



## UWS Academic Portal

### I think I don't feel sick

Pöhlmann, Katharina Margareta; Maior, Horia A.; Föcker, Julia; O'Hare, Louise; Parke, Adrian; Ladowska, Aleksandra; Dickinson, Patrick

*Published in:*  
CHI 2023

*DOI:*  
[10.1145/3544548.3581063](https://doi.org/10.1145/3544548.3581063)

Published: 19/04/2023

*Document Version*  
Peer reviewed version

[Link to publication on the UWS Academic Portal](#)

#### *Citation for published version (APA):*

Pöhlmann, K. M., Maior, H. A., Föcker, J., O'Hare, L., Parke, A., Ladowska, A., & Dickinson, P. (2023). I think I don't feel sick: exploring the relationship between cognitive demand and cybersickness in virtual reality using fNIRS. In A. Schmidt, K. Väänänen, T. Goyal, P. O. Kristensson, A. Peters, & S. Mueller (Eds.), *CHI 2023: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* [20] (Conference on Human Factors in Computing Systems - Proceedings). Association for Computing Machinery. <https://doi.org/10.1145/3544548.3581063>

#### **General rights**

Copyright and moral rights for the publications made accessible in the UWS Academic Portal are retained by the authors and/or other copyright owners and it is a condition of accessing publications that users recognise and abide by the legal requirements associated with these rights.

#### **Take down policy**

If you believe that this document breaches copyright please contact [pure@uws.ac.uk](mailto:pure@uws.ac.uk) providing details, and we will remove access to the work immediately and investigate your claim.

Pöhlmann, K. M., Maior, H. A., Föcker, J., O'Hare, L., Parke, A., Ladowska, A., & Dickinson, P. (2023). I think I don't feel sick: exploring the relationship between cognitive demand and cybersickness in virtual reality using fNIRS. In A. Schmidt, K. Väänänen, T. Goyal, P. O. Kristensson, A. Peters, & S. Mueller (Eds.), *CHI 2023: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* [20] (Conference on Human Factors in Computing Systems – Proceedings). Association for Computing Machinery.

© ACM, 2023. This is the author's version of the work. It is posted here by permission of ACM for your personal use. Not for redistribution. The definitive version was published in *CHI 2023: Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* [20] Association for Computing Machinery. <https://doi.org/10.1145/3544548.3581063>

# I think I don't feel sick: Exploring the Relationship Between Cognitive Demand and Cybersickness in Virtual Reality using fNIRS

Katharina Pöhlmann  
katharina.pohlmann@glasgow.ac.uk  
University of Glasgow  
Glasgow, United Kingdom

Horia A. Maior  
University of Nottingham  
Nottingham, United Kingdom

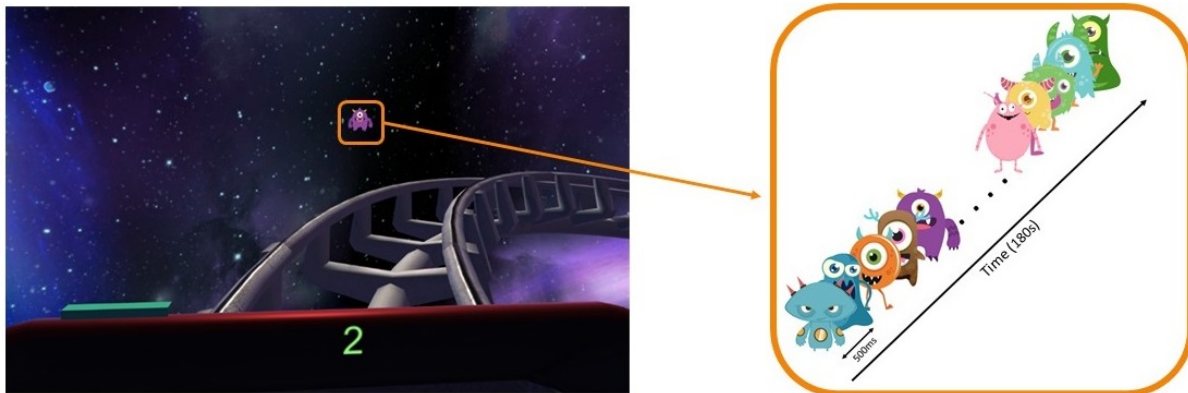
Julia Föcker  
University of Lincoln  
Lincoln, United Kingdom

Louise O'Hare  
Nottingham Trent University  
Nottingham, United Kingdom

Adrian Parke  
University of the West of Scotland  
Glasgow, United Kingdom

Aleksandra Landowska  
University of Nottingham  
Nottingham, United Kingdom

Patrick Dickinson  
University of Lincoln  
Lincoln, United Kingdom



**Figure 1: Left Side: Example of the Virtual Roller Coaster Environment Displaying the RSVP task and the Cybersickness Rating Scale. Right Side: Schematic Illustration of a Typical Rapid Serial Visual Presentation (RSVP) Task Trial**

## ABSTRACT

Virtual Reality (VR) applications commonly use the illusion of self-motion (vection) to simulate experiences such as running, driving, or flying. However, this can lead to cybersickness, which diminishes the experience of users, and can even lead to disengagement with this platform. In this paper we present a study in which we show that users performing a cognitive task while experiencing a VR rollercoaster reported reduced symptoms of cybersickness. Furthermore, we collected and analysed brain activity data from our participants during their experience using functional near infra-red

spectroscopy (fNIRS): preliminary analysis suggests the possibility that this technology may be able to detect the experience of cybersickness. Together, these results can assist the creators of VR experiences, both through mitigation of cybersickness in the design process, and by better understanding the experiences of their users.

## CCS CONCEPTS

• **Human-centered computing** → **Human computer interaction (HCI)**.

## KEYWORDS

cybersickness; virtual reality; cognitive demand; fNIRS; HMD

## ACM Reference Format:

Katharina Pöhlmann, Horia A. Maior, Julia Föcker, Louise O'Hare, Adrian Parke, Aleksandra Landowska, and Patrick Dickinson. 2023. I think I don't feel sick: Exploring the Relationship Between Cognitive Demand and Cybersickness in Virtual Reality using fNIRS. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems (CHI '23)*, April 23–28, 2023, Hamburg, Germany. ACM, New York, NY, USA, 16 pages. <https://doi.org/10.1145/3544548.3581063>

Permission to make digital or hard copies of all or part of this work for personal or classroom use is granted without fee provided that copies are not made or distributed for profit or commercial advantage and that copies bear this notice and the full citation on the first page. Copyrights for components of this work owned by others than the author(s) must be honored. Abstracting with credit is permitted. To copy otherwise, or republish, to post on servers or to redistribute to lists, requires prior specific permission and/or a fee. Request permissions from [permissions@acm.org](mailto:permissions@acm.org).  
CHI '23, April 23–28, 2023, Hamburg, Germany  
© 2023 Copyright held by the owner/author(s). Publication rights licensed to ACM.  
ACM ISBN 978-1-4503-9421-5/23/04...\$15.00  
<https://doi.org/10.1145/3544548.3581063>

## 1 INTRODUCTION

Virtual Reality (VR) headsets are not only used for gaming and entertainment but are increasingly employed in education [43, 56], for training applications [41, 57], and for treatment and therapy [22, 29, 75]. VR is a promising tool for these applications, as the increased sense of immersion and presence compared to more traditional platforms (e.g. desktop computers) has been shown to improve outcomes and performance [4, 86, 97]. Moreover, VR allows designers to create experiences which would be dangerous or costly to recreate using traditional methods [25, 41]. VR experiences can however, cause adverse motion sickness-like symptoms (cybersickness) in users [49], with the primary cause of such symptoms believed to be the mismatch between perceived and expected visual and vestibular motion [80, 81, 91].

Many VR applications, including training and immersive gaming experiences, that use virtual environments which exceed the bounds of room-scale VR rely on locomotion techniques that induce such a mismatch between the senses. The experience of cybersickness caused by these (and other) effects can lead to a decrease in enjoyment and engagement, potentially affecting users' sense of presence as well as training and treatment outcomes [96, 101], additionally limiting uptake, and the commercial or therapeutic success of VR applications. A significant amount of research has been conducted into mitigation for VR cybersickness, most of which has so far focused on investigating the effects of sensory inputs on symptoms, such as field of view (FOV) restrictions or speed of motion (e.g., [21, 24, 48]). Such interventions can, however, diminish presence and lead to disorientation [17, 26].

Existing work in motion-induced sickness (where users experience actual physical motion) has shown that it can be influenced by higher cognitive processes [10, 47, 69]. There has been a small amount of related work in VR environments, but the relationship between cognitive demand and cybersickness in VR caused by visual motion has not yet been explored. Since many VR applications already involve an aspect of cognitive demand, such as in game search or attention tasks, there is a need to better understand the relationship between cognitive load and cybersickness, as this could help designers to better anticipate the levels of cybersickness experienced by users, and their need for mitigations. Thus, our work, presented in this paper, focuses on developing a better understanding of this relationship.

### 1.1 Exploring the Use of Physiological Measures of Cybersickness

Cybersickness is generally captured using self-report measures (e.g. [44, 46]), typically deployed after completing an experience, or by interrupting the experience (thus undermining participants' sense of immersion). This makes it difficult for researchers to gather data on the temporal dynamics of the development of cybersickness and such measures may even inadvertently influence participants' perception of symptoms [103].

Physiological sensors could provide a method of assessing the continuous experience and intensity of symptoms, and could also be used as real-time feedback to adapt VR experiences, dynamically driving closed-loop mitigation. With physiological sensors becoming less invasive and more portable, there is an emerging trend to

embed physiological sensors within VR headsets. For example, the recent HP G2 Reverb Omnicept headset includes eye tracking, heart rate sensors, and face tracking cameras. In our work, we also explore the possible use of physiological measures to understand users' experience of cybersickness. We chose to use frontal-lobe functional near-infrared spectroscopy (fNIRS) sensors, a non-invasive, portable and low-cost method of monitoring brain activity [39]. This technology is of particular interest for our study as it has previously shown potential as a measure in HCI research (eg. [59]), and has been associated with the detection of cognitive demand [12, 18, 64, 72] and emotional arousal [7, 31, 33]. Furthermore, when used for entire brain coverage, fNIRS has shown the potential to detect brain activity associated with motion sickness in car journeys which is primarily reflected in posterior regions but also shows some related activity in frontal areas [105]. Unlike Zhang et al.'s study, we use frontal-lobe fNIRS sensors only (as displayed in Fig. 3), primarily because such a configuration could be deployed as an integral part of a VR head-mounted display, and so is more likely to be widely deployed and available to developers. Recent work has also suggested that such a set up might be able to detect cybersickness induced by VR exposure [100].

Our work is the first to address these concerns through a lab study examining the relationship between cybersickness and cognitive load, and a preliminary exploration of the use of fNIRS as a physiological measure of cybersickness. This research provides insight for a future in which cybersickness across VR experiences can be detected and mitigated via headset-embedded physiological sensors and manipulating cognitive demand.

### 1.2 Contributions

Through the work presented in this paper, we make the following contributions:

- We present the results of a user study which demonstrates that performing a cognitive task while immersed in VR can mitigate the experience of cybersickness, which has significant implication for the design of future VR experiences.
- We explore and propose the potential for frontal-lobe fNIRS as a physiological measure of cybersickness, and present preliminary findings as a point for discussion.
- Our findings validate and extend previous works which show that fNIRS measurements over the frontal-lobe can be associated with the detection of cognitive demand in VR, comparable with subjective techniques.

In the rest of our paper we firstly present relevant existing work related to cybersickness in VR, and the use of fNIRS as a physiological measure of brain activity. We then proceed to describe our study, in which participants were seated on a virtual roller coaster (see Figure 1 and 2) in VR, while performing a rapid serial visual presentation task (RSVP, see Figure 1). This highly controlled cognitive task was chosen to investigate the effects of cognitive demand on cybersickness and cybersickness on task performance. We then proceed to present our findings in Section 5, which show that performing a cognitive task in VR can partially mitigate the experience of cybersickness, and provide some preliminary evidence that frontal-lobe fNIRS may be a suitable physiological measure for evaluating cybersickness. We conclude with a discussion of our

results, in which we make recommendations for the future design of VR experiences, and consider how fNIRS might be further developed as a real-time feedback tool for understanding and improving user experiences in VR.

