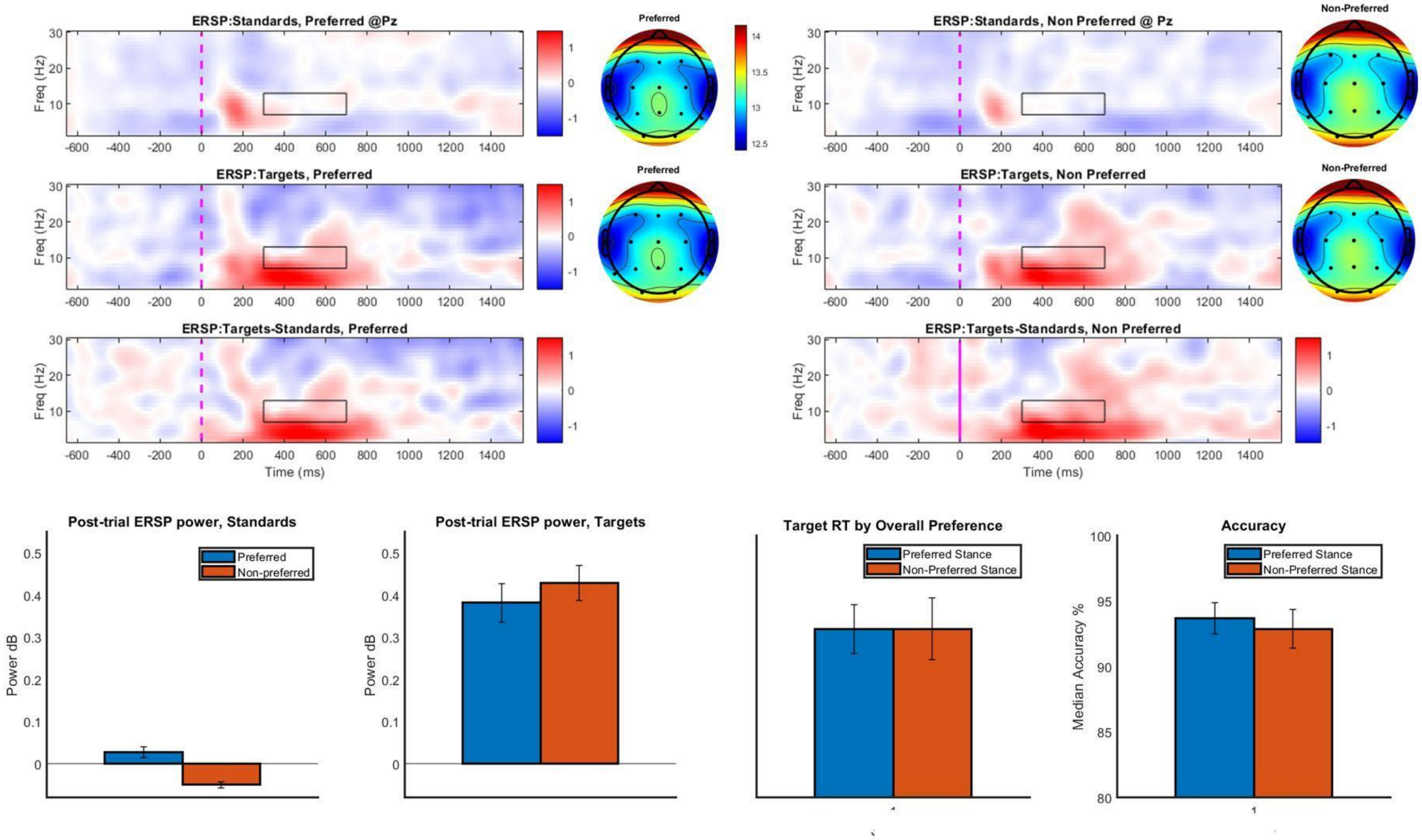

**Figure 4.6.** Study #4 EEG Spectra. (A): Preferred ERSP. (B): Non-preferred ERSP. (C): Averaged Post-stimulus alpha power for standard tones. (D): Averaged Post-stimulus alpha power for Target tones.

## 4.4 Discussion

The purpose of this chapter was to explore the dynamics of alpha power in a set of mobile studies. The motivation to conduct this analysis was motivated by several factors. First, we start with the observation that during our cycling mobile paradigms, we have found a reliable N1 ERP effect in conditions of increased cognitive load. However, in terms of spectral activity, our experiments have shown mixed results. To better address the lack of replicability of results in the alpha frequency, we proposed an analysis of spectral activity using two powerful approaches, the FOOOF method, and ERSPs to measure induced and evoked alpha activity respectively.

