Université de Montréal

Attention, Concentration, and Distraction measure using EEG and Eye Tracking in Virtual Reality

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Mémoire présenté à la Faculté des études supérieures
en vue de l'obtention du grade de Maître ès sciences (M.Sc.)
en computer science

decembre, 2022

Université de Montréal
Faculté des études supérieures

Ce mémoire intitulé:

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a été évalué par un jury composé des personnes suivantes:

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Mémoire accepté le: 4 avril 2023

RÉSUMÉ

La concentration est importante dans l'apprentissage, Le trouble du déficit de l'attention avec ou sans hyperactivité, la conduite automobile et dans de nombreux autres domaines. Par conséquent, les systèmes de tutorat intelligents, les systèmes de diagnostic du trouble du déficit de l'attention avec ou sans hyperactivité et les systèmes de détection de la distraction au volant devraient être capables de surveiller correctement les niveaux d'attention des individus en temps réel afin de déduire correctement leur état attentionnel. Nous étudions la faisabilité de la détection de la distraction et de la concentration en surveillant les niveaux d'attention des participants pendant qu'ils effectuent des tâches cognitives en utilisant l'Électroencéphalographie et l'Eye Tracking dans un environnement de réalité virtuelle. En outre, nous étudions la possibilité d'améliorer la concentration des participants en utilisant la relaxation en réalité virtuelle. Nous avons mis au point un indicateur qui estime les niveaux d'attention avec une valeur réelle en utilisant les données EEG. L'indicateur indépendant du participant basé sur les données EEG que nous avons utilisé pour évaluer les niveaux de concentration des participants prédit correctement l'état de concentration avec une précision (F1 = 73%). De plus, le modèle de distraction indépendant des participants, basé sur les données d'Eye Tracking, a correctement prédit l'état de distraction des participants avec une précision (F1 = 89%) dans un cadre de validation indépendant des participants.

mots clés: eye tracking, EEG, réalité virtuelle, distraction, concentration, attention.

ABSTRACT

Attention is important in learning, Attention-deficit/hyperactivity disorder, Driving, and many other fields. Hence, intelligent tutoring systems, Attention-deficit/hyperactivity disorder diagnosis systems, and distraction detection of driver systems should be able to correctly monitor the attention levels of individuals in real time in order to estimate their attentional state. We study the feasibility of detecting distraction and concentration by monitoring participants' attention levels while they complete cognitive tasks using Electroencephalography and Eye Tracking in a virtual reality environment. Furthermore, we investigate the possibility of improving the concentration of participants using relaxation in virtual reality. We developed an indicator that estimates levels of attention with a real value using EEG data. The participant-independent indicator based on EEG data we used to assess the concentration levels of participants correctly predicts the concentration state with an accuracy (F1 = 73%). Furthermore, the participant-independent distraction model based on Eye Tracking data correctly predicted the distraction state of participants with an accuracy (F1 = 89%) in a participant-independent validation setting.

Keywords : eye tracking, EEG, virtual reality, distraction, concentration, attention.

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LIST OF ABBREVIATIONS

ADHD	Attention-deficit/hyperactivity disorder
ANOVA	Analysis of Variance
AOI	Area of Interest
AUC	Area Under the Curve
CPT	Continuous Performance Test
DL	Distance Learning
DSM-5	Diagnostic and Statistical Manual, Fifth edition
EEG	Electroencephalography
ELM	Extreme Learning Machine
HEG	Hemoencephalography
ITS	Intelligent Tutoring System
KNN	K-Nearest Neighbors
lapSVM	laplacian Support Vector Machine
LDA	Linear Discriminant Analysis
LPOGCV	Leave-P-Groups-Out-Cross-Validation
MANOVA	Multivariate Analysis of Variance
MOOC	Massive Open Online Courses
MW	Mind Wandering
OCSVM	One Class Support vector Machine
PSD	Power Spectral Density
RBF-SVM	Radiant Basis Function Support Vector Machine
ROC	Receiver Operating Characteristic Curve
SBN-SC	tatic Bayesian Network with Supervised Clustering

SMOTE	Synthetic Minority Oversampling Technique
SS-ELM	Semi-Supervised Extreme Learning Machine
SSL	Semi-Supervised Learning
SVM	Support Vector Machine
TSVM	Transductive Support Vector Machine
VIF	Variance Inflation Factor
VR	Virtual Reality
WCST	Wisconsin Card Sorting Task

ACKNOWLEDGMENTS

This research project may mark the end of my academic career, I feel relieved, yet afraid of what is coming next.

First, I want to thank my research director Claude Frasson, and Hamdi Ben Abdessalem, who were always present to answer me when I had problems in my research, and for their patience and kindness towards me. This research probably wouldn't have been completed without your help. I am also grateful to members of the jury for accepting to take a critical look at my work.

Then, I am deeply thankful to my father, who encouraged me to come study in Canada and supported me financially all this time. I also want to thank my mother, who fully accepted my decision to go study abroad, which is very difficult for every mother to accept. I don't think I will ever be able to repay them back what they did for me.

I want to thank Antoine, who I met at my lab, and the person who tested my experiment the most and never refused to do it even once. I am really glad for the help you provided me with. And Yen, the director of the lab, who I think is a fantastic person.

Finally, I also want to thank all my dear friends who supported me emotionally when times got hard and particularly Asmaa, my life partner, for being here, and for all the support she gave me during these past three years in Montreal despite the distance.

CHAPITRE 1

INTRODUCTION

1.1 Statement of the Problem

The COVID-19 pandemic required educational institutions to adopt new policies as part of lock-down restrictions and pandemic mitigation strategies to continue their activities. As a result, higher education institutions in Canada transitioned to remote teaching.

In Canada, 101,572 injuries resulted from accidents including motor vehicles in 2020. Despite the decrease in injuries compared to 2019, the number of fatalities due to motor vehicle accidents did not decrease ; 1762 deaths in 2019 compared to 1745 in 2020. Moreover, in 2020, while 26% of personal injuries resulting from collisions were in rural areas, it represented 54% of fatalities due to collisions [1].

Attention-deficit/hyperactivity disorder (ADHD) is recognized as the most common neurodevelopmental disorder, [26] reported an overall prevalence estimate across Canada provinces for adults of 2.9% and an overall estimate across five provinces for children and youth of 8.6%. It is characterized by inattention, hyperactivity, and impulsivity [10]. Causes of ADHD can be diverse, as well as factors related to this condition among patients [55]. Although ADHD is often treated pharmacologically and can produce improvement in symptomatology, some patients present side effects to these drugs, highlighting the importance of developing other alternative options.

The rapidly increasing popularity of online courses was not without challenges, particularly during the COVID-19 pandemic, which has impacted a large part of the lives of individuals beyond learning. In [34], surveys examining the impacts of COVID-19 and emergency remote learning on approximately 155,000 students in Canada were reviewed. Findings on the educational experiences of individuals revealed many issues, including issues related to motivation and concentration. For example, more than 70% of undergraduates and graduate students indicated they could not be attentive during the online learning period.

Analysis of many reports shows that driver's inattention is one of the main contributors to motor vehicle crashes more than 25% of the time [1]. Tasks handled while driving a car have evolved from simple ones, such as controlling the radio to more complex and demanding ones, such as smartphone manipulation and interaction with complex vehicle systems, which are perceived as distractions [71] discerns four types of **distraction** – cognitive, manual, visual and auditory – and describes text messaging as the riskiest **distraction** because it requires mental, manual and visual **attention** from the driver which demonstrates the complexity of smartphone usage while driving. Additional measures are needed to help individuals focus better while driving and avoid the numerous distractions surrounding them on-road, including cell phones. A system that is able to monitor the **distraction** of individuals in real-time while driving could detect any increase in **distraction** levels and inform drivers to bring their focus back to the road.