## 2 RELATED WORK

Cybersickness is similar to motion sickness and describes adverse symptoms experienced when immersed in a computer-generated virtual environment [20, 49, 70, 96]. Virtual environments that involve user locomotion resulting in optic-flow are particularly prone to causing cybersickness symptoms, due to a conflict between perceived and expected physically and visually experienced self-motion. [49, 81]. These symptoms include, oculomotor-like symptoms, like eye strain, headaches or blurred vision to motion sickness-like symptoms such as nausea, dizziness, vertigo or stomach awareness.

### 2.1 The Relationship Between Cognitive Demand and Cybersickness

In our work we investigate the effects of performing a cognitive task on cybersickness symptoms, while experiencing visual motion in VR. To our knowledge, no previous works have examined this; however, a number of related studies have investigated the effects of cognitive processes on motion-induced sickness in other types of environments.

For example, recent work by Nooij et al. [69] showed that users' beliefs about the possibility of perceived motion actually occurring can affect motion sickness symptoms. In their case, users experienced less sickness while viewing rotational motion when seated in a chair capable of rotating. Mental engagement in a task can also reduce the experience of motion sickness levels. For example, performing cognitive tasks while immersed in a motion sickness inducing environment can distract from experiencing symptoms, such as nausea [10]: in this case, Bos et al. [10] induced motion sickness by blindfolding participants and exposing them to off-vertical axis rotation. Listening to music has also been theorised to reduce motion sickness, particularly music liked by the user, which creates a positive emotion [47, 74], suggesting that such positive effects are likely, and not only due to simple distraction from motion sickness symptoms. This notion is also supported by work investigating the effects of a simple counting task on motion sickness elicited by whole body pitch oscillation, that found no reduction of motion sickness in relation to such a task [102].

Motion sickness and cybersickness have also been found to reduce with repeated exposure to a sickness inducing environment [23, 45, 106], with recent research suggesting that cognitive distraction might facilitate these habituation effects, resulting in a speedier reduction of cybersickness symptoms over time [107]. Together, this body of work suggests that adding a cognitive task to a potentially cybersickness-inducing experiences in VR might not only have immediate beneficial effects on symptoms (and the users' experience), but can also help reduce future negative experiences in such environments.

Conversely, some previous work has investigated the effects of motion sickness on task performance. For example, motion sickness induced by driving simulators has shown to have negative after effects on participants performance on an n-back task [89] as well

as reaction times for emergency breaking tasks [82]. Similarly, in a virtual navigation task presented on a concave screen, participants performed worse when they experienced cybersickness [50]. In contrast, in a high-fidelity driving simulator no negative effects of motion sickness on driving performance were found. [38].

Dahlman et al. showed that participants in an optokinetic drum that experienced stronger visually induced motion sickness performed worse on short term memory tasks [19]; similarly, performance on working memory task has been shown to be negatively affected by motion sickness induced in a rotating chair [71]. Participants in Matsanga's et al.'s study [63] performed a multitasking battery (memory search task, arithmetic problem task, visual and auditory reaction tasks) in VR, while seated on a motion platform: their performance declined with increases motion sickness. However, relatively little work has examined the effects of cybersickness in VR headsets (based on visual motion alone) on task performance. Salgado et al. [84] and Stanney et al. [92] both found that cybersickness reduced performance on locomotion tasks; however, no work has yet investigated the effects of cybersickness on cognitive task performance in VR.

### 2.2 Measures of Cybersickness

One of the most commonly used scales to measure cybersickness is the Simulator Sickness Questionnaire (SSQ) developed by Kennedy and colleagues [44] to accommodate symptom specific to exposure to virtual simulators. The questionnaire generates three sub-scales: Nausea, Oculomotor and Disorientation. The SSQ is generally applied before and after exposure, and therefore is unable to give information about the development of symptoms over time.

A simple and fast method to measure cybersickness symptoms while immersed in the virtual environment was introduced with the Fast Motion Sickness Scale (FMS) [46]. The FMS can be administered during stimulus presentation, with motion sickness intensity being rated verbally every minute on a 20-point scale. This allows for a continual measure of cybersickness intensity.

*2.2.1 Neuronal correlates of Cybersickness.* Ideally, it would be possible to measure a user's experience of cybersickness without them needing to self-report (or be made aware of it). EEG, due to its high temporal resolution, has been used to detect changes in neuronal activity associated with motion sickness (e.g. in simulators or moving vehicles) as well as cybersickness [15, 50, 52, 55, 66, 66]. Evidence from these studies indicates that measurable neuronal changes may be associated with self reported sickness symptoms.

However, EEG can be cumbersome to set up, many times requiring contact gel, or uncomfortable dry electrodes, which make it difficult to deploy in consumer products. In our work, we explore the use of frontal-lobe fNIRS as an alternative measure of neuronal correlates related to cybersickness, which could more easily be integrated into commercial head mounted displays, as shown by [100].

## 2.3 fNIRS and Cybersickness

fNIRS is a non-invasive brain imaging method that uses near infrared (NIR) light (in the 650–1000 nm wavelength range) to measure regional hemodynamic responses associated with neuron behaviour. fNIRS can monitor changes in oxygenated (HbO) and deoxygenated (HbR) hemoglobin that can be correlated with changes in brain activity. A significant change in brain activity in a particular region is considered when a negative correlation between HbO and HbR is detected [16, 104]. fNIRS has a higher temporal resolution compared to fMRI, a higher spacial resolution compared to EEG [85], and has been successfully used to measure brain activity in different brain regions such as the prefrontal cortex [3, 60, 73], the motor cortex [34, 88], the auditory cortex [77], and others.

Recently, fNIRS has been explored by the HCI community as a physiological measure, due to its portability, non-invasive nature, low cost, relatively easy setup, and resilience to naturalistic movement artefacts [60, 72, 78, 90]. It has been established as an objective measure of cognitive demand, with more mentally demanding tasks corresponding to higher brain activity (higher levels of HbO and lower levels of HbR [16, 104]) over frontal areas [12, 18, 60, 64, 72]. Aside from workload, fNIRS measurements were used to detect changes correlating to other processes and states such as emotion [36, 77], pain response [27], or clinical applications to support brain-impaired patients [1, 35]. The experience of cybersickness and motion sickness has been shown to be reflected in related brain activity over predominantly posterior regions, such as the occipital and parietal cortex, using EEG [13–15, 55], and for motion sickness in a driving simulator, using fNIRS [105]. However, there has also been evidence suggesting that frontal brain areas are involved in the experience of motion sickness [68, 100, 106].

In our work, we conjecture that the experience of cybersickness is governed by higher cognitive processing, and relies on similar processes to those needed to perform cognitive tasks. We therefore expect that the experience of cybersickness will also be reflected in neuronal changes found in the frontal lobe area of the brain. This idea is also supported by findings from Zhang et al. [105], who detected hemispheric asymmetry in car passengers experiencing motion sickness. More activity was found over the left hemisphere, particularly over visual areas (occipital lobe) and parietal regions, which is inline with studies using MRI/fMRI to study motion sickness [67, 83], but also over the *frontal lobe*. Findings by Yamamura et al., who integrated a one sensor fNIRS device into their VR headset, also highlighted the potential for frontal lobe fNIRS to be used to detect cybersickness [100]. This suggests the possibility that cybersickness could be detected using only frontal-lobe fNIRS sensors (which could be embedded in a VR head mounted display).

## 3 STUDY OVERVIEW

In our study we investigated the effect of cognitive demand and visual motion on cybersickness, and its neuronal correlates, for participants experiencing a VR roller coaster simulation. We further investigated the effect of cybersickness on their task performance.

We posed the corresponding research questions:

- RQ1: Can increased cognitive task load reduce the experience of cybersickness symptoms resulting from perceived motion in VR?

- RQ2: Can the experience of cybersickness be potentially detected in frontal lobe brain activity using fNIRS?
- RQ3: Does the experience of cybersickness reduce performance on a cognitive task in VR?

## 3.1 Study Design

The study was designed to be *within-subject* with *mental task demand* and *visually represented motion* as independent variables and cybersickness and mental demand as dependent variables. The experiment consisted of four experimental conditions in which the participant was seated on a virtual roller coaster which either moved along a track or was stationary and an attentional task (RSVP) being presented in front of them that they either had to perform or solely use as their fixation point:

- (C1) Motion with Cognitive task
- (C2) No Motion with Cognitive Task
- (C3) Motion with No Cognitive Task
- (C4) No Motion with No Cognitive task

The roller coaster was placed in a simple “space-like” background environment, comprising a planet surface and distant astronomical features. This environment was chosen as it gives the participant information about their virtual relative orientation, whilst containing few details which might distract from the task (see Figure 2). It took 60 seconds for the roller coaster to simulate a complete round of the track (see Figure 2). This simulation was chosen to elicit a strong sensation ofvection. The roller coaster moved at an average speed of 1 unit per second which was affected by gravitational forces (roller coaster track going up vs roller coaster track going down). After each round the roller coaster decelerated to an almost stop and accelerated again to begin the next round. Each condition was presented twice, and lasted for 3 minutes resulting in 6 rounds (6 minutes) of the roller coaster for the two motion conditions (C1, C3) and 6 minutes of being seated on the stationary roller coaster in the no-motion conditions (C2, C4).

A rapid serial visual presentation (RSVP) task was chosen to manipulate cognitive load in the experiment. The RSVP task was chosen for this study as it is widely used as a way of reducing attentional resources available for other cognitive processes [40]. and it represents a highly controlled and easy to manipulate version of an in game activity, such as reacting to enemies in a shooting game. In the task, a series of visual stimuli appear rapidly in time at the same point in visual space, relative to the participant. The participant is given a target stimuli to respond to, and has to press a button as fast as possible whenever the target appears in the sequence. In this study ten colourful images of “monsters” were chosen as stimuli for the RSVP (see Figure 1). These monsters were always presented in front of the roller coaster carriage that the participant was seated on. In C1 and C2, two out of the 10 presented monsters were designated as targets. Targets were chosen randomly meaning that each participant had two different targets in each condition. In C3 and C4, participants were presented with the RSVP images, but did not have to respond to any target. Each RSVP stream was presented for 180 seconds and contained 360 images (monsters) including the target monsters and the distractor monsters, (see Figure 1). The images were presented randomly at a rate of 2 Hz,

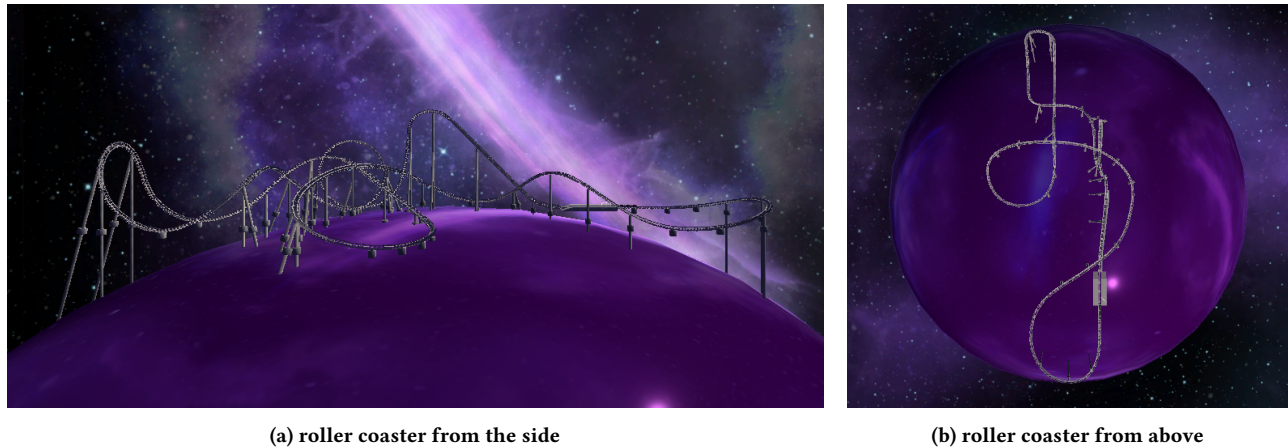


Figure 2: Roller coaster track as seen from the side (a) and from above (b)

targets were never presented one after another to avoid attentional blink [79, 87].

The RSVP stream was presented in *no-cognitive demand* conditions (C3, C4) as a fixation point to ensure that the visual properties of the task were consistent across all conditions. Excluding the RSVP from the visual display in the *no-cognitive demand* conditions would have resulted in differing visual input between the conditions which likely would have affected participants experience of cybersickness. To reduce confounds related to the presentation of the task (RSVP stream) in the *no-cognitive demand* conditions we varied the targets in each *cognitive task* trial to ensure that none of the monsters were perceived as always being a target, resulting in 8 out of the 10 presented monsters being targets at some point for each participant. We found that none of the participants reacted to the RSVP task by pressing the *target* button on their controller in the *no-cognitive demand* trials suggesting that this manipulation was successful.