Additionally, we used a modified repeated-measures ANOVA using a permutation-based Fmax statistic to test for effects in the data. Another key point is that the data from the four studies were preprocessed, filtered, corrected, and segmented using matching scripts. By keeping these settings constant, we believe we have a better opportunity to test for effects in the alpha frequency.

### *Behavioral results*

Except for study #1, target accuracy and reaction times were collected in all studies. No differences in accuracy or reaction times were obtained in study #2, though accuracy and reaction times were better in the roadway condition. This might reflect greater arousal in the busier environment relative to the more relaxed park environment. As previously discussed by (Scanlon et al., 2020), behavioral effects might be independent of the significant modulations found in the mobile EEG paradigm. A similar pattern was found in study #3; while no significant differences were observed in accuracy, we found significantly greater reaction times in the low-traffic lane relative to heavy traffic. As figure 4.5g shows, a linear increase in reaction times going from low to heavy traffic conditions suggests an increase in behavioral alertness toward heavy traffic. No significant differences in accuracy or reaction times were observed in study #4, though there was a trend for better accuracy in the preferred stance condition. Since the accuracy bar plots show average mean accuracy greater than 90%, it is possible that the task difficulty was not great enough to cause a drop in performance between experimental conditions.

### *FOOOF results*

Before comparing the temporal, ERSP alpha dynamics among the selected studies, we first compared the average alpha power between the conditions of each study using the FOOOF algorithm. It is important to notice that the selected studies all tested for spectral differences in the alpha band, yielding mixed results. However, to ensure that the lack of replicability was not due to differences in analysis settings, we used the matching preprocessing settings to re-test grand-average alpha powers. Relative to traditional spectral analyses, FOOOF allows for extracting more data features not analyzed within the selected studies. We employed the FOOOF algorithm to separate the aperiodic or background spectra from the periodic spectra.

Figure 4.2 shows a summary of the grand-averaged spectral results for all studies. For study # 1, we predicted to find a decrease in alpha power during outdoor cycling relative to indoor sitting. As expected, Figure 4.2d shows that the most visually prominent alpha peak difference was found in the non-moving, indoor condition from study #1. Notably, the original study by (Scanlon, Townsend, et al., 2019) first reported a marginal decrease in alpha amplitude outdoors. However, this difference did not yield statistical significance. The present results found that relative to the indoor condition, the introduction to the external environment and motor task led to significant decreases in alpha power.

Given the well-documented inverse relationship between alpha power and cortical excitability, the decrease in alpha power observed outdoors suggest a greater state of excitability outdoors where participants process greater sensory and physical stimulation (Chen et al., 2022; Kelly et al., 2006; Rihs et al., 2007; Storzer et al., 2016). The decrease in alpha power outdoors aligns with the results from (Dehais et al., 2019), who showed a decrease in alpha power under increased cognitive load during simulation flying. Likewise, (Zink et al., 2016) found a decrease in alpha power in motion relative to stationary pedaling. They suggested that increases in task difficulty and mental workload could be driving the differences in alpha, but without ruling out the influence of physical engagement.

Given the similarities between the conditions in study #2 and #3, these results will be discussed together. For study #2, we hypothesized to find decreases in alpha power in the busy roadway relative to the quiet park. There were no significant grand-averaged alpha power differences between these conditions; however, upon inspecting figure 4.2, panel D, one can observe a trend towards increased alpha power during the park condition relative to the busy roadway. For study #3, we predicted finding lower alpha power in heavy traffic relative to quiet traffic. Interestingly, in figure 4.2, panel D shows the highest alpha peak for the low traffic condition, suggesting an alpha power decrease towards the loudest traffic conditions. Taken together, for urban environment paradigms, when movement complexity is equal (e.g., sub-aerobic biking in condition a) and low between conditions (e.g. sub-aerobic biking in condition b), one might expect a reduction in alpha power as the product of task difficulty or the environment. In this case, we only found a significant difference between traffic conditions in the urban lanes study and not in the bike-parks study, where we expected a difference in alpha power between traffic and the quiet park.