ADHD is the most common neurodevelopmental disorder in children, with an estimated worldwide prevalence of around 5 percent [20] and can persist into adulthood [74]. It is characterized by inattention, hyperactivity, and impulsivity [10]. ADHD is a risk factor for later unfavorable outcomes such as academic and professional failure, social difficulties, criminal behavior, and transport accidents [15, 69]. Using neurofeedback to teach individuals with ADHD how to control their **attention** could help treat this condition. Neurofeedback is a non-invasive procedure that helps guide people self-control of brain functions by measuring brain waves and providing feedback, usually in the form of audio or video content.

Distraction, inattention, and lack of concentration play an important role in our current society, by being the main cause of many problems such as ineffective learning and mortal accidents while driving, or by being an important solution to severe conditions such as ADHD.

1.2 Background and Need

Attention is the cognitive process of selectively focusing on a specific aspect of information, whether it's sensory input, thoughts, or actions, while ignoring other potentially irrelevant stimuli [38, 59]. It allows us to allocate our limited cognitive resources to specific tasks or stimuli [70].

Concentration often used interchangeably with attention, was recently described as a state of selective reception of information and is related to the amount of information that can be processed at a time [46]. In other words, concentration is the focus of attention on a particular task, thought, or activity.

Distraction refers to the divertion of attention away from a primary task or focus by external or internal stimuli [68]. Distractions can significantly impact our ability to concentrate, leading to decreased productivity, reduced accuracy, and impaired learning. Common distractions can include external factors like noise, visual stimuli, or interruptions, as well as internal factors like thoughts, emotions, or physical sensations [27].

Attention can be divided into two categories. External attention is concerned with the senses ; visual attention is the process of directing and locking the sight on an object or an area from the environment and optionally in order to process the information relative to the latter. Auditory attention in the same way attends to a single audio source, possibly among many. In contrast to the two types of attention mentioned, the second category, internal attention, does attend to a thought rather than a physical object [70]. This categorization of attention also fits the taxonomy of external and internal attention proposed in [19].

In [67], authors proposed a system that uses electroencephalogram on learners enrolled in MOOCs (Massive Open Online Course) to measure their **concentration** and **attention** levels. The system collects data from the learners in real-time and produces regular feedback in real-time based on their **concentration** level, and the learning material will be adapted to the learner's needs to improve the overall learning experience. A MOOC is an online course aimed at unlimited participation and open access via the Web ; many MOOCs had over 100,000 enrolled students [65]. Electroencephalogram (EEG) is a method of recording the electrical and magnetic field activity produced by the neurons of the brain [22]. EEG has been used extensively for brain research concerned with affect and cognition [13, 17, 18, 32, 44, 46]. Authors developed a system to monitor the personal **concentration** level of learners in real-time using eye tracking technology in [42]. Eye tracking is the process of measuring either the point of gaze or the motion of an eye relative to the head [4]. Additionally, modern eye trackers are able to provide additional data including human pupil diameter, and rate of openness of the eye. This system was intended to be used in real applications such as intelligent tutoring systems, and other e-learning systems.

In [73], the differences in EEG behavior between simple driving and distracted driving were investigated, using collected data in a driving computer simulation, they subsequently developed a system based on machine learning that could detect distracted driving correctly 85% of the time. Machine learning is a subfield of artificial intelligence, it leverages sample data to build models that can generalize to unseen data. Machine learning is widely used in a variety of applications [5]. Moreover, [72] generated and successfully tested a robust measure of the general allocation of **attention** of drivers using eye tracking technology in an on-road setting.

In [24], the effect of neurofeedback on working memory in children with ADHD was investigated. They found an improvement in a measure of working memory in children who did the neurofeedback training, with the beneficial effects still present a year after the training. Neurofeedback is a type of biofeedback that teaches self-control of brain functions to subjects by measuring brain waves and providing a feedback signal [50]. Moreover, [51] undertook a meta-analysis of published studies to determine whether EEG neurofeedback significantly improves the symptoms of ADHD in children and reported a significant improvement in the inattention condition, underlining the potential of EEG neurofeedback in ADHD treatment.

Concentration is important in daily life as much in studies as in work, it enables faster comprehension, improves memory, helps to focus on a task, and ignores irrelevant thoughts which help in achieving goals more efficiently but unfortunately staying concentrated is not always obvious and easy. In medicine, **concentration** is relevant when studying multiple aspects of attention deficit hyperactivity disorder (ADHD) and can be helpful and informative. While driving, if not constantly concentrated, drivers are at risk of severe injuries and even death sometimes. During a learning session, the learners who correctly process the information are usually more concentrated than the others, while distracted learners have more trouble understanding the content. Thus, a meaningful way to discern effective learning is to rely on the **concentration** levels of the learners, where high **concentration** levels imply effective learning from the learners whereas sustained poor levels of **concentration** are an indicator of ineffective learning.

Virtual Reality (VR) is an advanced technology that simulates environments realistically. It lives in the intersection of many fields, including electronic engineering, simulation, and computer graphics [75]. Current consumer-grade VR devices are composed mainly of a headset that displays the virtual environments and reacts to the head movements of the user and a pair of right and left controllers to interact with the environment. The virtual simulation can be extended to other senses, including touch using haptic devices such as vests with vibrotactile elements [7]. Moreover, current VR headsets can be equipped with eye tracking technology.

In [6], the effects of learning in virtual reality (VR) compared to traditional textbook style and watching videos were studied. Results showed that learners in VR had improved overall performance in learning (knowledge acquisition and understanding) compared to learners watching videos. Moreover, learners in VR showed better performance for "remembering" than learners in traditional and video conditions. Higher engagement in VR compared to other conditions was also reported.

In [30], an advanced VR driving simulator was developed, a VR driving simulator with tools to enhance the driving experience including naturalistic audio, touch, and motion. Results suggest that this environment can help researchers design highly immersive and inexpensive experiments with less effort using virtual reality. Furthermore, this platform may also be used to simulate critical or dangerous scenarios safely while observing more authentic human behavior.

Authors compared two tests for identifying ADHD in children in [63], a traditional and virtual reality method. Results indicated that the VR method predicted ADHD presentations better than the traditional one. It also differentiated better between ADHD and non-ADHD students. These findings show the potential advantages of using virtual reality in ADHD assessment, as it facilitates the diagnosis of ADHD and the differentiation of its presentations in a realistic environment that is virtual reality.

Concentration, **attention**, and **distraction** have been researched extensively in different areas, including learning, driving, and ADHD using EEG and eye tracking [42, 67, 71]. While vast experiments have been conducted in real-world settings, little was done in virtual reality. Consumer-grade eye tracking devices constrain the user always to look ahead, and devices that enable the user to rotate the head freely are high-priced. With the existing VR technology, multiple consumer-grade VR devices are equipped with eye-tracking technology similar to high-priced eye-tracking devices. Research indicated higher learning performance and engagement in VR compared to classic methods [6], suggesting that current and new learning methods and platforms could target this technology soon, including MOOCs and ITSs. Moreover, results showed that VR could be better for ADHD assessment than classic methods, indicating that neurofeedback with **attention** monitoring could treat ADHD in VR better. Furthermore, a tool to design driving experiments in VR was developed, and results indicated that it could be used to create highly immersive and inexpensive driving experiments easily. Such a tool could help to advance research on distracted driving by providing simulation results that generalize to real-life conditions.