## 4 METHOD

### 4.1 Participants

Forty participants took part in this study, participants were recruited through social media as well as an internal recruitment system, and each was compensated with £10 for their time. Due to technical issues with the fNIRS device, data from three participants were not recorded, and so all data for these participants were removed. Another three participants terminated the experiment early because they were unable to tolerate cybersickness symptoms, while another four participants did not report any cybersickness symptoms, and were therefore also removed. This resulted in a final sample size of 30 participants, who ranged in age from 18 to 39 years ( $M = 22.97$ ,  $SD = 4.97$ ). Seventeen participants identified as female, eleven as male, and two as gender non-binary. Six participants had never used VR before, while the remaining 24 had various degrees of previous VR experience. Twenty-one of them had used VR less than 10 times prior to participating in the experiment while two of the participants had extensive VR experience. All experimental procedures were approved by the University of Lincoln's Ethics

committee. Individuals suffering from photosensitive epilepsy as well as pregnant individuals were excluded from the study.

### 4.2 Measures

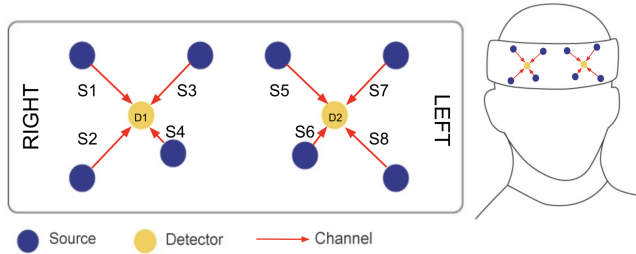
We used the following measures during and after the study conditions to record the corresponding dependant variables:

**Cybersickness :** Before and after each condition participants filled out the SSQ to assess their overall experience of cybersickness. To estimate participants experience of cybersickness while immersed in the virtual environment, they continuously rated their symptoms on the FMS scale, ranging from 0 ("no sickness at all") to 20 ("severe sickness"). A scale was placed in front of them as part of the roller coaster carriage displaying their current level of motion sickness, thereby, allowing them to constantly check their current rating and adapt it if necessary (see Figure 1). The experiment was terminated if participants reached a score of 15, to try to prevent participants from becoming too sick. Participants were informed of this threshold and knew the experiment would end if it was reached. The threshold was reached by the three participants, which terminated the experiment early. The rapid administration of the scale allows for the quantification of the time course of cybersickness.

**Mental Demand:** The NASA-TLX [32] was administered after each condition, and was used to assess perceived mental workload.

**Physiological measure:** Changes in brain activity were measured using the Octamon wireless fNIRS system (Artinis Medical Systems, Elst). The data was collected using Oxysoft. The probe was covering the frontal cortex and consists of 8 infrared light sources and 2 detectors arranged in 8 data channels (S1 to S8), including two short-separation channels (S4 and S6) as presented in Figure 3. A channel of data is formed by a source (e.g. S1) and a near by detector (e.g. D1). The distance between the emitters and detectors was 35 mm, and 10 mm for the short separation channels. Each channel reports two measurements: HbO (oxygenated hemoglobin), and HbR (deoxygenated hemoglobin). The data was recorded using the Oxysoft software (provided by Artinis Medical Systems, Elst, The Netherlands). fNIRS emitters used 760 nm and 850 nm wavelengths and the fNIRS data was acquired at 10 Hz.

The optodes were positioned on participants forehead as shown in Figure 3. Event markers were automatically inserted through a port communication with the VR environment developed internally.



**Figure 3: Sensor layout for the Artinis Octamon device includes 8 infrared light sources (blue colour) and 2 infrared light detectors (yellow) forming 8 channels (red arrows) of data split into two groups (Left vs Right).**

### 4.3 Hypotheses

Based on our research questions and study design we formulated the following hypotheses:

**H1** Conditions elicitingvection due to roller coaster motion cause more cybersickness compared to conditions in which it is stationary. This will be reflected in higher FMS ratings and SSQ scores. Confirming previous work [49].

**H2:** Performing a cognitive task will reduce the experience of cybersickness symptoms in C1 compared to C3. This will be reflected in lower FMS ratings, and SSQ scores (relating to RQ1).

**H3:** Performance on the cognitive task reduces with increasing experiences of cybersickness (relating to RQ3).

**H4:** Conditions in which the roller coaster is in motion are expected to be more cognitively demanding compared to when it is stationary, because cognitive processes associated with cybersickness utilises similar brain regions as the cognitive task (frontal cortex). This will be reflected in higher NASA-TLX scores and higher brain activity over the frontal cortex (measured by fNIRS) for C3 compared to C4 (relating to RQ2).

**H5:** Conditions in which participants perform the attentional task are more mentally demanding compared to the conditions in which no task is performed. This will be reflected in higher NASA-TLX scores and higher brain activity over the frontal lobe (measured by fNIRS). Confirming previous work [12, 18, 64, 72].

### 4.4 Procedure

Participants were provided with information about the study and gave informed consent. Participants performed a training condition in VR to get used to the controls, such as increasing and decreasing the cybersickness rating (see Figure 1), and responding to the target monsters. After training, the fNIRS devices was fitted and they started the study conditions. The conditions were presented in two blocks. Each condition was presented once per block, with counterbalanced ordering based on a latin square design. There was a break period between the blocks, during which participants

could remove the headset. Before and after each condition participants verbally gave their SSQ ratings and after each condition they additionally gave their NASA-TLX ratings. After the pre-condition SSQ, a baseline period of 30 seconds occurred in which the VR display was black and no sound was playing followed by instructions telling the participant which condition they would perform next, and which monsters were their targets in the cognitive demand conditions (instructions were visible for 5 seconds). Each experimental condition lasted for 3 minutes, this was the equivalent of 3 rounds on the roller coaster (in the motion condition). The experimental conditions were followed by the post questionnaires (SSQ and NASA-TLX) and a break (3 minutes). During the break a black screen was displayed, and relaxing meditation music played. Participants were instructed that to relax they could close their eyes in this time period. After the break, the next pre-condition SSQ was presented, with this procedure repeating four times in each block. After performing the second block the fNIRS was removed, and participants were debriefed.

### 4.5 Data Analysis

We used linear mixed effect models to analyse the effect of motion and cognitive task on cybersickness and cognitive demand. Linear mixed effect models, in comparison to more traditional ANOVAs, have advantages in their ability to model non-linear individual characteristics and deal with missing data. Additionally, they allow for multiple observations from the same observer [53]. The modelling of individual differences as random effects is an important feature and advantage of these models. In the following results, participant was included as a random effect in the models, to account for variability in effects across participants. Following the examples of Winter [99], models were compared to a null model (missing the variable of interest) using a likelihood ratio test, in order to obtain a difference in Bayes Information Criterion ( $\Delta$ BIC). In this context, BIC may be used as a criterion for model selection, representing a model's likelihood, and can be seen comparable to the effect size of a predictor [30]. Differences lower than 2 are considered to be weak evidence, and a negative difference indicates evidence in support of the null model, rather than the alternative model [42]. Additionally, based on Lorah [58], we also calculated Cohen's  $f^2$  for significant fixed effects. For comparison we also include analyses performed using repeated measures aligned rank transform (ART) ANOVAs.

Participants' performance on the RSVP task in the two motion conditions was analysed using the detection sensitivity index  $d'$  (based on false alarm and hit rates).  $d'$  was calculated based on the procedure proposed by Bendixen and Andersen [8]. A response is considered a hit rather than a false alarm if it occurs in a predefined interval in which a response is possible. We chose this interval to be 700ms which allowed participants to respond to a target for its entire presentation and an additional 200ms after the target had disappeared. To investigate the relationship between cybersickness and performance repeated measures correlations were performed.

### 4.6 fNIRS Data Processing

The fNIRS data was analysed using NIRS Toolbox [85]. At first the data was down sampled to 4 Hz. Next, the raw signals were converted to optical density changes and then to HbO and HbR



estimates using Beer-Lambert law, with a partial path length correction of 0.1 for both wavelengths [93]. We used the Temporal Derivative Distribution Repair (TDDR) method to correct motion artifacts [28]. On the first level analysis we used autoregressive iteratively-reweighted least squares approach to estimate betas for each tasks activation [6]. The method was tested and validated previously against other approaches and showed better sensitivity than other regression-based fNIRS data analysis methods in dealing with fNIRS noise that violates assumptions of linear model [85]. The method uses both prewhitening and robust regression to correct the noise. The model provides an approach to better deal with motion-related outliers and reduces the effect of correlations in the noise of the fNIRS data (see [37] for the review).

It is common practice to use 60s or shorter task blocks when analysing fNIRS data; however we wished to investigate user responses over the duration of their immersion. We therefore analysed and report data from the first 60s, and entire 180 seconds, for each condition. Correspondingly, we applied a 180s and a 60s BoxCar function, used to model hemodynamic response. For group analysis, mixed effects model was used to determine effects of the condition as fixed effects, and subject as a random effect (formula="beta -1 + cond + (1|subject)"). The advantage of using mixed effects models is that they allow modelling both fixed and random effects in a data and therefore increase power of a model [95]. The false discovery rate (FDR) correction was used with the significance level set at 0.05 ( $q \leq 0.05$ ) [9]. Contrast analyses were used to assess differences between each condition.

## 5 RESULTS

### 5.1 The Effect of Motion and Cognitive Demand on Cybersickness

**5.1.1 Continuous Measure of Cybersickness (FMS).** Motion Sickness ratings (FMS) were predicted using a linear mixed effect model including Motion type (moving vs stationary), cognitive demand (cognitive task vs no-cognitive task) and their interaction as fixed effects, and the intercept for participant as random effect. The function used for the model is as follows:

$$Model = lmer (Motion\ Sickness \sim Motion\ Type *Cognitive\ Demand + (1|Participant))$$

A significant effect of motion type on motion sickness was found,  $F(1, 207) = 171.82$ ,  $p < .001$ ,  $f^2 = .84$ ,  $\Delta BIC = 117.17$ . Participants experienced more motion sickness when the roller coaster was moving ( $M = 2.60$ ,  $SD = 2.90$ ) compared to it being stationary ( $M = 0.53$ ,  $SD = 1.30$ ). This provides support for Hypothesis H1. A significant effect of cognitive demand (task or no task) on motion sickness was found,  $F(1, 207) = 4.81$ ,  $p = .029$ ,  $f^2 = .03$ ,  $\Delta BIC = -3.96$ . Participants experienced less motion sickness when they were performing a cognitive task ( $M = 1.39$ ,  $SD = 2.50$ ) compared to when they were not ( $M = 1.74$ ,  $SD = 2.44$ ). No significant effect of their interaction on motion sickness was found,  $F(1, 207) = 2.21$ ,  $p = .138$ . A Tukey post hoc test revealed that when the roller coaster was in motion, sickness ratings were lower when undertaking the task (C1;  $M = 2.31$ ,  $SD = 3.04$ ) compared with no task (C3;  $M = 2.89$ ,  $SD = 2.73$ ,

$t(207) = 2.60$ ,  $p = .049$ ,  $d = .20$ ), supporting Hypothesis H2. However, when stationary, there was no significant difference between undertaking the cognitive task (C2;  $M = 0.47$ ,  $SD = 1.26$ ) compared with no task (C4;  $M = 0.58$ ,  $SD = 1.34$ ),  $t(207) = 0.50$ ,  $p = .959$ ,  $d = .08$ . The motion condition resulted in higher motion sickness ratings compared to the no motion condition both when participants were performing a cognitive task (C1 vs. C2;  $t(207) = 8.22$ ,  $p < .001$ ,  $d = .79$ ) and when they were not (C3 vs. C4;  $t(207) = 10.32$ ,  $p < .001$ ,  $d = 1.07$ ). The motion condition with cognitive task (C1) caused higher motion sickness ratings compared to the no motion condition without a cognitive task (C4;  $t(207) = 7.72$ ,  $p < .001$ ,  $d = .74$ ) and similarly the motion condition without a cognitive task (C3) caused more motion sickness compared to the no motion condition with a cognitive task (C2;  $t(207) = 10.82$ ,  $p < .001$ ,  $d = 1.14$ ) (see Figure 4a).