The results from studies #2 and #3 can be further discussed in the context of motor demands. Previous studies have shown that alpha power decreases during walking (Cao & Händel, 2019). Some have argued that the decrease in alpha power reflects increases in sensory processing during walking (Malcolm et al., 2018; Storzer et al., 2016), while Cao and colleagues (2020) showed that alpha desynchronization was independent of visual stimuli during walking. Other cycling paradigms found that walking leads to greater desynchronization of alpha relative to cycling (Storzer et al., 2016). They suggested that the monotonous nature of cycling was associated with less cortical excitation than walking. Taken together, this analysis shows that when the task and analysis settings were matched in the cycling studies, we still observed a pattern of reduced alpha power in the conditions with the increased environmental load. This pattern was present even in study #2, where we failed to observe significant differences.

For study #4, we predicted a decrease in alpha power during the non-preferred riding relative to the preferred riding stance. No significant differences in alpha power were observed between these conditions. As previously discussed by (Robles et al., 2021), the lack of differences in alpha power could be explained by a general increase in motor load brought about by the riding task. Interestingly, this is the only study where all conditions occur under the same environment. Notably, although the running track was located indoors, this environment was fairly complex with other users, sounds, and distractors. This means that while some key features of the track (light, temperature) did not vary between the preferred and non-preferred riding, the combination of a complex environment and motor task caused might have reduced the participant's cognitive resources to the point where no differences could be detected. In this sense, sustained alpha power is a reliable predictor of cognitive load outdoors.

### *ERSP results*

To better understand the temporal dynamics of alpha activity during motion, we performed an ERSP analysis on the stimulus-evoked alpha activity for the target and standard tones. For this analysis, we were interested in the short-term changes in alpha power following experimental events. Given the methodological approach used in this analysis, our goal was to explore the role of alpha desynchronization for the target tones under different environmental and movement demands.

For study #1, we predicted a stronger ERD in the indoor environment relative to the outdoor condition. We found a significant desynchronization of alpha power towards the target tones indoors (figure 4.3, suggesting increased task engagement in the indoor condition

(Klimesch et al., 1993; Peng et al., 2015), as well as a  more active stimulus processing (Klimesch et al., 2007). Furthermore, the amount of alpha desynchronization has been previously linked to task relevance (Boiten et al., 1992; Doppelmayr et al., 1998). A possible interpretation of these findings is that when exposed to the outdoor environment, participants could no longer allocate cognitive resources toward the target tones shown indoors. The plethora of stimuli could induce this change in available resources while participants rode outdoors. Another point to consider is that in the outdoor condition, participants moved freely on a bike. It is also possible that factors such as the increase in sensory and internal processing (Ladouce et al., 2019) or the increase in motor demands (Cao et al., 2020) might have also contributed to the decrease in available resources during motion.

Studies #2 and #3 provide an opportunity to focus on the temporal dynamics of alpha power in various environments while the motor task was kept constant between conditions. For study #2, we predicted a greater post-stimulus alpha desynchronization in the quiet park relative to traffic. We found a significantly larger post-stimulus alpha desynchronization towards the target tones in the quiet park. These findings are consistent with the results from study #1 described above. Notably, these results show that when participants complete the oddball tasks in the quietest environments (the lab chamber in study # 1 and the park in study #2), the level of alpha desynchronization is greater than in busier conditions. Taken together, the observed differences in alpha desynchronization in study #2 could reflect an increase in attentional resources during the park (Pfurtscheller & Lopes da Silva, 1999). An important consideration is that in this paradigm, the motor complexity of the dual task was held constant between conditions. Unlike study #1 above, the desynchronization shown in study #2 can be fully attributed to increased environmental demands and not to increased motor complexity.

For study #3, we predicted finding the largest alpha desynchronization in the low traffic relative to the intermediate or heavy traffic conditions. We found no significant differences in post-stimulus alpha desynchronization between the three urban bicycle lanes. While these results are inconsistent with those in studies #1 and #2, the lack of consistent results in study #3 might be explained by the physical attributes of the experimental conditions. Study #3 was the only cycling paradigm from the selected studies where participants experienced a "true" street environment in all conditions. This increase in environmental complexity in all conditions might have decreased the possibility of finding a significant alpha effect. In other words, when environmental complexity is increased, the evoked changes in alpha observed in studies #1 and #2 go away.

For study #4, we hypothesized finding greater alpha desynchronization during the preferred riding stance. We found no significant difference in desynchronization between conditions. Several points should be discussed following these results. First, this was the only study where the physical environment was unchanged between conditions. Therefore, this design provided an opportunity to evaluate how an increase in motor complexity during the non-preferred condition could influence evoked alpha dynamics. The lack of significant effects in study #4 might be related to the type of task used. Since sensations such as movement flow and other sensory processes were almost identical between conditions, participants might have experienced a similar level of cortical excitability during skateboarding (Ladouce et al., 2019; Sauseng et al., 2009).