1.3 Purpose of the Study and Research Questions

While online courses are becoming increasingly popular, learners reported that one of the main problems in distance learning is the lack of engagement. However, results from research indicate higher learning performance and engagement in VR compared to classic methods, suggesting that online education could benefit from VR and extend to other distance learning methods such as ITSs and MOOCs.

Patients diagnosed with ADHD tend to be inattentive, hyperactive, and impulsive. Researchers reported that ADHD at a young age could lead to poor long-term outcomes.

Attention neurofeedback training was said to be successful at improving symptoms of ADHD. Other research also showed that VR could be better for ADHD assessment than classic methods, indicating that neurofeedback with **attention** monitoring could treat ADHD in VR better.

Distraction was reported to be one of the main contributing factors in fatal collisions of motor vehicles. Numerous methods to measure **distraction** and alert drivers have been reported. A VR tool was developed to design driving experiments in VR, and results indicated that it could easily create highly immersive and inexpensive driving experiments. Such a tool could help to advance research on distracted driving by providing simulation results that generalize to real-life conditions.

Attention Restoration Theory (ART) is a psychological framework suggesting that exposure to natural environments facilitates the restoration of voluntary attention capacity, reducing mental fatigue and enhancing cognitive functioning. ART emphasizes the restorative effects of nature on cognitive resources through the engagement of involuntary attention, allowing voluntary attention systems to recover [39].

Gao et al. assessed ART with VR and EEG and showed that the experience had positive restorative effects on the individuals' attentional fatigue and negative mood [29]. In [12] authors used relaxation in Virtual Reality to study the possibility of decreasing negative emotions in the elderly including frustration, anxiety, and apathy, and showed a decrease in anxiety and frustration, and an increased performance in exercises related to attention. These results highlight the possibility to improve the attentional state of individuals using relaxation in VR.

Attention, concentration, and distraction are interrelated cognitive processes that determine our ability to focus and efficiently complete tasks. Attention serves as the basis for concentration, which is the ability to maintain focus on a particular task or thought. Distraction, on the other hand, disrupts our ability to concentrate and can lead to reduced productivity and effectiveness. Thus, an improvement of the attentional state leads to an increase in concentration, while an increase in distraction leads to a decrease in concentration and attention.

The external aspect of attention is concerned with the senses, therby, Eye Tracking is suitable to investigate an element of external attention, which is visual attention, while EEG captures the brainwaves and can be used to assess the internal aspect of attention.

Following the problems caused by distraction, and lack of concentration, this research has two goals. The first goal is to develop a means to assess the attentional state of individuals through concentration and distraction, and use it as a monitoring tool. The second goal of this study is to find means improve the attentional state of individuals, i.e. improve concentration, and/or decrease distraction. We will pursue these goals by developing a Virtual Reality environment, where we can collect EEG and Eye Tracking data, and explore attention improvement strategies.

Following the purpose of this study, we ask the following questions :

1. Is it possible to detect and monitor the **concentration** and **distraction** levels of individuals while completing cognitive tasks using EEG and Eye Tracking in a Virtual Reality environment ?
2. Is it possible to improve the **concentration** level, and decrease the **distraction** level of individuals using relaxation Virtual Reality ?

CHAPITRE 2

STATE OF THE ART

2.1 Introduction

The state-of-the-art addresses three areas related to measures of **concentration**, **attention**, and **distraction**, while completing different cognitive tasks, using eye tracking and EEG. Other studies related to these terms are also referenced.

Sections 2.2 and 2.3 introduce the main tools and data features we use to study **attention**, **distraction**, and **concentration** in this study. Section 2.2 introduces EEG and section 2.3 introduces Eye tracking.

Section 2.4 addresses research related to remote learning (distance learning, online courses, MOOCs, etc.) and presents promising and applicable solutions to monitor the **concentration** level of learners and enhance their learning.

Section 2.5 focuses on research studies about distracted drivers in real settings and in simulation, and how **distraction** monitoring and detection tools can make driving safer and avoid on-road crashes.

Section 2.6 discusses research related to inattention symptoms in ADHD conditions for children and how existing methods for assessing **attention** could help an ADHD diagnosis.

Section 2.7 introduces the attention restoration theory and shows its application and results in Virtual Reality.

2.2 EEG

The existence of electrical activity in the brain was discovered more than a hundred years ago and called electroencephalogram or EEG. The activity of the neurons of the brain produces electrical and magnetic fields that can be recorded with electrodes at a close distance [22]. EEG (Electroencephalogram) has been used extensively for brain research concerned with affect and cognition [18, 44, 46, 53, 58, 62].

There are two types of EEGs with respect to body invasion, invasive EEGs are those recorded from electrodes that have been surgically implanted in the brain and provide much better signal quality than the other alternative [9]. Non-invasive EEGs do not require any surgery and electrodes are placed on the scalp of the subjects. Non-invasive EEGs are easy to set up and do not restrict the experiments, unlike invasive EEGs and other tools that require the subject to stay put. A major reason for the popularity of non-invasive EEGs is the pronounced trade-off between the price and the signal quality that makes profound research achievable with a low-cost model.

EEG signal is usually described in terms of rhythmic activity that is divided into bands (or waves) by frequency. Delta waves (0 – 4 Hz) are most relevant in deep sleep state but also in waking and attention states, an excess in Delta waves during waking may cause learning disabilities. Theta waves (4 – 8 Hz) are most relevant in early sleep and drowsiness states but also in arousal, an excess in Theta waves during waking can also result in learning disabilities. Alpha waves (8 – 12 Hz) are relevant in a relaxed awareness state. Beta waves (12 – 30 Hz) are relevant in active thinking, **concentration**, and sometimes stress. Gamma waves ($>$ 30 Hz) are associated with high **concentration** and cognitive functioning, low levels of Gamma waves in the waking state may suggest learning difficulties [3, 18, 44, 46]. In addition to that, a detailed classification of Beta waves is SMR (12 – 15 Hz) which is associated with musing thought, and mid-Beta (15 - 20 Hz) which is associated with active thinking and focus. The magnitude of the brain waves depends upon the localization of the measurement and varies significantly across the different areas of the cerebrum.

The 10-20 system of Electrode placement is an internationally recognized method to describe the location of EEG Electrodes [33], each electrode placement site has a letter to identify the lobe or area of the cerebrum it is reading from ; pre-frontal (Fp), frontal (F), temporal (T), parietal (P), occipital (O), and central (C) even though there is no central lobe ; due to their placement, and depending on the individual, the “C” electrodes can exhibit/represent EEG activity more typical of frontal, temporal, and some parietal-occipital activity. There are also (Z) sites ; a “Z” (zero) refers to an electrode placed on the midline sagittal plane of the skull, (FpZ, Fz, Cz, Oz) and is present mostly for reference/measurement points and does not represent either hemisphere adequately. “Z” electrodes are often utilized as “grounds” or “references”.

2.3 Eye Tracking

Eye trackers are a means to measure the position (point of gaze) and the movement of the eye. The position of the eye is represented by 2D or 3D coordinate point relative to an origin, while the movement of the eye is relative to the head.