Using ART-ANOVA a significant effect of motion type on cybersickness was found,  $F(1, 87) = 181.74$ ,  $p < .001$ ,  $\eta_p^2 = .68$ . A significant effect of cognitive demand on cybersickness was found,  $F(1, 87) = 15.32$ ,  $p < .001$ ,  $\eta_p^2 = .15$ . A significant effect of their interaction was found,  $F(1, 87) = 10.32$ ,  $p = .002$ ,  $\eta_p^2 = .11$ .

**5.1.2 Overall Experience of Cybersickness (SSQ).** SSQ Scores were predicted using a linear mixed effect model including Motion type (moving vs stationary), cognitive demand (cognitive task vs no-cognitive task) and their interaction as a fixed effect and the intercept for participant as random effect. Analyses on the three subscales (Nausea, Oculomotor, Disorientation) showed similar results; hence, for brevity, we only report results for total SSQ score. The function of the model is as follows:

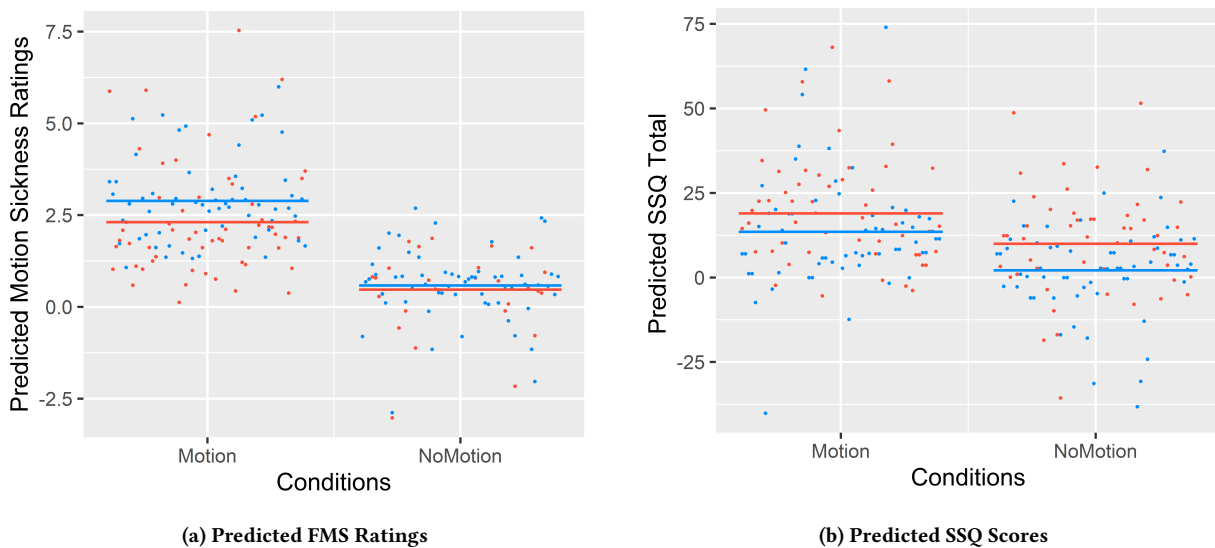
$$Model = lmer (SSQ\ Score \sim Motion\ Type *Cognitive\ Demand + (1|Participant))$$

A significant effect of motion type on SSQ total scores was found,  $F(1, 207) = 24.55$ ,  $p < .001$ ,  $f^2 = .12$ ,  $\Delta BIC = 12.9$ . Participants reported higher SSQ total scores when the roller coaster was moving ( $M = 16.24$ ,  $SD = 20.55$ ) compared to it being stationary ( $M = 6.05$ ,  $SD = 14.87$ ). This provides further support for Hypothesis H1. A significant effect of cognitive demand on SSQ total scores was found,  $F(1, 207) = 10.42$ ,  $p = .002$ ,  $f^2 = .05$ ,  $\Delta BIC = -0.3$ . Participants reported higher total SSQ scores when they were performing a cognitive task ( $M = 14.46$ ,  $SD = 18.99$ ) compared to when they were not ( $M = 7.82$ ,  $SD = 17.70$ ). No significant effect of their interaction on total SSQ scores was found,  $F(1, 207) = 0.35$ ,  $p = .555$ . This result fails to provide support for Hypothesis H2.

Using ART-ANOVA a significant effect of motion type on SSQ scores was found,  $F(1, 87) = 20.39$ ,  $p < .001$ ,  $\eta_p^2 = .10$ . A significant effect of cognitive demand on SSQ scores was found,  $F(1, 87) = 10.33$ ,  $p = .002$ ,  $\eta_p^2 = .05$ . No significant effect of their interaction was found,  $F(1, 87) = 0.76$ ,  $p = .762$ .

### 5.2 Development of Cybersickness over Time

Motion Sickness (FMS) ratings were predicted using a linear mixed effect model including Condition Type (C1, C2, C3, C4), time (18 time points, 10 second intervals), with their interaction as fixed effects, and the intercept for participant as random effect. The function of the model is as follows:



**Figure 4: Predicted (a) FMS, (b) SSQ Scores for the motion and no motion condition. Red lines represent cognitive demand conditions and blue lines represent no-cognitive demand conditions.**

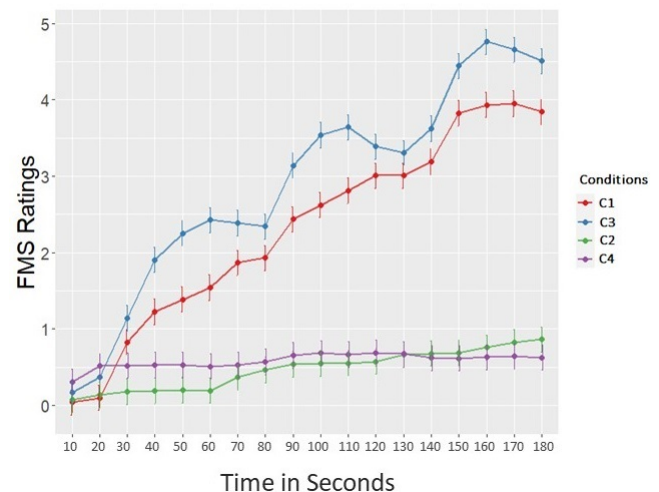
*Model = lmer (Motion Sickness~ Condition \*Time+ (1|Participant))*

A significant effect of Condition on motion sickness was found,  $F(1, 2123) = 4.54, p = .004, f^2 = .81, \Delta BIC = 1217.3$ . Participants experienced more motion sickness when the roller coaster was moving and they were not performing a task (C3) ( $M = 2.89, SD = 2.73$ ) compared to when they were (C1) ( $M = 2.31, SD = 3.04, t(2123) = 7.15, p < .001, d = 0.20$ ). For the no motion conditions, no significant difference in motion sickness was found between the no cognitive demand (C4) ( $M = 0.58, SD = 1.34$ ) and the cognitive demand conditions (C2) ( $M = 0.47, SD = 1.26, t(2123) = 1.37, p = .519, d = 0.08$ ). All other comparisons between conditions were significant ( $p < .001$ ). A significant effect of time on motion sickness was found  $F(1, 2123) = 599.72, p < .001, f^2 = .46, \Delta BIC = 769.2$ . Motion sickness ratings increased by  $0.23(\pm 0.01)$  every 10 seconds. A significant effect of their interaction on motion sickness was found,  $F(1, 2123) = 122.62, p < .001, f^2 = .17, \Delta BIC = 317.3$ . Time had a stronger effect on conditions in which the roller coaster was moving compared to the ones in which it was stationary (see Figure 5).

### 5.3 The Effect of Motion and Cognitive Demand on Perceived Workload

Total raw NASA-TLX Scores were predicted using a linear mixed effect model including Motion type (rollercoaster moving vs rollercoaster stationary), cognitive demand (cognitive task vs no-cognitive task) and their interaction as fixed effect and the intercept for participant as random effect. The same results were found for all dimensions of the NASA-TLX, therefore, for brevity only the total NASA-TLX scores are reported here. The function of the model is as follows:

*Model = lmer (NASA-TLX Scores~ Motion Type \*Cognitive Demand+ (1|Participant))*

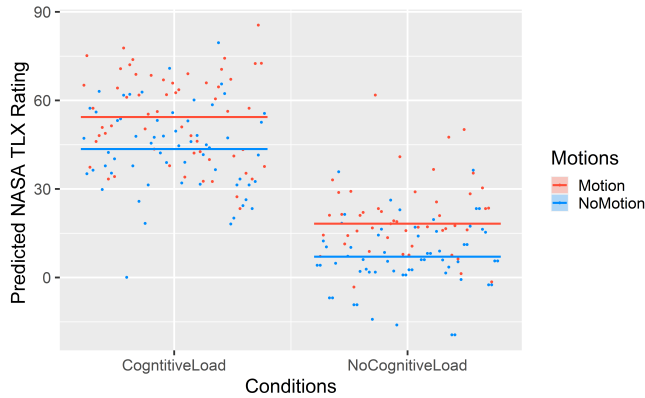


**Figure 5: FMS Ratings over the time period of a trial (180 seconds). Each line representing one of the four conditions: (C1) Motion - Cognitive task, (C2) No Motion - Cognitive task, (C3) Motion - No Cognitive task and (C4) No Motion - No Cognitive task (including error bars).**

A significant effect of motion type on total NASA-TLX scores was found,  $F(1, 207) = 35.40, p < .001, f^2 = 0.17, \Delta BIC = 22.2$ . Participants reported higher mental demand when the roller coaster was moving ( $M = 36.31, SD = 28.02$ ) compared to it being stationary ( $M = 25.30, SD = 26.02$ ). This provides support for Hypothesis H4. A significant effect of cognitive demand on NASA-TLX scores was found,  $F(1, 207) = 384.79, p < .001, f^2 = 1.86, \Delta BIC = 209.6$ . Participants reported higher mental demand when they were performing

a cognitive task ( $M = 48.95$ ,  $SD = 24.05$ ) compared to when they were not ( $M = 12.66$ ,  $SD = 16.77$ ). No significant effect of their interaction on NASA-TLX scores was found,  $F(1, 207) = 0.01$ ,  $p = .925$ . This provides support for Hypothesis H5.

Using ART-ANOVA a significant effect of motion type on NASA-TLX scores was found,  $F(1, 87) = 19.28$ ,  $p < .001$ ,  $\eta_p^2 = .18$ . A significant effect of cognitive demand on NASA-TLX scores was found,  $F(1, 87) = 251.02$ ,  $p < .001$ ,  $\eta_p^2 = .74$ . No significant effect of their interaction was found,  $F(1, 87) = 0.16$ ,  $p = .686$ .



**Figure 6: Predicted NASA-TLX Scores for the cognitive load and no-cognitive load condition. Red lines represent motion conditions and blue lines represent no-motion conditions.**

#### 5.4 RSVP Task Performance

Task performance ( $d'$ ) was predicted using a generalised linear model, including motion (roller coaster moving vs stationary) as fixed effect. The function of the models is as follows:

$$Model = glm(Task\ Performance \sim Motion)$$

A significant effect of motion on task performance ( $d'$ ) was found,  $\chi^2(1) = 6.80$ ,  $p = .009$ ,  $\Delta BIC = 1.73$ . Participants performed the RSVP task more successfully in the no motion condition ( $M = 1.46$ ,  $SD = 0.79$ ) compared to the motion condition ( $M = 1.97$ ,  $SD = 0.67$ ).

Reaction Time was predicted using a generalised linear mixed effect model, including motion (roller coaster moving vs stationary) as fixed effect and the intercept of Participant as random effect. The function of the models is as follows:

$$Model = glmer(Reaction\ Time \sim Motion + (1|Participant))$$

A significant effect of cognitive load on reaction time was found,  $\chi^2(1) = 21.60$ ,  $p < .001$ ,  $\Delta BIC = 13.55$ . Participants responded faster in no motion condition ( $M = 483ms$ ,  $SD = 38ms$ ) compared to the motion condition ( $M = 506ms$ ,  $SD = 32ms$ ).