### *4.5 Limitations to generalizability*

There are several limitations that must be discussed. The main limitation is that the data analyzed in this chapter were collected from different subjects. Instead, these studies took place over different years, over a different cohort of participants. This could compromise the extent to which these results could be generalized to the population. However, the participants recruited in the four studies were recruited from the campus community and from introductory psychology courses where their ages and educational levels fall within the university of Alberta average. Another major limitation is that the selected studies failed to record the participant's subjective sense of task difficulty. This could have provided valuable insight into the subjective experience for each task, especially when no behavioral differences were observed.

### *4.6 Conclusion*

In this chapter, we selected four mobile studies from our workgroup to better understand the dynamics of alpha power during motion. We matched the hardware, software, and preprocessing settings, to compare grand-average and stimulus-evoked alpha power dynamics between studies. By extracting the background alpha activity from the periodic activity, we found a general trend of decreased grand-average alpha power towards conditions with increased environmental demands. Likewise, we found a trend for greater post-stimulus alpha desynchronization in the indoor environment and the quietest outdoor environment (park).

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# Chapter 5 - Conclusions

In this dissertation, we employed mobile EEG paradigms to investigate the neural mechanisms involved in sustained attention. An advantage of mobile paradigms is the possibility of collecting EEG signals over a range of behaviors and places away from the laboratory. This approach comes in response to the views that laboratory-isolated environments might limit the study of dynamic attention (Gramann et al., 2014; Ladouce et al., 2017). Furthermore, by testing robust paradigms such as the oddball P3 or alpha spectral analyses, mobile EEG research can extend the lab-based findings into ecologically valid settings (Ladouce et al., 2017; Makeig et al., 2009). Our first goal was to develop a mobile EEG skateboard paradigm. By introducing this new method, we extended the range of possibilities for mobile studies beyond walking and cycling.

Furthermore, we tested for the degree to task interference participants experience when exposed to various urban cycling environments. In this study, we found modulations in the N1 ERP based on the level of environmental noise participants experienced. While these findings are consistent with previous workgroup findings (Scanlon et al., 2020; Scanlon, Townsend, et al., 2019), other findings regarding alpha activity (8-12 Hz) were mixed between our studies. Finally, we matched and re-analyzed the data from four mobile studies to address the discrepancy regarding our alpha results. By unifying the data treatment approach, we found a pattern of decreased sustained alpha power in conditions of low environmental complexity. We also found a stronger post-stimulus alpha desynchronization pattern in these low-environmental complexity environments, suggesting better stimulus processing under low environmental load.

The main goal of this research was to better understand selective attention under motion and in unstructured environments. To accomplish this research, dual-task mobile paradigms used the classic oddball task (Squires et al., 1975) when subjects were in motion. Specifically, we asked the following questions: (1) how is EEG activity modulated when participants are exposed to increased motor load; (2) how does EEG activity change in response to increased environmental complexity? The first question was addressed in the experiment in chapter 2. In this experiment, we developed a skateboard paradigm to introduce a navigation module that greatly minimizes motion relative to walking (Beurskens et al., 2016; Wagner et al., 2014) or cycling (Scanlon, Townsend, et al., 2019; Storzer et al., 2016). This introduces fewer artifacts improving data accuracy (Luck, 2014; Oliveira et al., 2016a). We demonstrated the feasibility and validity of the skateboard paradigm in recording the classic oddball P3 (Kok, 2001; Squires et al., 1975). However, we failed to observe differences in P3 amplitude between the subject's preferred and unpreferred skating stances. While previous literature has found a decrease in P3 amplitude under increased motor load (Ladouce et al., 2019; Reiser et al., 2019; Zink et al., 2016), our results alight with mobile studies that failed to observe a difference in P3 amplitude during increased motor load (Gramann et al., 2010; Protzak et al., 2020). Because participants experienced the sensory and physical sensations of motion regardless of riding stance, it is possible that the lack of P3 effects was due to increased visual sensory processing (Ladouce et al., 2019).

In chapter 2, the grand-average alpha power was compared between experimental conditions. We found no differences in alpha power in the movement conditions. These results did not align with previous mobile studies showing a trend toward a decrease in alpha power during increased motor load (Storzer et al., 2016; Zink et al., 2016). We did find significant differences in the alpha range between a resting state condition and the riding conditions. Given the nature of the dual task, we attributed this change in alpha power to an increase in sensory and visual processing during motion (Cao et al., 2020; Leone et al., 2017; Malcolm, Foxe, Butler, Molholm, & Sanctis, 2018).