Eye trackers come in various types. Screen-based eye trackers are mounted on or near a computer screen, this setup forces the subject to sit down and stay put to interact with the screen, this type of device is usually used in controlled lab environments and gives accurate measurements of the gaze. The presence of a large head box makes the subject able to slightly move without decreasing the accuracy. Head-mounted eye trackers are fitted near the subject’s eye, this setup allows him to move freely which makes it ideal for tasks performed in the natural environment, although the accuracy starts to suffer when practicing very hectic activities like football for example.

Eye tracking data can be transformed into eye movement information containing meaningful insights. Saccades are defined as rapid movements of eyes between fixations. Fixations are defined as pauses of eyes over informative regions of interest [64]. Eye tracking has been extensively used previously in affect detection [40] [49].

2.4 Learning

In [41], the feasibility of monitoring the personal **concentration** level of learners in real-time was studied by analyzing pupillary response and eye blinking patterns using a simple commercial eye tracker and web camera.

The experimental design to collect the data was simple, during the experiment, participants were instructed to focus on a white (+) sign on a black screen for 5 minutes. Feature extraction was done for each time window of duration T, four features were used in total. Participants’ faces were captured using a web camera, and a C++ image processing program was used to extract eye state data. Finally, the number of eye blinks and duration of open eye state for time window T was computed. Eye tracking data were obtained using an eye tribe eye tracker. Average pupil size variation was computed for time window T. Rate of missing data was also computed using the number of recorded data in T (the eye tracker does not record data when it does not detect participants' eyes).

OCSVM binary classification model with 10% outliers was trained for each participant using a time window $T = 1s$ (300 data samples). The model returns 1 when the "concentrated" state was predicted, and -1 otherwise. Then, to monitor levels of attention, this model was used to make multiple predictions over a period of time and average the result, a value greater than zero would suggest that the participant was concentrated, and a value lower than zero would suggest that the participant was not concentrated during this period of time. The experiments were conducted on an Intel i7 Quad Core 3.50 GHz PC with 16G RAM.

To validate the monitoring method, participants performed four tasks with a duration of five minutes for each task :

- Finding hidden figures.
- Watching music videos.
- Solving mathematical problems.
- Thinking about current worries and looking elsewhere (a non-concentration task).

The average level of **concentration** in tasks 1-3 (concentration state) was significantly higher than in task 4 (non-concentration state). Experimental results suggest that the system can be used for various real applications such as intelligent tutoring systems, e-learning systems, etc.

In [36], the feasibility of integrating commercial off-the-shelf (COTS) eye trackers to monitor **attention** during interactions with a learning technology called Guru is studied. Consumer off-the-shelf (COTS) eye trackers are cheap eye trackers that cost between 100$ and 150$.

The study focuses on mind wandering (MW), a form of distraction. It is a phenomenon characterized by a shift in attention from task-related to task-unrelated thoughts and can happen spontaneously or intentionally. The study is divided into three parts. First, the authors show that the eye data collected from the COTS eye tracker are valid. Next, they show the data are sufficient to detect mind wandering, which is a form of attention. Finally, the authors investigate whether MW detection could be improved using local eye features.

Guru is an ITS designed to teach biology. It communicated with students using synthesized speech through an animated agent, while students communicated by typing responses, which are analyzed with natural language processing techniques. To collect eye data, an EyeTribe eye tracker was attached to the computer below the screen. The experiment software went through different iterations during development. Each time, the feedback of the participants was considered to improve the software. Feedback from the students included their opinion of the calibration process and the clarity of the instructions during the experiment. 135 students participated in the study (9th and 10th graders), 41% of participants were males. Each participant completed a 30-minute Guru session, took a break, then completed another 30-minute session on a different topic. 85% of sessions were considered valid. The 15% missing sessions were a result of incorrect drivers for USB 3.0 ports, background system updates, and calibration failure.

To study mind wandering, auditory thoughts probes were inserted at random intervals (every 90-120 seconds) during the Guru session, participants had to press the “N” key if they were not minded wandering, “I” if they were intentionally (deliberately) mind wandering, or “U” if they were unintentionally (spontaneously) mind wandering. The difference between intentional and unintentional mind wandering was not considered. Participants encountered an average of 12 probes over the course of each session with a mean MW rate of 28%. The features were calculated from 30-second windows preceding the probes. Three types of gaze features were used :

- Global gaze features calculated using Open Gaze and Mouse Analyzer ; eye movements measures by fixations and saccades including fixations duration, fixations dispersion, saccades duration, saccades length, saccades absolute angle, saccades relative angle, saccades velocity, horizontal saccades proportion, and fixation saccade ratio. For each feature in the 30-second time window, mean, median, minimum, maximum, standard deviation, range, kurtosis, and skew were calculated, yielding 57 global features.

- Local gaze features : the screen space was divided using a 10 x 8 grid yielding 80 regions (features) of equal size. Each feature received a weight proportional to the number of gaze fixations into the corresponding area.
- Context features : Other non-gaze features related to the experiment have been calculated.

Bayesian network models were used to discriminate between MW observations and non-MW observations using 2,334 samples. Since only 23% of the samples were MW, the authors used SMOTE algorithm to create synthetic samples for the minority class in order to have balanced classes.

Synthetic Minority Oversampling Technique (SMOTE) is a data augmentation technique that addresses the imbalanced classes problem by creating new samples of the minority class synthetically from existing examples. To validate the models, leave-several-participants-out cross-validation was used, it is a validation method that consists in training on data from a subset of participants and testing on the rest, the procedure is repeated multiple times and the average results are taken.

The metrics used to assess the models were F1 score, recall, and precision. Models using different feature types all outperformed the chance-level baseline. The best models performed the same with an F1 score of 59%, they used respectively global features and local features. Surprisingly, the model that combined global and local features had a lower performance with an F1 score of 46%. An analysis of global features was also carried out using Cohen's d-effect size measure. Cohen's d was computed by calculating the difference of each feature across MW and non-MW divided by the pooled standard deviation.

Positive d values for a feature indicate higher values for instances of MW compared to instances of Not MW. 20 features (out of 57) were consistent with a small size effect (d value of 0.2), and the rest of the features had a d value less than 0.2. Furthermore, Cohen's d absolute values were used to rank features by their contribution. Fewer fixations and saccades were found for MW, and fixations were more dispersed. Saccades were slower, longer, and covered a smaller range of angles during MW.

Motivated by the shortcomings of actual learning methods, wireless EEG recording device was used in [47] to design a tool that can assess the attentiveness of students while learning in class or from home. They reported from other research, while investigating the effects of sleep disorders on attention, that greater Theta activity was found when subjects were inattentive.

Additionally, authors reported from another study involving reading books and answering questionnaires that Alpha activity was slightly higher when subjects were relaxed, whereas Beta activity was greater when subjects were attentive.

In this research, 24 participants performed four tasks :

- Ordering images task.
- Choosing answers based on illustrations task.
- Multiple choice task.
- Rest task.

Subjects completed the experiment under two scenarios where the second contained interference created by a discussion between two people in order to distract the subjects, the subjects were asked to report the content of the overheard conversation at the end of the experiment.

Researchers and subjects reviewed together the video footage of the experiment to determine whether they were attentive or not, and passages, where the subjects were not sure about their mental, were discarded in both scenarios.