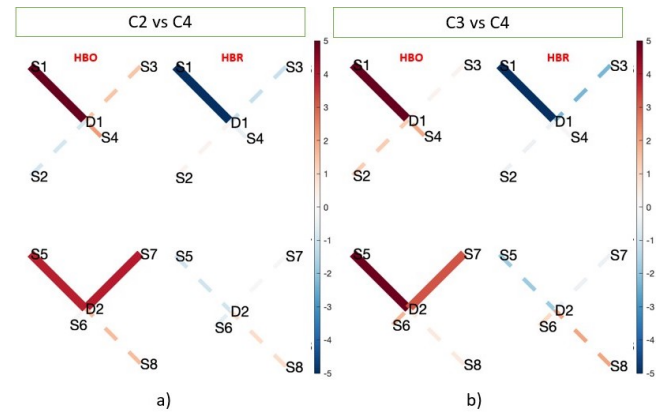
**5.4.1 Relationship between Cybersickness and Task Performance.** A repeated measures correlation [5] was conducted to investigate the relationship between cybersickness (FMS ratings and SSQ scores) and task performance ( $d'$  and reaction times). A moderate negative relationship was found between performance on the task ( $d'$ ) and FMS ratings ( $r(29) = -.43$ ,  $p = .015$ ,  $N = 30$ ), a strong positive relationship was found between FMS ratings and reaction time ( $r(29) = .57$ ,

$p < .001$ ,  $N = 30$ ). Participants that rated their experience of cybersickness higher on the FMS scale performed worse on the RSVP task and took longer to react to targets. A moderate positive relationship between SSQ scores and reaction time was found ( $r(29) = .45$ ,  $p = .012$ ,  $N = 30$ ). Participants that scored higher on the SSQ also reacted slower to the targets. These results provide support for Hypothesis H3, and we accept the hypothesis.

#### 5.5 fNIRS Results

In this section we first report results using the 180s block analysis, followed by the 60s analysis.

**5.5.1 180 second analysis.** In the Table 1 we report all significantly activated channels with beta values, SE, t-stat values, p-values, and q-values obtained from the 180 seconds block analysis. We considered significant differences in channels where HbO and HbR were negatively correlated [16]. These results are also displayed in Fig. 7 and Fig. 8, where a solid line indicates a significant increase or decrease in activation (HbO or HbR) in a particular channel when comparing the study conditions.



**Figure 7: Schematic Illustration of the significant activation channels in the fNIRS data (180 seconds per trial) generated using fNIRS toolbox [85]. Hbo and Hbr represent oxygenated, respectively, deoxygenated hemoglobin levels resulting from the fNIRS measurements. A solid line indicates a significant increase or decrease in activation. a) shows an increase in activation (S1 region) during the cognitive task (study condition C2 compared to C4). b) shows a significant increase in brain activation (S1 region) when experiencing motion (study condition C3 compared to C4).**

The fNIRS results indicate a significant increase in brain activation for Channel S1-D1 (see Fig. 3 and Table 1) when comparing conditions C2 and C4 (see Fig 7a), and C3 and C4 (see Fig 7b). These results provide further support for Hypotheses H4 and H5 respectively, and we therefore accept these hypotheses.

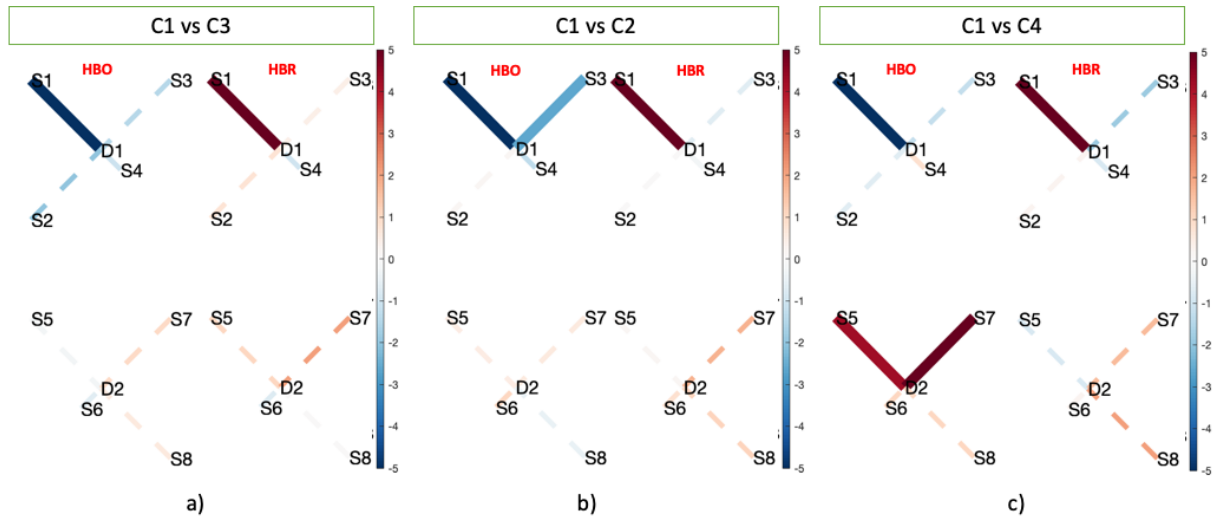
The results also indicated a significant drop in brain activation in the same brain region (S1-D1) when participants performed a cognitive task in the presence of VR motion (C1). This result was significant when compared with all study conditions (C1 compared to C1, C1 compared to C2 and C1 compared to C4 - see Fig. 8).

**Table 1: fNIRS results for 180 seconds analysis. Only statistically significant results are shown.**

Source-Detector	Type	Condition	Beta	SE	tstat	p	q
S1-D1	'hbo'	'C1-C2'	-0.0017	0.0004	-37.2453	0.0006	0.0009
S1-D1	'hbr'	'C1-C2'	0.0026	0.0001	32.8690	0.0001	0.0001
S1-D1	'hbo'	'C1-C3'	-0.0016	0.0004	-34.3807	0.0007	0.0001
S1-D1	'hbr'	'C1-C3'	0.0024	0.0008	30.2051	0.0003	0.0002
S1-D1	'hbo'	'C1-C4'	-0.0012	0.0001	-21.7539	0.0004	0.0007
S1-D1	'hbr'	'C1-C4'	0.0017	0.0001	19.1428	0.0001	0.0001
S1-D1	'hbo'	'C2-C4'	0.0005	0.0001	12.954	0.0001	0.0001
S1-D1	'hbr'	'C2-C4'	-0.0008	0.0001	-11.423	0.0001	0.0001
S1-D1	'hbo'	'C3-C4'	0.0005	0.0004	10.6686	0.0001	0.0003
S1-D1	'hbr'	'C3-C4'	-0.0007	0.0001	-9.3090	0.0002	0.0001

**Table 2: fNIRS results for 60 seconds analysis. Only statistically significant results are shown.**

Source-Detector	Type	Condition	Beta	SE	tstat	p	q
S1-D1	'hbo'	'C2-C4'	0.0134	0.0031	4.2707	0.0001	0.0004
S1-D1	'hbr'	'C2-C4'	-0.0113	0.0034	-3.3094	0.0011	0.0088



**Figure 8: Schematic Illustration of the significant activation channels in the fNIRS data (180 seconds per trial) generated using fNIRS toolbox [85]. Hbo and hbr represent oxygenated, respectively, deoxygenated hemoglobin levels resulting from the fNIRS measurements. A solid line indicates a significant increase or decrease in activation. Our results indicated that when performing a cognitive task in the presence of VR motion (C1) there is a decrease in brain activation (S1 region) as compared to all other conditions: a) C3, b) C2 and c) C4**

**5.5.2 60 Seconds Task Analysis.** This section shows our analysis for the fNIRS data when considering only the first 60 seconds of exposure [76]. We considered significant differences in channels where Hbo and Hbr were negatively correlated [16]. The results indicate a significant increase in brain activation for Channel S1-D1 (see Fig. 3 and Table 2) when comparing conditions C2 and C4. The activation seen when comparing C3 and C4 in the 180s analysis was not evident in the 60s analysis.

## 6 DISCUSSION

We begin this section by briefly summarising our study results, and then proceed to discuss insights that we have gained into the relationship between cybersickness and cognitive load, both in terms of perceived user experience, and neural processing. We then present some implications of these insights for creators of VR experiences, focusing on considerations for the design of applications, and the potential deployment of fNIRS sensors in commercial settings, including ethical considerations. We conclude by describing limitations, and possible future work.

## 6.1 Summary of Findings

The FMS data collected during our study indicated that participants experienced higher levels of cybersickness in the conditions which included visual motion when compared to those with no motion, and that cybersickness increased over time (as visualised in Figure 5). However, under the experience of motion, participants reported lower levels of cybersickness when undertaking a cognitive task compared to when they were not. Cybersickness experienced by participants overall was rather low which could be explained by the short trial durations (3min). Differences between the cognitive demand and the none-cognitive demand conditions were significant but had a relatively small effect size; results should therefore be interpreted with caution. These short trials were chosen, however, to be suitable for fNIRS analyses as these currently do not allow for longer time windows. Higher levels of cybersickness when in motion were also evident from the SSQ results. However, SSQ data also showed higher levels of cybersickness when completing the task, which is contrary to the results of our FMS data.

Participants reported higher levels of perceived workload on the NASA-TLX questionnaire both when undertaking the task, and when experiencing motion. Task performance was lower when participants experienced the motion conditions, and correlated negatively with cybersickness (reported using FMS).

Our fNIRS data showed activation on the S1-D1 channel corresponding to the right dorsolateral prefrontal cortex (DLPFC), under certain conditions. Using 60s block analysis, higher levels of activation occurred when participants were undertaking the cognitive task (compared to no task), in the conditions without motion. This was also observed using 180 second block analysis; however we additionally saw a significant activation on the same channel when participants experienced motion (compared to no motion), when no task was being performed. There were also a drop in activation in the motion + task condition *C1*, when compared to each of the other conditions.

## 6.2 Insights into Cybersickness and Cognitive Load

Whilst our FMS results show support for Hypothesis H2 (performing a cognitive task reduces the experience of cybersickness during motion), this support is not evident in our SSQ data. This difference may be due to a number of factors. Firstly, it is possible that these measures represent slightly different constructs (the SSQ is intended to measure a broader range of symptoms). We also note that FMS data is collected continually during participants experiences, whilst SSQ data was collected post-hoc. Our results could therefore reflect temporal differences in participant's experiences, possibly including differences in recovery times for conditions. In addition, performing both the cognitive task and experiencing motion sickness could be more fatiguing, and so reflected more in the post-hoc SSQ scores.

Whilst there is mixed support for H2, we consider that our FMS results are small but robust (for example, temporal development is consistent), and more reflective of participants experiences *during* their exposure to VR, and so on balance we consider that there is sufficient supporting evidence for this hypothesis.

**6.2.1 Neural Processing and Cybersickness.** Prefrontal fNIRS has previously been discussed as a physiological measure of cognitive demand [3, 60, 72, 73, 90], where the right prefrontal cortex is believed to play an important role. As expected, our study replicated these findings: in the absence of visual motion, a significant activation was found over the right DLPFC when participants were engaged in the cognitive task, compared to when they were not. Aside from supporting previous results, this suggests that our fNIRS data collection and processing is robust.

The corresponding activation found for the motion predictor variable is of more interest to our study: when not engaging in the task, a corresponding activation was found over the same area (DLPFC) when participants experienced motion, as compared to when they did not (180s analysis). Additionally, we note that the motion-related activation only appeared in the 180s analysis, and is not detected early in the exposure (60s). This phenomenon could be caused by a number of factors, such as exposure to visual motion or other internal processes, such as vection, boredom or fatigue. However, if this was caused by perceived visual motion then we expect to see the same result after 60s. We therefore conjecture that, since cybersickness also increases during exposure to motion, the activation is related to participants' processing of cybersickness, rather than to processing the visual motion itself. If this is the case, then, not only may prefrontal fNIRS sensors be able to detect users' experience of cybersickness induced by visual motion, but it may also be the case that the cognitive process of cybersickness relies on the same attentional resources as those used by the cognitive task in our study (since they occur on the same brain region). Researchers and practitioners should then be aware that frontal lobe activation could correspond to different user experiences. While we consider that this finding should be validated through further experimental work, measuring other related concepts, such as vection or fatigue, it would have significant implications for the designers of VR experiences, which we expand in Section 6.3. They also have implications for those using frontal-lobe fNIRS in non-VR research settings, such as training or therapy, where users might inadvertently experience sickness induced by visually perceived motion. Whilst our results were obtained using VR, previous work has indicated that fNIRS can detect motion sickness [105], and so fNIRS users should be aware that sickness due to various causes might interfere with fNIRS readings.