In chapter 3, we deployed a cycling paradigm to three different urban lanes varying in traffic volume. By manipulating the environment where subjects completed the dual task, we could understand how attentional mechanisms work under everyday conditions. In this chapter, we measured the N1, P3, and alpha activity while participants completed the oddball task in the different bike lanes. We found a notable modulation in the N1 amplitude when participants were exposed to the heavy traffic sounds relative to the low traffic intensity sounds. These results were consistent with (Scanlon, Cormier, et al., 2019; Scanlon et al., 2020; Scanlon, Townsend, et al., 2019), who originally observed this N1 effect towards traffic sounds. We further replicated this effect by showing that the observed N1 modulation is sensitive to various levels of traffic noises. These studies suggest that during the completion of an auditory oddball task outdoors, the N1 might serve as an auditory filtering mechanism to suppress the surrounding noise. Importantly, we also failed to observe differences in P3 or alpha power amplitudes between conditions in this study. Because chapter 3 employed the methodology developed by (Scanlon, Townsend, et al., 2019), we were motivated to take a closer look at the dynamics of alpha power by employing a different analysis approach on various mobile datasets within our workgroup.

In chapter 4, we aimed to re-analyze a group of mobile EEG datasets from our workgroup, which included the studies from chapters 2 and 3. First, to better address the lack of replicability regarding alpha findings in our workgroup, the processing settings were matched between studies. Second, we extracted several features from the spectral data using the Fitting Oscillations & One Over F, or FOOOF (Donoghue et al., 2020) to understand better how grand-averaged alpha power changes between the conditions of each study, respectively. Furthermore, we looked at stimulus-evoked features in alpha power via an alpha-related desynchronization analysis (Pfurtscheller, 1991). The goal of this analysis was to compute the temporal changes of alpha power relative to the baseline power. As alpha desynchronization (ERD) has been associated with good task performance (Klimesch et al., 2006; Mirjalili et al., 2022; Tenke et al., 2015), we assessed participant's alpha desynchronization in the selected studies. An important observation is that these studies allow for the individual assessment of alpha between no motion and outdoor motion (study #1), between matched motion in changing environments (studies #2 and #3), and between a matched environment in varying motion (study#4). In chapter 4, we found a significant trend for decreased grand-averaged alpha power toward the busier environments. We also found that only indoors and in the quiet park environment participants showed the largest post-stimulus alpha desynchronization toward the target tones.

Overall, the results from this research demonstrate the feasibility of employing novel mobile paradigms, such as the skateboard from chapter 2, to record EEG in complex environments. While we failed to observe significant differences in the P3, chapter 3 shows other ERP components, such as the N1, showed to be a sensitive electrophysiological measure of increased cognitive load outdoors. In chapter 4, we were interested in addressing what happened when recording alpha power in the context of environmental increases vs motor complexity. These results are mixed. We found a trend for decreased global alpha power during the outdoor condition and modulation in alpha desynchronization indoors in study #1. In study # 2, we found no significant differences in grand-averaged alpha power between the park and busy roadway, even though the FOOOF plots show a decrease in alpha peak for the busy road relative to the park. This effect was again significant in study #3, where we found a larger decrease of alpha power towards heavy traffic relative to low traffic. Taken together, we show that grand-average alpha power can significantly decrease between conditions varying in environmental demands.

There is an interesting pattern of alpha desynchronization in studies #2 and #3. For experiment #2, we found a significant post-stimulus desynchronization in the park relative to the busy road. This was expected given the assumption that the park was the quieter environment, where the participants could process the task tones better. In experiment # 3, we found no differences in ERD between the urban lanes. An explanation for this lack of findings is that perhaps since the task environments experienced surrounding traffic, participants failed to allocate the same amount of task resources toward the task stimuli. Taken together, chapter 4 suggests that in conditions where the experimental settings are consistent, alpha power shows a different profile towards the busier environments. This could reflect the increased excitation required to process the ongoing stimuli from complex environments (Babiloni et al., 2014; Başar & Güntekin, 2012; Bazanova & Vernon, 2014).

Our results are inconclusive when it comes to the effect of motor load in alpha rhythms. The analysis of study #4 in chapter 4 aimed to understand how increases in motor complexity influence the participants' cognitive resources. The lack of significant effects observed in study # 4 might suggest that either the motor task load was equally high during e-skateboarding or the increase in sensory and visual processing during motion might have led to a global change in alpha power to the point where no difference in alpha dynamics can be observed.

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