A wireless EEG dry sensor was employed to record signals from one channel $Fp1$ at a $512Hz$ sampling rate, and ground and reference sensors were placed on the left ear of the subjects. The recorded signal was preprocessed by applying a band pass filter ($0.1 \sim 50$Hz) followed by a Fast Fourier Transform, finally, four power band features are produced from the recordings - Delta ($0.5 \sim 3$Hz), Theta ($4 \sim 7$Hz), Alpha ($8 \sim 13$Hz) and Beta ($14 \sim 30$Hz). The last feature was computed using the ratio of the power bands

Alpha and Beta.

To assess attentiveness, a support vector machine classifier was trained on the data collected during the experiment with two labels (attentive and inattentive), to prevent the effects of imbalance between the number of attentive and inattentive samples on the accuracy of the classifier, the same number of attentive and inattentive samples were selected for the training. k-fold cross-validation with $k = 5$ was employed to estimate the accuracy of the model.

Consequently, the average accuracy of the classification model hit 70% for certain parameter values. The accuracy of recognition of the attentive state hit 90% meanwhile the accuracy of recognition of the inattentive state did not exceed 60% with multiple parameter values. The effect of each feature on training was also observed, all the features affected the accuracy of the classifier, but the additional feature Alpha/Beta and Delta affected the classification accuracy by far the most, authors reported from another research that changes in Delta activity are related to the linguistic acquisition, and because the learning method in this experiment belongs to a category, the Delta feature is relevant.

To evaluate the performance of the model, the authors used accuracy as a metric, which is the ratio of the number of correct predictions to the total number of predictions. The accuracy of the different trained models went up to 76.82% on the data of the training set using a k-fold cross-validation approach.

In [41], eye tracking data was used to monitor the levels of attention of learners ranging from the “concentrated” state to the “non-concentrated” state.

To monitor attention levels, a time window of one second was used, the authors did not justify this choice, and no other values were tried. Moreover, few eye features were used to discriminate between attention states, namely, blinks and eye openness. Experimenting with more eye features should be useful to better understand the most relevant ones. Finally, only one task was used to collect eye data, fixating a cross on the screen. Looking away from the object of interest is indeed detrimental to learning, but is not enough to induce the attention state of learners.

A clever method of monitoring based on averaging predictions of binary classification was used in this research and was not observed in others. This method was deeply explored in our study but was not retained. In this study, the authors also attempted to validate their method of assessing attention levels by comparing results during tasks demanding different levels of attention. This approach was used in our study to validate the distraction methodology.

In the study [36], eye tracking data was used to detect wind-wandering (distraction) by monitoring the levels of attention of learners.

In this research, only one problem was observed. The predictive ability of the model was indeed higher than the chance level, but it was still low compared to reports from other studies.

This study contained two very useful pieces of work. First, an extensive list of features was extracted from eye tracking data, and the most relevant features were cited, namely, eye saccades and fixations. Then, to evaluate the performance of the mind wandering prediction model, authors used a procedure called “Leave-p-groups-out cross-validation”, which enables to, estimate effectively the performance of the model when fed with new data, and estimate effectively the performance of the model in case of participant-dependent data. Those results were used in our study to detect distraction when computing relevant features, and when estimating the performance of our models.

In [47], EEG was used to monitor the attention states of learners and to discriminate between the attentive state and the inattentive state.

While the procedure and data analysis in this study do not show flows, only one classification algorithm was applied. No attempt to improve the developed model was done.

In addition to EEG band power features previously employed, authors used the Beta/Alpha ratio as a feature following the observation that Beta power increases during concentration and that Alpha power decreases during concentration. This newly added feature contributed the most to the predictions of the model showing its usefulness. This approach was used as a stepping stone in our study to model a real-valued indicator of levels of attention using EEG.

2.5 Driving

In [48], a real-time participant-dependent system to detect drivers' distractions using semi-supervised learning methods was developed. 41 experienced drivers aged from 21 to 65 (20 males) participated in the study. They were given time to practice driving as well as secondary tasks.

Data from 7 subjects had to be excluded resulting in a dataset of 34 participants (23 males). Participants performed two types of driving : driving without a secondary task and driving while completing a secondary task. The main driving task consisted of following a leading car, and the length of data collected from each participant ranged from 73 to 270 seconds. The secondary task was a cognitive distraction task.

Participants were shown a target sound and were presented with a series of target and non-target sounds and had to count the number of times the target sound was presented. A sound was presented for 320 ms with a two-second interval between two sounds. The distraction task lasted on average 50 seconds and was repeated nine times for each participant. Eye and head data were collected at 60 Hz using a faceLAB eye tracker. For each participant, the eye tracker was calibrated for 15 minutes.

A total of 15 features were output by the faceLAB software :

- Head position (three features).
- Head rotation (three features).
- Left gaze rotation (two features).
- Right gaze rotation (two features).
- Saccade binary value indicating if a saccade occurred or not.
- Blink binary value indicating if a blink occurred or not.
- Blink frequency.
- Blink duration for a window 60 seconds.

- Percentage of extended periods with practically closed eyes in a time window (with an eye closure parameter of 0.75 and a three-minutes time window).

The objective of the experiment was to compare semi-supervised learning (SSL) methods with supervised learning ones. Two SSL algorithms Laplacian Support Vector Machine (LapSVM) and Semi-Supervised Extreme Learning Machine (SS-ELM) algorithms were compared with four supervised learning methods :

- Static Bayesian Network with Supervised Clustering (SBN-SC).
- Extreme Learning Machine (ELM).
- Support Vector Machine (SVM).
- Transductive SVM (TSVM).

Observations for the classification problem were created using a 10-second sliding window with 95% overlap. 25 features were used for the classification problem (the mean of the first 10 features, and the standard deviation of all the features). The binary labels were defined based on experimental conditions (i.e driving without a secondary task or driving with the secondary task). The classes were not balanced and the not-distracted/distracted ratio was 0.45.

To evaluate the models, accuracy, G-mean, sensitivity, and specificity were used as a metric. All the models were evaluated on the same data, using the mean value of a three-time repeated 4-fold cross-validation. All the models created are subject-dependent. A feature analysis was carried out to understand the contribution of each feature in this classification problem. First, two rankings for individual features were made, a ranking of the correlation coefficient with the labels, and a class separability ranking based on Linear Discriminant Analysis (LDA).

Results revealed that gaze features are by far more important than others. A comparison of the models' performance showed that SBN-SC was the least accurate model. The best model in terms of performance was the SS-ELM, while the best performance/speed ratio model was the SVM. A grid search for optimal parameter values was conducted based on the test G-mean, showing that the models are relatively robust to hyperparameter change.

In [23], a system capable of distinguishing distracted driving (i.e. situations caused by secondary tasks) from not-distracted driving (i.e., Solely focusing on the primary task of driving) was developed using EEG signal. 8 subjects aged between 20 and 40 participated in the study. They were all legally able to drive and were asked to avoid drinking alcoholic beverages and taking any medication that makes them feel drowsy or sleepy. The experiment was conducted while driving a real car.

EEG data were collected while undergoing five types of driving :

- **Normal driving :** driving without any secondary task for two minutes (The data collected in this phase are used for reference).
- **Phone Conversation :** Picking up the phone from the holder.
- **Dialing and talking for about 2 min**.
- **Texting :** Picking up the phone from the holder.
- **Typing and sending a specific message**.

The two other types were Question and Spelling Questions.