We also note that these findings, while preliminary, are aligned with previous works which indicated that users can be distracted from experiencing cybersickness [10, 107]. However, rather than the cognitive task simply distracting from cybersickness, we suggest that this decrease in cybersickness may be due to the sharing of attentional resources by these two processes. This notion of shared cognitive resources is aligned with cognitive load theory [54], which states that a high load on the processes of cognitive control can decrease or interfere with the performance of other tasks using the same cognitive processes, and is further supported by our other results. Firstly, those obtained using the NASA-TLX: not only did participants rate conditions in which they were performing the RSVP task as more mentally demanding, they also rated conditions in which the roller coaster was in motion as more demanding (see Figure 6). Secondly, we point to the observed reduced activation on the S1-D1 channel when participants experienced both motion

and the cognitive task together. Whilst this would seem a counter-intuitive result, we note that work by Mandryk et al. [62] found a cap on attentional resources in dual-task conditions using fNIRS. This suggests that our results indicate either a reduction or redistribution of processing cognitive resources, resulting from an interaction of the processing of cybersickness and the cognitive task. This could also explain the reduction in task performance when experiencing cybersickness.

### 6.3 Implications for the Design of VR Applications

Based on our findings, we firstly recommend that VR developers consider the interplay between cybersickness induced by visual motion and cognitive processing, when designing VR games, as well as learning and training applications. For example, when anticipating that cybersickness may occur, and considering particular mitigations (such as narrowing field of view [2]), developers may also consider what level of cognitive load their users are experiencing, and whether such mitigations are necessary, or could be reduced. This may be particularly applicable to developers of action games, where players often experience a high cognitive load at particular points during game play, and so may not experience as much cybersickness as might be otherwise expected. Since cybersickness mitigations may compromise user experience in other ways, we recommend that developers actively evaluate the levels of sickness that players experience, through user research, in order to assess what degree of mitigation is necessary.

In some cases, increasing cognitive load could in fact be used as a mitigation in its own right. Introducing new cognitive tasks into a VR experience may not always be a viable design option, but in cases where the user is engaged in either game play, or a learning experience, it may be feasible to increase the demand placed on the player. Note that we do not recommend the addition of new cognitive tasks into a VR experience as a means of mitigating cybersickness. Rather we suggest that developers consider the level of cognitive demand already offered by the experience. For example, in an action game, the difficulty level could be increased or decreased (for example spawning more or less enemies), or in a training simulation, more difficult tasks could be presented.

Although we did not measure participants' sense of presence in our study, we note that our RSVP task was not presented as an integrated part of the environment, which may have had a negative effect on participants' sense of presence. A strong sense of presence can have a positive effect on training and learning outcomes in VR environments [4, 86, 97]; therefore, VR applications should generally be designed to maximise presence, with cognitive task being integrated into the virtual environment. Presence has also shown to negatively correlate with perceived mental demand in a VR surgical training simulation [11], as well as cybersickness [96] further highlighting a complex inter-relationship between these three phenomena, which warrants further study.

**6.3.1 The use of fNIRS.** Frontal-lobe fNIRS headsets are still relatively expensive; however, unlike other neural sensing technologies, they are easy to deploy. Current work (such as that presented in this paper) is still investigating how fNIRS data can be used to understand aspects of user experience. We consider it likely that

fNIRS sensors may be deployed in commercial headsets in future, as so be available to the creators of commercial applications, such as games. Currently, however, this technology is only realistically available for smaller scale deployment.

Our preliminary results suggest that frontal-lobe fNIRS may possibly be able to detect the experience of cybersickness, and if so, then, this could be used by designers and developers to better understand the experiences of their users. Firstly, as we have mentioned, it would be useful for developers of games to understand, during play testing, when players experience cybersickness. Current fNIRS headsets could be used to do this, and offer the potential for more convenient and detailed profiling than questionnaires.

If and when fNIRS is deployed commercially, it could be further used by designers to create adaptive experiences for users. For example, if a particular player is experiencing high levels of sickness, this could be detected by the software at run time and used to initiate mitigations. This would be particularly beneficial for players who are more susceptible to cybersickness, and so could increase the accessibility and uptake of VR games and applications. We therefore advocate for more research into understanding the relationship between cybersickness and fNIRS sensor data.

**6.3.2 Ethical Issues of Using fNIRS Data.** VR headsets are already incorporating physiological sensors, and, as we have suggested, this could include fNIRS sensors in future, giving designers and developers access to data about their users' brain activity. This does raise significant issues about how this data is collected and used, not only in research [65, 94, 98], but also in commercial applications, and overlaps with other ethical concerns over the collection of data from the users of VR systems, such as, for example, the sharing of data with other users [61], or the use of physiological data in general [65].

In particular, our work highlights that researchers are still exploring how fNIRS data can reveal information about users, and developers should be mindful of this. Information about brain function might contain medical data, or other sensitive data about users that they themselves might not even be aware of (for example, in our case, susceptibility to cybersickness). Designers and developers therefore need to give considerable thought as to how they store, use or share physiological data obtained from users, and also how they might respond to more refined information being made available through fNIRS sensors in future. Designers should also be transparent with users about how physiological data is used, and provide options for users to maintain control of their own data.

### 6.4 Limitations and Future Work

Our work is subject to a number of limitations, which we discuss in this section. Firstly, we note that our study elicited cybersickness using illusory motion. While this is a common trigger for cybersickness in VR, it is not the only scenario in which it may occur. It may be that cybersickness caused by other experiences in VR may be processed differently. Furthermore, the results obtained using FMS were not consistent with those obtained using the SSQ. FMS ratings also reflected an overall weak experiences of cybersickness with the effect of cognitive demand on FMS ratings being rather small. Whilst we consider that our FMS results are robust, and more detailed than those obtained using the SSQ, further investigation

of this difference is warranted, and may expose a more nuanced relationship between cybersickness and cognitive load than we have identified here.

Future work investigating the relationship of cognitive demand and cybersickness should be undertaken to find out whether the small positive effects of cognitive demand on cybersickness found for these low sickness inducing environments translates to simulations inducing stronger symptoms of motion sickness with longer durations. The effect of cognitive demand on cybersickness could possibly differ for such scenarios compared to our results with the onset and the maximum experience of motion sickness being differently affected by varying cognitive demand.

We have suggested that there is a relationship between the processing of cybersickness and cognitive load. Again, this is an initial finding, and warrants further exploration in order to determine the nuances of this relationship; for example, to what extent cybersickness is affected under different levels of cognitive load, and/or different types of task. Here we compared conditions in which no cognitive task had to be performed with conditions including a cognitive task. Cognitive demand using the RSVP paradigm could however also be manipulated by varying the speed of the presentation as well as the number of targets [51]. This manipulation could be applied in future research to further investigate the effect of cognitive demand on cybersickness and give insight on how different levels of demand or task difficulty can affect ones experience of cybersickness symptoms. We recognise that sustained experience of illusory motion in VR, coupled with cognitive tasks, is most likely to be associated with game experiences, and we believe that this would be a valuable context for further work on understanding this relationship. Future work could also focus on what types of cognitive tasks show these beneficial effects, and how they can be best integrated into the existing VR environment to maintain users' sense of presence. These cognitive tasks should not be perceived as separate but rather as part of the virtual world.

The virtual environment used as a proof-of-concept in our study is rather controlled, with participants experiencing passive self-motion following a predefined trajectory (roller coaster track). Work using a less controlled virtual environment that participants were able to explore themselves while searching for targets also found positive effects of cognitive distraction on cybersickness[107]. Based on this we suggest that increasing cognitive demand should reduce adverse symptoms in any virtual environment that is likely to cause cybersickness based on active and passive locomotion.

While we have suggested that fNIRS may be able to detect cybersickness, our study represents only a preliminary investigation of this relationship. The delayed onset of fNIRS activation is congruent with the temporal development of sickness, but only provides partial evidence. For example, it is possible that other processes are involved, or that the processing of illusory motion is contributory factor. We therefore advocate for more detailed study of the detection of cybersickness using fNIRS, possibly focusing on the detection of levels of cybersickness, which would represent a useful tool for designers and developers of VR systems. We also note that in our experiments we detected frontal lobe activation after 180s of exposure motion conditions, which was not detected after 60s. If this is due to the experience of cybersickness, the question arises as to how long fNIRS data would need to be collected in order to

reliably detect it. This is difficult to generalise from our study, as participants reported relatively low levels of cybersickness: it seems likely that less data would be required for more intense experiences. We suggest that further work to validate our results could also investigate whether this is the case. We also note that cybersickness is a highly individual experience, and that users also adapt to it over time, so some degree of personalisation and adaptation of system parameters may also be appropriate for robust detection.

Finally, we believe that fNIRS is a potentially very useful tool, both for research and for commercial developers seeking to create adaptive VR experiences. Our work has examined cybersickness and cognitive load specifically, but we believe that there is potential for this technology to be used to explore and enhance other aspects of user experience. We have also focused on frontal lobe sensors, as these are the most accessible and most likely to be integrated with existing headsets, but investigations using more complex sensor arrays is also of interest as possible future work. For example, in our case the experience of cybersickness while performing a cognitive task will most likely activate a much more complex pattern of brain areas (not just frontal areas) including several visual brain areas (such as MT). Further analysis, such as Connectivity analysis and an increased number of sensors covering the entire head would be important to draw further conclusions about the underlying neural mechanisms of the interaction between cybersickness and cognitive task demand.

## 7 CONCLUSIONS

In this paper we have studied the relationship between cognitive demand and cybersickness in VR, and also explored the neural relationship between these process using fNIRS. We used an experimental setup in which participants performed a cognitive task in VR, while seated on a roller coaster. We collected data about their feelings of nausea and workload, as well as neurological data about their brain activity, using frontal-lobe fNIRS. Our results indicate that symptoms of cybersickness may be partially mitigated by engaging in a cognitive task.

Analysis of our fNIRS data suggests an inter-relationship between the processing of cybersickness and cognitive load, and that they are both processed in the pre-frontal cortex. This further suggests that fNIRS may be used to detect the experience of cybersickness in users. we have highlighted the potential for the designers of VR experiences to make use of these findings when mitigating for cybersickness, and also the potential for fNIRS to be deployed in commercial VR headsets, and leveraged by developers to create adaptive experiences, especially for the players of VR games.

## ACKNOWLEDGMENTS

**Data Access Statement** Data sets for behavioural and fNIRS data are available for researchers upon request. This research received funding from the European Research Council (ERC) under the European Union's Horizon 2020 research and innovation programme (#835197, *ViAJeRo*) and the Engineering and Physical Sciences Research Council [EP/T022493/1].

## REFERENCES

- [1] Androu Abdalmalak, Daniel Milej, Lawrence Yip, Ali R Khan, Mamadou Diop, Adrian M Owen, and Keith St Lawrence. 2020. Assessing time-resolved fNIRS

- for brain-computer interface applications of mental communication. *Frontiers in Neuroscience* (2020), 105.
- [2] Samuel Ang and John Quarles. 2020. GingerVR: An Open Source Repository of Cybersickness Reduction Techniques for Unity. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. 460–463.
  - [3] Hasan Ayaz, Patricia A Shewokis, Scott Bunce, Kurtulus Izzetoglu, Ben Willems, and Banu Onaral. 2012. Optical brain monitoring for operator training and mental workload assessment. *Neuroimage* 59, 1 (2012), 36–47.
  - [4] J Bacca, S Baldiris, R Fabregat, S Graf, and G Kinshuk. 2014. Augmented Reality Trends in Education: A Systematic Review of Research and Applications. *Educational Technology & Society*, 17 (4), 133–149. (2014).
  - [5] Jonathan Z Bakdash and Laura R Marusch. 2017. Repeated measures correlation. *Frontiers in psychology* 8 (2017), 456.
  - [6] Jeffrey W Barker, Araldan Aarabi, and Theodore J Huppert. 2013. Autoregressive model based algorithm for correcting motion and serially correlated errors in fNIRS. *Biomedical optics express* 4, 8 (2013), 1366–1379.
  - [7] Robert CA Bendall, Peter Eachus, and Catherine Thompson. 2016. A brief review of research using near-infrared spectroscopy to measure activation of the prefrontal cortex during emotional processing: the importance of experimental design. *Frontiers in human neuroscience* 10 (2016), 529.
  - [8] Alexandra Bendixen and Soren K Andersen. 2013. Measuring target detection performance in paradigms with high event rates. *Clinical Neurophysiology* 124, 5 (2013), 928–940.
  - [9] Yoav Benjamini and Yosef Hochberg. 1995. Controlling the false discovery rate: a practical and powerful approach to multiple testing. *Journal of the Royal statistical society: series B (Methodological)* 57, 1 (1995), 289–300.
  - [10] Jelte E Bos. 2015. Less sickness with more motion and/or mental distraction. *Journal of Vestibular Research* 25, 1 (2015), 23–33.
  - [11] Marie-Stéphanie Bracq, Estelle Michinov, Bruno Arnaldi, Benoît Caillaud, Bernard Gibaud, Valérie Gourant, and Pierre Jannin. 2019. Learning procedural skills with a virtual reality simulator: An acceptability study. *Nurse education today* 79 (2019), 153–160.
  - [12] Scott C Bunce, Kurtulus Izzetoglu, Hasan Ayaz, Patricia Shewokis, Meltem Izzetoglu, Kambiz Pourrezaei, and Banu Onaral. 2011. Implementation of fNIRS for monitoring levels of expertise and mental workload. In *International Conference on Foundations of Augmented Cognition*. Springer, 13–22.
  - [13] Ufuk Celikkan. 2019. Detection and Mitigation of Cybersickness via EEG-Based Visual Comfort Improvement. In *2019 3rd International Symposium on Multidisciplinary Studies and Innovative Technologies (ISMSIT)*. IEEE, 1–4.
  - [14] Yu-Chieh Chen, Jeng-Ren Duann, Shang-Wen Chuang, Chun-Ling Lin, Li-Wei Ko, Tzyy-Ping Jung, and Chin-Teng Lin. 2010. Spatial and temporal EEG dynamics of motion sickness. *Neuroimage* 49, 3 (2010), 2862–2870.
  - [15] Shang-Wen Chuang, Chun-Hsiang Chuang, Yi-Hsin Yu, Jung-Tai King, and Chin-Teng Lin. 2016. EEG alpha and gamma modulators mediate motion sickness-related spectral responses. *International journal of neural systems* 26, 02 (2016), 1650007.
  - [16] Xu Cui, Signe Bray, and Allan L Reiss. 2010. Functional near infrared spectroscopy (fNIRS) signal improvement based on negative correlation between oxygenated and deoxygenated hemoglobin dynamics. *Neuroimage* 49, 4 (2010), 3039–3046.
  - [17] James J Cummings and Jeremy N Bailenson. 2016. How immersive is enough? A meta-analysis of the effect of immersive technology on user presence. *Media psychology* 19, 2 (2016), 272–309.
  - [18] Adrian Curtin and Hasan Ayaz. 2018. The age of neuroergonomics: towards ubiquitous and continuous measurement of brain function with fNIRS. *Japanese Psychological Research* 60, 4 (2018), 374–386.
  - [19] Joakim Dahlman, Anna Sjörs, Johan Lindström, Torbjörn Ledin, and Torbjörn Falkmer. 2009. Performance and autonomic responses during motion sickness. *Human factors* 51, 1 (2009), 56–66.
  - [20] Simon Davis, Keith Nesbitt, and Eugene Nalivaiko. 2014. A systematic review of cybersickness. In *Proceedings of the 2014 conference on interactive entertainment*. 1–9.
  - [21] Johannes Dichgans and Thomas Brandt. 1978. Visual-vestibular interaction: Effects on self-motion perception and postural control. In *Perception*. Springer, 755–804.
  - [22] Kim Dockx, Esther MJ Bekkers, Veerle Van den Bergh, Pieter Ginis, Lynn Rochester, Jeffrey M Hausdorff, Anat Mirelman, and Alice Nieuwboer. 2016. Virtual reality for rehabilitation in Parkinson's disease. *Cochrane Database of Systematic Reviews* 12 (2016).
  - [23] Joshua E Domeyer, Nicholas D Cassavaugh, and Richard W Backs. 2013. The use of adaptation to reduce simulator sickness in driving assessment and research. *Accident Analysis & Prevention* 53 (2013), 127–132.
  - [24] HB-L Duh, JW Lin, Robert V Kenyon, Donald E Parker, and Thomas A Furness. 2001. Effects of field of view on balance in an immersive environment. In *Proceedings IEEE Virtual Reality 2001*. IEEE, 235–240.
  - [25] Sharon L Farra, Matthew Gneuh, Eric Hodgson, Burhan Kawosa, Elaine T Miller, Ashley Simon, Nathan Timm, and Jackie Hausfeld. 2019. Comparative cost of virtual reality training and live exercises for training hospital workers for evacuation. *Computers, informatics, nursing: CIN* 37, 9 (2019), 446.
  - [26] Ajoy S Fernandes and Steven K Feiner. 2016. Combating VR sickness through subtle dynamic field-of-view modification. In *2016 IEEE symposium on 3D user interfaces (3DUI)*. IEEE, 201–210.
  - [27] Raul Fernandez Rojas, Xu Huang, and Keng-Liang Ou. 2019. A machine learning approach for the identification of a biomarker of human pain using fNIRS. *Scientific reports* 9, 1 (2019), 1–12.
  - [28] Frank A Fishburn, Ruth S Ludlum, Chandan J Vaidya, and Andrei V Medvedev. 2019. Temporal derivative distribution repair (TDDR): a motion correction method for fNIRS. *Neuroimage* 184 (2019), 171–179.
  - [29] Liviu A Fodor, Carmen D Cotet, Pim Cuijpers, Stefan Szamoskozi, Daniel David, and Ioana A Cristea. 2018. The effectiveness of virtual reality based interventions for symptoms of anxiety and depression: A meta-analysis. *Scientific reports* 8, 1 (2018), 1–13.
  - [30] Schwarz Gideon et al. 1978. Estimating the dimension of a model. *The annals of statistics* 6, 2 (1978), 461–464.
  - [31] Evelyn Glotzbach, Andreas Mühlberger, Kathrin Gschwendtner, Andreas J Fallgatter, Paul Pauli, and Martin J Herrmann. 2011. Prefrontal brain activation during emotional processing: a functional near infrared spectroscopy study (fNIRS). *The open neuroimaging journal* 5 (2011), 33.
  - [32] Sandra G Hart and Lowell E Staveland. 1988. Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research. In *Advances in psychology*. Vol. 52. Elsevier, 139–183.
  - [33] Martin J Herrmann, A-C Ehlis, and Andreas J Fallgatter. 2003. Prefrontal activation through task requirements of emotional induction measured with NIRS. *Biological psychology* 64, 3 (2003), 255–263.
  - [34] Christina Hirth, Hellmuth Obrig, Kersten Villringer, Andeas Thiel, Johannes Bernarding, Werner Mühlnickel, Herta Flor, Ulrich Dirnagl, and Arno Villringer. 1996. Non-invasive functional mapping of the human motor cortex using near-infrared spectroscopy. *Neuroreport* 7, 12 (1996), 1977–1981.
  - [35] Keum-Shik Hong and M Atif Yaqub. 2019. Application of functional near-infrared spectroscopy in the healthcare industry: A review. *Journal of Innovative Optical Health Sciences* 12, 06 (2019), 1930012.
  - [36] Xin Hu, Chu Zhuang, Fei Wang, Yong-Jin Liu, Chang-Hwan Im, and Dan Zhang. 2019. fNIRS evidence for recognizably different positive emotions. *Frontiers in human neuroscience* 13 (2019), 120.
  - [37] Theodore J Huppert. 2016. Commentary on the statistical properties of noise and its implication on general linear models in functional near-infrared spectroscopy. *Neurophotonics* 3, 1 (2016), 010401.
  - [38] Elizaveta Igoshina, Frank A Russo, Robert Shewaga, Bruce Haycock, and Behrang Keshavarz. 2022. The relationship between simulator sickness and driving performance in a high-fidelity simulator. *Transportation research part F: traffic psychology and behaviour* 89 (2022), 478–487.
  - [39] Frans F Jöbsis. 1977. Noninvasive, infrared monitoring of cerebral and myocardial oxygen sufficiency and circulatory parameters. *Science* 198, 4323 (1977), 1264–1267.
  - [40] Julian S Joseph, Marvin M Chun, and Ken Nakayama. 1997. Attentional requirements in a 'preattentive' feature search task. *Nature* 387, 6635 (1997), 805–807.
  - [41] Alexandra D Kaplan, Jessica Cruit, Mica Endsley, Suzanne M Beers, Ben D Sawyer, and Peter A Hancock. 2021. The effects of virtual reality, augmented reality, and mixed reality as training enhancement methods: A meta-analysis. *Human factors* 63, 4 (2021), 706–726.
  - [42] Robert E Kass and Larry Wasserman. 1995. A reference Bayesian test for nested hypotheses and its relationship to the Schwarz criterion. *Journal of the American statistical association* 90, 431 (1995), 928–934.
  - [43] Sam Kavanagh, Andrew Luxton-Reilly, Burkhard Wuensche, and Beryl Plimmer. 2017. A systematic review of virtual reality in education. *Themes in Science and Technology Education* 10, 2 (2017), 85–119.
  - [44] Robert S Kennedy, Norman E Lane, Kevin S Berbaum, and Michael G Lilienthal. 1993. Simulator sickness questionnaire: An enhanced method for quantifying simulator sickness. *The international journal of aviation psychology* 3, 3 (1993), 203–220.
  - [45] Robert S Kennedy, Kay M Stanney, and William P Dunlap. 2000. Duration and exposure to virtual environments: sickness curves during and across sessions. *Presence: Teleoperators & Virtual Environments* 9, 5 (2000), 463–472.
  - [46] Behrang Keshavarz and Heiko Hecht. 2011. Validating an efficient method to quantify motion sickness. *Human factors* 53, 4 (2011), 415–426.
  - [47] Behrang Keshavarz and Heiko Hecht. 2014. Pleasant music as a countermeasure against visually induced motion sickness. *Applied ergonomics* 45, 3 (2014), 521–527.
  - [48] Behrang Keshavarz, Aaron Emile Philipp-Muller, Wanja Hemmerich, Bernhard E Riecke, and Jennifer L Campos. 2019. The effect of visual motion stimulus characteristics on vection and visually induced motion sickness. *Displays* 58 (2019), 71–81.
  - [49] Behrang Keshavarz, Bernhard E Riecke, Lawrence J Hettinger, and Jennifer L Campos. 2015. Vection and visually induced motion sickness: how are they related? *Frontiers in psychology* 6 (2015), 472.