High-pass and low-pass filters with cut-off frequencies of 0.5–50 Hz were applied to preprocess the data. Next, the data were segmented into chunks of 2-second duration with an overlap of 75%. The choice of the window size was based on the authors' experience. 37 features were extracted for each channel including Pearson skewness measure, Short time Fourier transform, Band power, Statistical hypothesis test, Moments of distribution (3, 4, 5), Wavelet Mean, Wavelet Power, Wavelet standard deviation, Approximate Shannon entropy, Katz fractal dimension, Auto-regressive parameters, Higuchi fractal dimension, and Entropy of sub-bands. The total number of features was 592 for the 16 EEG channels.

Dimensionality reduction methods Linear Discriminant Analysis (LDA) and Neighborhood Preserving Embedding (NPE) are both used on the 37 features of each channel to produce one new feature, resulting in 32 features in total (16 features from LDA and 16 features from NPE). LDA is a supervised linear method that finds a projection to maximize data separation. ReliefF feature selection technique is applied next for feature selection.

ReliefF is a supervised method that uses an objective function to rank features, it can be used for dimensionality reduction, and feature selection. The authors made three models to discriminate between the distracted state and the non-distracted state, a model using the 592 features, a model using 16 features from LDA, and a model using 16 features from NPE. The average accuracy resulting from a 10-fold cross-validation was respectively 98.47%, 96.21%, and 97.53%. The most relevant feature regions in the classification problem of distracted drivers were the frontal and parietal regions.

The two studies [23, 48] aimed to distinguish the "distracted" state from the "not distracted" state while driving.

To extract features, a sliding window with a length of 10 seconds was used in [48], while a length of two seconds was used in [23]. The choice was based in the first study was not justified, while in the second study, it was based on experience. Moreover, to have more data, segments of data used to extract features were overlapped. In the first study, an overlap of 95% was used, while in the second study, an overlap of 75% was used. In both studies, the choice of the overlap degree between data segments was not justified.

The studies on distracted driving contributed mainly with one novelty, ranking of feature importance. Having a great number of features is usual in machine learning. Unfortunately, the performance of learning algorithms is considerably affected by the number of features. A way to solve this problem is to select only highly relevant features and abandon the rest.

Two algorithms were proposed to rank features. The first algorithm is based on the Linear discriminant analysis (LDA) method and does individual feature selection, that is, it selects each feature independently from the rest. This approach is not necessarily optimal, for it does not take into account the inter-feature correlation. The second algorithm ReliefF, is a feature ranking method that is sensitive to feature interactions.

2.6 ADHD

Authors assessed the feasibility of integrating an eye tracker with the MOXO-dCPT for ADHD diagnosis in [45]. They investigated two hypotheses ; 1) while performing the CPT, ADHD patients would gaze for longer durations at regions that are irrelevant for success in the task (e.g., the AOI in which distractors are presented) compared to healthy controls, and 2) combining eye movement measures with the conventional MOXO-dCPT indices would enhance the discriminative capacity of the CPT, compared to that attained using only the conventional indices. 66 undergraduate students participated in the study, half of them had a previous diagnosis of ADHD (ADHD group) and half of them were healthy and did not have attentional impairments (control group). Participants were requested not to take stimulant medications in the 24 hours prior to participating in the study.

Continuous performance tests (CPT) include rapid presentation of visual and/or auditory stimuli over a relatively long period of time, during which participants are required to respond to target stimuli while ignoring others. At the beginning of the experiment, participants first filled out questionnaires and underwent SCID-5-RV used for ADHD diagnosis, before performing the MOXO-dCPT which is a variant of CPT. Several measures were taken to limit the impact of fatigue on the study including a break before starting the CPT, and times for the experiments that were performed in the morning or early afternoon.

Participants were then moved to a sound-isolated room with black curtains behind the computer screen, to minimize external distractions, then they were calibrated to the eye tracker. The eye tracking device used was an EyeLink 1000 (SR Research Ltd., Mississauga, Ontario Canada) at a 250 Hz sampling rate with an accuracy of approximately 0.5°, and a computer to collect participants' interactions during the experiment. The MOXO-dCPT lasts 18.7 minutes and consists of eight blocks, in each block 59 stimuli are presented (34 targets, and 25 non-targets), participants were instructed to press the spacebar when a target stimulus is presented and to refrain from pressing the spacebar when a non-target one is presented. While completing the test, auditory and/or visual distractors would appear on-screen above, below, or to the side of the stimulus. Four indices were calculated post-experiment :

- **Attention :** number of correct responses during on-screen stimulus presentation or during the inter-stimulus interval following it.
- **Timeliness :** number of correct responses only during on-screen stimulus presentation.
- **Impulsivity :** number of spacebar clicks during non-target stimulus presentation.
- **Hyperactivity :** number of spacebar clicks that did not count for impulsivity.

To assess the extent of visual **attention** directed at the task area compared to regions that are irrelevant for success in the MOXO-dCPT, the participant's field of view was divided into four areas of interest (AOIs) :

- **Task AOI :** The only region relevant to the task, containing the target and non-target stimuli.
- **Distractors AOI :** The screen region in which the distractors were presented.
- **Peripheral AOI :** All other screen regions.
- **Outside the screen AOI :** Regions beyond the computer screen.

Moreover, Relative AOI gaze duration ; the proportion of time the gaze was directed towards the AOI, relative to the total gaze duration, was computed for each AOI, and for each participant. All analyses were based on two-tailed hypotheses, with $p < .05$ marking statistical significance. Effect sizes were measured according to Cohen. A multivariate analysis of variance (MANOVA) was used to compare the eye movement measures between the ADHD group and the control group. t-test and chi-square tests were used to compare the two groups in all other measures (including CPT measures) and a welch t-test was applied in case of non-homogeneity in variance. Pearson product-moment correlation was performed between CPT measures and eye movement measures, then variance inflation factor (VIF) was used to assess multicollinearity between the measures. Logistic regression was used to predict group membership using eye measures, the model was then used to combine eye movement measures into a continuous probability scale.

Two-stage hierarchical logistic regression was then used to determine whether the continuous probability scale could be used to enhance the predictions of the CPT indices. In the first stage, the model only included CPT indices, while in the second stage, the continuous probability scale was added. A receiver operating characteristic (ROC) curve was computed and the area under the curve (AUC) was used to assess the predictive power of the models. Following MANOVA, significant group differences were found in all eye movement measures ; the ADHD group gazed less time at the task AOI and more at other AOIs than the control group. Moreover, effect size values were above the minimum recommended in all eye measures, thus all the measures were selected for further analysis.

Significant differences were found between groups in CPT measures following t-tests, especially impulsivity and timeliness with high effect size values, they were thus considered for further analysis. Following VIF analysis, task AOI gaze duration, and distraction AOI gaze duration had a collinearity coefficient r=-0.99, thus the one with the lower effect size (second measure) was omitted from further analysis, and the rest of the eye measures were kept. The logistic regression model that used eye measures achieved an accuracy of 90.91% for the control group and an accuracy of 66.67% for the ADHD group.

The first stage of hierarchical logistic regression using timeliness and impulsivity measures produced a model with 78.79% accuracy for the control group and 69.7% accuracy for the ADHD group. The second stage model which used the combined scale probability measure in addition to timeliness and impulsivity measures achieved 81.82% accuracy for the control group and 75.76% accuracy for the ADHD group. The ROC curve indicated excellent discriminative capacity of the combined scale model (AUC = 0.826). Eye movement measures significantly differentiated between the ADHD group and control group ; the ADHD group spent significantly more time than others gazing at regions not relevant to the success of the task.