- [50] Young Youn Kim, Hyun Ju Kim, Eun Nam Kim, Hee Dong Ko, and Hyun Taek Kim. 2005. Characteristic changes in the physiological components of cybersickness. *Psychophysiology* 42, 5 (2005), 616–625.
- [51] Thomas Kosch, Albrecht Schmidt, Simon Thanheiser, and Lewis L Chuang. 2020. One does not simply RSVP: mental workload to select speed reading parameters using electroencephalography. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*. 1–13.
- [52] Eric Krokos and Amitabh Varshney. 2022. Quantifying VR cybersickness using EEG. *Virtual Reality* 26, 1 (2022), 77–89.
- [53] Charlene Krueger and Lili Tian. 2004. A comparison of the general linear mixed model and repeated measures ANOVA using a dataset with multiple missing data points. *Biological research for nursing* 6, 2 (2004), 151–157.
- [54] Nilli Lavie, Aleksandra Hirst, Jan W De Fockert, and Essi Viding. 2004. Load theory of selective attention and cognitive control. *Journal of experimental psychology: General* 133, 3 (2004), 339.
- [55] Chin-Teng Lin, Shang-Wen Chuang, Yu-Chieh Chen, Li-Wei Ko, Sheng-Fu Liang, and Tzyy-Ping Jung. 2007. EEG effects of motion sickness induced in a dynamic virtual reality environment. In *2007 29th annual international conference of the IEEE engineering in medicine and biology society*. IEEE, 3872–3875.
- [56] Wei-Kai Liou and Chun-Yen Chang. 2018. Virtual reality classroom applied to science education. In *2018 23rd International Scientific-Professional Conference on Information Technology (IT)*. IEEE, 1–4.
- [57] Kartik Logishetty, Branavan Rudran, and Justin P Cobb. 2019. Virtual reality training improves trainee performance in total hip arthroplasty: a randomized controlled trial. *The bone & joint journal* 101, 12 (2019), 1585–1592.
- [58] Julie Lorah. 2018. Effect size measures for multilevel models: Definition, interpretation, and TIMSS example. *Large-Scale Assessments in Education* 6, 1 (2018), 1–11.
- [59] Horia A. Maior, Richard Ramchurn, Sarah Martindale, Ming Cai, Max L. Wilson, and Steve Benford. 2019. FNIRS and Neurocinematics. In *Extended Abstracts of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland UK). Association for Computing Machinery, New York, NY, USA, 1–6.
- [60] Horia A Maior, Max L Wilson, and Sarah Sharples. 2018. Workload alerts—using physiological measures of mental workload to provide feedback during tasks. *ACM Transactions on Computer-Human Interaction* 25, 2 (2018).
- [61] Divine Maloney, Guo Freeman, and Andrew Robb. 2021. Social Virtual Reality: Ethical Considerations and Future Directions for An Emerging Research Space. In *2021 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*. 271–277.
- [62] Kevin Mandrick, Gérard Derosiere, Gérard Dray, Denis Coulon, Jean-Paul Micallef, and Stéphane Perrey. 2013. Prefrontal cortex activity during motor tasks with additional mental load requiring attentional demand: a near-infrared spectroscopy study. *Neuroscience research* 76, 3 (2013), 156–162.
- [63] Panagiotis Matsangas, Michael E McCauley, and William Becker. 2014. The effect of mild motion sickness and sopite syndrome on multitasking cognitive performance. *Human factors* 56, 6 (2014), 1124–1135.
- [64] Serena Midha, Horia A Maior, Max L Wilson, and Sarah Sharples. 2021. Measuring mental workload variations in office work tasks using fNIRS. *International Journal of Human-Computer Studies* 147 (2021), 102580.
- [65] Serena Midha, Max L Wilson, and Sarah Sharples. 2022. Ethical Concerns and Perceptions of Consumer Neurotechnology from Lived Experiences of Mental Workload Tracking. *life* 25 (2022), 28.
- [66] Byung-Chan Min, Soon-Cheol Chung, Yoon-Ki Min, and Kazuyoshi Sakamoto. 2004. Psychophysiological evaluation of simulator sickness evoked by a graphic simulator. *Applied ergonomics* 35, 6 (2004), 549–556.
- [67] Jungo Miyazaki, Hiroki Yamamoto, Yoshikatsu Ichimura, Hiroyuki Yamashiro, Tomokazu Murase, Tetsuya Yamamoto, Masahiro Umeda, and Toshihiro Higuchi. 2015. Inter-hemispheric desynchronization of the human MT+ during visually induced motion sickness. *Experimental brain research* 233, 8 (2015), 2421–2431.
- [68] Vitaly Napadow, James D Sheehan, Jieun Kim, Lauren T LaCount, Kyungmo Park, Ted J Kaptchuk, Bruce R Rosen, and Braden Kuo. 2013. The brain circuitry underlying the temporal evolution of nausea in humans. *Cerebral cortex* 23, 4 (2013), 806–813.
- [69] Suzanne AE Nooij, Christopher J Bockisch, Heinrich H Bühlhoff, and Dominik Straumann. 2021. Beyond sensory conflict: The role of beliefs and perception in motion sickness. *PLoS One* 16, 1 (2021), e0245295.
- [70] Stephen Palmisano, Robert S Allison, and Juno Kim. 2020. Cybersickness in head-mounted displays is caused by differences in the user's virtual and physical head pose. *Frontiers in Virtual Reality* 1 (2020), 587698.
- [71] Merle G Paule, John J Chelonis, Donna J Blake, and John L Dornhoffer. 2004. Effects of drug countermeasures for space motion sickness on working memory in humans. *Neurotoxicology and teratology* 26, 6 (2004), 825–837.
- [72] Evan M Peck, Daniel A Fergan, Beste F Yuksel, Francine Lalooses, and Robert JK Jacob. 2014. Using fNIRS to measure mental workload in the real world. In *Advances in physiological computing*. Springer, 117–139.
- [73] Evan M M Peck, Beste F Yuksel, Alviitta Ottley, Robert JK Jacob, and Remco Chang. 2013. Using fNIRS brain sensing to evaluate information visualization interfaces. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. 473–482.
- [74] Katlyn Peck, Frank Russo, Jennifer L Campos, and Behrang Keshavarz. 2020. Examining potential effects of arousal, valence, and likability of music on visually induced motion sickness. *Experimental Brain Research* 238, 10 (2020), 2347–2358.
- [75] Melissa Peskin, Brittany Mello, Judith Cukor, Megan Olden, and JoAnn Difede. 2019. Virtual reality applications to treat posttraumatic stress disorder. In *Virtual Reality for Psychological and Neurocognitive Interventions*. Springer, 85–102.
- [76] Paola Pinti, Ilias Tachtsidis, Antonia Hamilton, Joy Hirsch, Clarisse Aichelburg, Sam Gilbert, and Paul W Burgess. 2020. The present and future use of functional near-infrared spectroscopy (fNIRS) for cognitive neuroscience. *Annals of the New York Academy of Sciences* 1464, 1 (2020), 5–29.
- [77] Michael M Plichta, Antje BM Gerdes, Georg W Alpers, Wilma Harnisch, S Brill, Matthias J Wieser, and Andreas J Fallgatter. 2011. Auditory cortex activation is modulated by emotion: a functional near-infrared spectroscopy (fNIRS) study. *Neuroimage* 55, 3 (2011), 1200–1207.
- [78] Felix Putze, Susanne Putze, Merle Sagehorn, Christopher Micek, and Erin T Solovey. 2022. Understanding HCI Practices and Challenges of Experiment Reporting with Brain Signals: Towards Reproducibility and Reuse. *ACM Transactions on Computer-Human Interaction (TOCHI)* 29, 4 (2022), 1–43.
- [79] Jane E Raymond, Kimron L Shapiro, and Karen M Arnell. 1992. Temporary suppression of visual processing in an RSVP task: An attentional blink? *Journal of experimental psychology: Human perception and performance* 18, 3 (1992), 849.
- [80] James T Reason. 1978. Motion sickness adaptation: a neural mismatch model. *Journal of the Royal Society of Medicine* 71, 11 (1978), 819–829.
- [81] James T Reason and Joseph John Brand. 1975. *Motion sickness*. Academic press.
- [82] René Reinhard, Ender Tutulmaz, Hans M Rutrecht, Patricia Hengstenberg, Britta Geissler, Heiko Hecht, and Axel Müttray. 2019. Effects of visually induced motion sickness on emergency braking reaction times in a driving simulator. *Human factors* 61, 6 (2019), 1004–1018.
- [83] Hiroyuki Sakai, Takumi Harada, Stephen K Larroque, Athena Demertzi, Tomoko Sugawara, Taeko Ito, Yoshiro Wada, Masaki Fukunaga, Norihiro Sadato, and Steven Laureys. 2022. Left parietal involvement in motion sickness susceptibility revealed by multimodal magnetic resonance imaging. *Human brain mapping* 43, 3 (2022), 1103–1111.
- [84] Débora P Salgado, Thiago B Rodrigues, Felipe R Martins, Eduardo LM Naves, Roman Flynn, and Niall Murray. 2019. The Effect of Cybersickness of an Immersive Wheelchair Simulator. *Procedia Computer Science* 160 (2019), 665–670.
- [85] Hendrik Santosa, Xuetong Zhai, Frank Fishburn, and Theodore Huppert. 2018. The NIRS brain AnalyzIR toolbox. *Algorithms* 11, 5 (2018), 73.
- [86] Matias N Selzer, Nicolas F Gazcon, and Martin L Larrea. 2019. Effects of virtual presence and learning outcome using low-end virtual reality systems. *Displays* 59 (2019), 9–15.
- [87] Kimron L Shapiro, Jane E Raymond, and Karen M Arnell. 1994. Attention to visual pattern information produces the attentional blink in rapid serial visual presentation. *Journal of Experimental psychology: Human perception and performance* 20, 2 (1994), 357.
- [88] Ranganatha Sitaram, Haihong Zhang, Cuntai Guan, Manoj Thulasidas, Yoko Hoshi, Akihiro Ishikawa, Koji Shimizu, and Niels Birbaumer. 2007. Temporal classification of multichannel near-infrared spectroscopy signals of motor imagery for developing a brain-computer interface. *NeuroImage* 34, 4 (2007), 1416–1427.
- [89] Joseph Smyth, Stewart Birrell, Alex Mouzakitis, and Paul Jennings. 2018. Motion sickness and human performance—exploring the impact of driving simulator user trials. In *International Conference on Applied Human Factors and Ergonomics*. Springer, 445–457.
- [90] Erin Treacy Solovey, Audrey Girouard, Krysta Chauncey, Leanne M Hirshfield, Angelo Sassaroli, Feng Zheng, Sergio Fantini, and Robert JK Jacob. 2009. Using fNIRS brain sensing in realistic HCI settings: experiments and guidelines. In *Proceedings of the 22nd annual ACM symposium on User interface software and technology*. 157–166.
- [91] Kay M. Stanney, Behrang Keshavarz, Heiko Hecht, and Ben D Lawson. 2014. CRC Press Inc.
- [92] Kay M Stanney, Kelly S Kingdon, David Graeber, and Robert S Kennedy. 2002. Human performance in immersive virtual environments: Effects of exposure duration, user control, and scene complexity. *Human performance* 15, 4 (2002), 339–366.
- [93] Gary Strangman, Maria Angela Franceschini, and David A Boas. 2003. Factors affecting the accuracy of near-infrared spectroscopy concentration calculations for focal changes in oxygenation parameters. *Neuroimage* 18, 4 (2003), 865–879.
- [94] Hilary Sutcliffe. 2011. A report on responsible research and innovation. *MATTER and the European Commission* (2011).
- [95] Sungho Tak and Jong Chul Ye. 2014. Statistical analysis of fNIRS data: a comprehensive review. *Neuroimage* 85 (2014), 72–91.
- [96] Séamas Weech, Sophie Kenny, and Michael Barnett-Cowan. 2019. Presence and cybersickness in virtual reality are negatively related: a review. *Frontiers in psychology* 10 (2019), 158.
- [97] David Weibel and Bartholomäus Wissmath. 2011. Immersion in computer games: The role of spatial presence and flow. *International Journal of Computer Games*

- Technology* 2011 (2011).
- [98] Max L Wilson, Serena Midha, Horia A Maior, Anna L Cox, Lewis L Chuang, and Lachlan D Urquhart. 2022. SIG: Moving from Brain-Computer Interfaces to Personal Cognitive Informatics. In *CHI Conference on Human Factors in Computing Systems Extended Abstracts*. 1–4.
- [99] Tom Winter. 2013. *Lost and Found*. Hachette UK.
- [100] Hiroo Yamamura, Holger Baldauf, and Kai Kunze. 2020. Pleasant Locomotion—Towards Reducing Cybersickness using fNIRS during Walking Events in VR. In *Adjunct Publication of the 33rd Annual ACM Symposium on User Interface Software and Technology*. 56–58.
- [101] Shun-nan Yang, Tawny Schlieski, Brent Selmins, Scott C Cooper, Rina A Doherty, Philip J Corriveau, and James E Sheedy. 2012. Stereoscopic viewing and reported perceived immersion and symptoms. *Optometry and vision science* 89, 7 (2012), 1068–1080.
- [102] Fleur D Yen Pik Sang, John F Golding, and Michael A Gresty. 2003. Suppression of sickness by controlled breathing during mildly nauseogenic motion. *Aviation, space, and environmental medicine* 74, 9 (2003), 998–1002.
- [103] Sean D Young, Bernard D Adelstein, and Stephen R Ellis. 2007. Demand characteristics in assessing motion sickness in a virtual environment: Or does taking a motion sickness questionnaire make you sick? *IEEE transactions on visualization and computer graphics* 13, 3 (2007), 422–428.
- [104] Meryem A Yücel, Alexander v Lühmann, Felix Scholkmann, Judit Gervain, Ippeita Dan, Hasan Ayaz, David Boas, Robert J Cooper, Joseph Culver, Clare E Elwell, et al. 2021. Best practices for fNIRS publications. *Neurophotonics* 8, 1 (2021), 012101.
- [105] Chenyang Zhang, Shuguang Li, Yaohua Li, Shengbo Eben Li, and Bingbing Nie. 2020. Analysis of motion sickness associated brain activity using fNIRS: a driving simulator study. *IEEE Access* 8 (2020), 207415–207425.
- [106] Li-Li Zhang, Jun-Qin Wang, Rui-Rui Qi, Lei-Lei Pan, Min Li, and Yi-Ling Cai. 2016. Motion sickness: current knowledge and recent advance. *CNS neuroscience & therapeutics* 22, 1 (2016), 15–24.
- [107] Celina Zhou, Clara Luisa Bryan, Evan Wang, N Sertac Artan, and Ziqian Dong. 2019. Cognitive distraction to improve cybersickness in virtual reality environment. In *2019 IEEE 16th International Conference on Mobile Ad Hoc and Sensor Systems Workshops (MASSW)*. IEEE, 72–76.