In a subsequent attempt to explain this behavior, the number of times each participant visited an AOI was analyzed, and was found that ADHD patients made significantly more visits to the task AOI than others, a cause of this may be that ADHD patients could have been drawn to distractors repeatedly. Combining findings from other studies and this one, the authors pointed toward a failure of ADHD patients to inhibit responses toward distractors.

Following the first logistic regression analysis, eye measures were combined into a unified scale, which can be interpreted as the index of distractibility of patients. This index had the highest effect size out of eye movement measures for differentiating the ADHD group from the control group, is also had the best discrimination capacity and contribution when combined with CPT measures, suggesting eye movement measures are a reliable neuropsychological diagnostic tool for ADHD.

Finally, the authors talked about future directions. All ADHD patients were undergraduate students, therefore likely representing highly functioning patients. The predictors of ADHD diagnosis were computed and tested on the same sample. Therefore, further validation is needed.

in [43], patients with ADHD were assessed using EEG and Eye Tracking in Virtual Reality. 120 children aged between 8 and 14 participated in the study, 60 children were diagnosed with ADHD according to the DSM-5 standard (ADHD group), the 60 other children were healthy and had normal physical examination indexes (control group).

During the experiment, participants had to wear an HTC Vive virtual reality headset (with an embedded eye tracker with a sampling rate between 120 and 380 Hz and accuracy of less than 0.5°) that comes with a controller, and a Neurosky Mindwave EEG headset. The actual experimentation was divided into two modes (distraction mode, and non-distraction mode) and both groups of participants undertook both modes while EEG and EYE Tracking data were recorded. A virtual classroom was used for the tasks of the experiment, and distractors were added to the virtual classroom, including flying birds in the classroom, students interacting in the classroom, and honking car sounds outside.

The experimentation consisted of three tasks. The first task was a CPT visual test, where letters appeared in the classroom and participants had to pull the handle of the controller when the letter “X” appeared immediately after the letter “A”. The second task was a CPT hearing task where the sound system randomly broadcasted a number in the range [0, 9] and participants had to pull the handle when they heard the number five. Test results for the first and second tasks included :

- Correct times.
- Missing times.
- Wrong times.
- Reaction times.
- Error rate of wrong times.

The last task was a classic Wisconsin card sorting task (WCST). Raw eye focus points were obtained, normalized, and mapped to coordinates on the screen. Eye data of the same participant were analyzed twice, and it was reported that the eye focus points of the participants were centered in a particular area when he was concentrated while being scattered otherwise. It was reported from other studies that, compared with EEG of normal people, EEG of ADHD patients show an increase in Delta wave power (1 – 3Hz), Theta wave power (4 – 7Hz), and Theta/Beta ratio, and a decrease in Alpha wave power (8 – 13Hz) and Beta wave power (14 – 30Hz).

In this study, brain wave power and **attention** index values were obtained from the EEG headset. EEG data provided strong analytical evidence of the performance of ADHD patients in the experiment. For future research, authors suggest conducting feature extraction of the EEG data and eye movement data such as number of fixations, mean time of eye fixation, number of saccades and mean extent of the saccade, and to improve the reliability of the test by using deep learning. To accurately record the body movement of the test taker during testing, authors also consider using smart watches or bracelets and other wearable devices which can collect movement data of the hands, feet, and other body parts for deeper analysis.

Neurofeedback is a non-invasive procedure that helps teach people self-control of brain functions by measuring brain waves and providing feedback usually in the form of audio or video content. It is well known and used as a complementary treatment to many brain dysfunctions including ADHD and depression. A hybrid EEG and HEG neurofeedback device in real-time was proposed in [61] to treat ADHD where the feedback was an action on a car in a video game, if the patient could concentrate the car would move forward otherwise it would stay still. HEG was used to overcome the problem of artifacts occurring from using EEG only, the rate of sampling of the recorded EEG signal was 200Hz. EEG signal was filtered into two frequency bands ; Alpha band ($7 \sim 13$Hz) and Beta band ($13 \sim 30$Hz) with a Butterworth filter.

The authors reported that participants need to maintain the activity of Beta waves while reducing Alpha waves' activity. The **concentration** index used was the ratio index Alpha/Beta of the power band Alpha and Beta, if the index is higher than a certain threshold the individual is considered concentrated and not concentrated otherwise, the threshold was calculated distinctly for each subject by employing a linear classification method on his EEG recordings.

10 participants took part in four activities (two non-concentration tasks then two concentration tasks) designed to appropriately separate between concentration and non-concentration, participants had to relax in tasks one and two, with closed eyes in task one and open eyes in task two. In task three participants had to play the card game and then resolve a mathematical problem in task four, the duration of each task was 50 seconds. After performing all four activities, from the HEG level of participants task one yielded better inattention while task three and task four induced comparable levels of **attention**.

Authors used sensitivity and specificity as metrics of performance for their model, in this case, sensitivity which is also called true positive rate, refers to the proportion of samples that were labeled as concentrated out of those that actually are concentrated.

Specificity, which is also called true negative rate, refers to the proportion of samples that received non-concentrated labels out of those that are actually non-concentrated.

The EEG neurofeedback specificity and sensitivity obtained were 70 percent and 90 percent respectively.

In [45], the authors try to improve the ADHD diagnosis ability of an existing method using eye tracking technology.

This study faced two problems. The first problem was that the methods were not tested with new data but only with training data, this made results not reliable. Furthermore, just a few eye features were used and doors for improvement are still open.

In contrast to many studies on attentional state detection that we went over, in this study, results are validated using hypothesis testing methods. Depending on the shape of the data and other parameters, different hypotheses testing methods were applied. Hypothesis testing is a way to test if the results of an experiment are meaningful. If your results are not repeatable, it means they happened by chance, and thus, they have little use.

As an example, in order to confirm the differences in eye features values between the two groups of patients (ADHD group and control group), a Multivariate Analysis of Variance test was carried out, and results showed that the two groups are significantly different.

In [43], both EEG and eye tracking were used for ADHD diagnosis in a virtual reality environment.

The major problem of this study was that the attention index was computed by the software that came with the EEG headset and no details about the method of computation were given.

In this study, the popularity of real-valued indicators for attentional state detection is highlighted again. Two indicators have been reported, the Beta/Alpha power band ratio that was previously mentioned in section 2.4, and the Beta/Theta power band ratio.

In [61], the authors proposed a neurofeedback device to treat ADHD using concentration and based on EEG data.

This study presented two problems. First, no details were given about the choice of the sliding window size to compute EEG features, like the previous studies referenced before. Next, the number of participants that performed the experiment was not sufficiently high to make the results reliable.

In this study, the real-valued attention index Beta/Alpha band power ratio was used as an indicator of concentration levels similar to section 2.4 and 2.6. Moreover, in contrast to other studies where accuracy was used as a metric, authors used specificity and sensitivity metrics to evaluate the performance of the model.

While accuracy is a meaningful metric in classification problems with balanced classes, i.e. where labels are uniformly distributed, it is not reliable when classes are not balanced. In this case, using sensitivity and specificity gives more meaningful results.

2.7 Restoration of Attention

Attention Restoration Theory (ART) is a psychological framework suggesting that exposure to natural environments facilitates the restoration of voluntary attention capacity, reducing mental fatigue and enhancing cognitive functioning. ART emphasizes the restorative effects of nature on cognitive resources through the engagement of involuntary attention, allowing voluntary attention systems to recover [39].

Gao et al. [29] employed virtual reality (VR) technology to investigate the physiological (electroencephalogram, EEG), and psychological (attention, positive mood, negative mood) responses and individual preferences for different urban environments based on ART.

120 participants were recruited and randomly assigned to experience six different types of environments varying in land use and vegetation structures : Grey space, blue space, open green space, partly open green space, partly closed green space, and closed green space. The physiological measurements of the EEG were used to investigate the physiological responses. Stroop color task was also used to assess the restoration of attention of participants afetr the visual stimulation.

It was found that the experience of the six environmental types through VR devices had positive restorative effects on the individuals' attentional fatigue and negative mood ; however, all the participants obtained the highest levels of physiological stress restoration when asked to close their eyes for relaxation. The physiological measurements of the EEG showed no significant differences among the selected types of environments.

It was discussed that while the partly open green space had the most positive effect on negative mood, the closed green space had the worst. The blue space and partly closed green space received higher recreational preference ratings than the other four environments, while the closed green space received the lowest recreational preference rating. Moreover, there was a strong positive correlation between people's preferences and the improvement of their positive mood.

In conclusion, this study shows that VR technology may be utilized as a possible surrogate measure to real scenes in evaluating human physiological and psychological restoration in the future. These findings can also provide theoretical basis and practical guidance for future optimal planning of urban restorative environments.

This study made an extensive use and mention of ART [39], and extended the theory by introducing Virtual Reality with multiple environments. Although the study used VR environments to investigate ART, the virtual environments used were results of camera photographs and not entirely virtual. Evaluating the attention using entirely virtual environments is necessary to assess ART in VR.

Hamdi et al. developed an immersive virtual reality environment to induce a state of relaxation in patients with Alzheimer's disease [12]. Patients wear a virtual reality headset and are immersed in an environment in which they can freely orient their gaze in 360 degrees. Cognitive tasks were integrated before and after the train journey to evaluate the impact of this therapeutic train on the patient's memory and cognitive performance. The results showed that immersion in virtual reality allowed for a decrease and isolation against external stimuli that can induce negative emotions. Patients showed a decrease in anxiety and frustration, and an increased performance in exercises related to attention.

Although the study of Hamdi et al. does not explicitly mention ART, it is clear they were inspired by this theory. The main focus of the study was decreasing negative emotions such as frustration using relaxation, and the attention layer was only scratched at the surface by mentioning the performance of the participants. Therefore, a deeper study using biosensors and focusing more on attention is needed in order to validate their reports.

This study can be considered an extension of [29], where the virtual environment was created from scratch rather the result of a camera photograph. The same virtual environment used in [12] will be used in the second part of our study to investigate the effects of relaxation in VR on the attention of participants.

2.8 Summary

In this chapter, we introduced EEG and Eye Tracking, the main two tools of interest in this study, and gave details about the most common features used in previous studies. Then we went through the literature concerned with detecting, **concentration** and **distraction** levels using EEG and Eye Tracking, in the context of learning, driving, and ADHD. We also went through the literature relevant for the imrpovement of attention. At the end of every section, we highlighted the gaps in the studies, as well as the novelties that each study contributed to.

Many gaps were identified throughout the literature. First, the length of the sliding window used to extract features has not been addressed. Next, the experimentations used to induce distraction or concentration were not validated in all the studies except [41]. Furthermore, the majority of studies to detect distraction and concentration only used binary discrimination, and only [61] used a real-valued indicator to model the attention state. Moreover, many studies proposed attention monitoring systems that were participant-dependent [41, 45, 48], which means the systems would not be reliable with new participants without proper training of the model. Finally, in the case of ART [39], we saw it was used in Virtual reality, but that the analysis of the effects was lacking.

The different studies included many novelties that were utilized in our research and will be described in the next chapter. In [41], a novel method to monitor attention levels using eye tracking data was presented. In [36], authors developed a participant-independent distraction detection system, in addition to using an extensive list of eye features. In [23, 48], the most relevant features in detecting distraction while driving were ranked. Finally, in [61], attention was modeled using a real-valued indicator instead of a binary value (attentive state or not attentive state).

CHAPITRE 3

METHODOLOGY

The first purpose of this study is to develop a means to assess the attentional state of individuals using EEG and Eye Tracking technologies while completing cognitive tasks in a Virtual Reality environment, and use it as a monitoring tool. The second purpose is to find methods to improve the attention levels. We put forward two hypotheses in this study : 1) it is possible to detect the different concentration and distraction levels of the participants using EEG and Eye Tracking in VR while completing cognitive tasks. 2) The concentration of the participants will increase and their distraction will decrease after relaxation compared to before the relaxation period.

The experiment consists of two parts. The first part is designed to study the first research question ; the feasibility of detecting and monitoring **distraction** and **concentration** using EEG and Eye Tracking. The second experiment targets the second research question ; the feasibility of increasing the concentration levels of participants and decreasing their distraction using relaxation. In this chapter, for each part, the rationale behind the structure is developed, and the procedure is detailed.

In the following sections, the experiment for collecting EEG and Eye Tracking data, as well as the analyses carried out, are explained.

In section 3.1, the data collection procedure is described. We start by explaining the intuition behind the methodology of the first part in section 3.1.1, then, dive into the methodology for studying the first research question and its details. Finally, more details on how the methodology was optimized are given. In section 3.1.2, the second part of the experiment is explored. We start by arguing why relaxation would be helpful in improving **attention**. Then, the methodology for studying the second research question is explained in detail.

In section 3.2, the different analyses methods are described and explained sequentially. Extraction of useful features in section 3.2.1, investigation of different parameters that affect features in section 3.2.2, validation of the distraction method in section 3.2.3, and the implementation of our strategy to assess **distraction** and **concentration** and improve attention levels in section 3.2.4 and 3.2.5.

3.1 Data Collection

The purpose of this experiment is to collect data from EEG and Eye Tracking while participants performed cognitive tasks. During the experiment, **distractions** are used to experimentally manipulate the levels of **attention** of participants.

3.1.1 Detection of concentration and distraction

Divergent thinking is a cognitive process that involves generating multiple, varied, and original ideas or solutions to a problem or challenge. It is often associated with creativity and lateral thinking, as it requires exploring different perspectives and approaches. Divergent thinking tasks typically have multiple possible answers and encourage open-ended exploration. **Convergent thinking** is a cognitive process that involves finding a single, correct, or optimal solution to a problem or challenge. It is often associated with analytical thinking, logic, and critical problem-solving skills, as it requires narrowing down multiple possibilities to arrive at the best answer. Convergent thinking tasks typically have one correct answer and involve systematic and focused analysis [11, 21, 31].

Divergent and convergent thinking are often viewed as complementary cognitive processes that contribute to creative problem-solving and decision-making. While divergent thinking focuses on generating multiple ideas and exploring different perspectives, convergent thinking narrows down the possibilities to find the best or most appropriate solution. Both types of thinking play crucial roles in various aspects of cognition, and fostering a balance between divergent and convergent thinking can lead to more effective problem-solving and innovative outcomes.

Most studies used tasks that require **convergent thinking** in order to manipulate **attention** levels when studying **concentration** and **distraction** [36, 45, 48] and reported the relevance of **frontal and parietal** brain areas in this setting, while no study with EEG reported relevant brain areas in concentration state using divergent thinking tasks.

[60] investigated the functional organization of different brain areas during convergent and divergent thinking using EEG. Results suggested that **convergent thinking** and divergent thinking produce different effects on brain areas in terms of EEG power band amplitudes. The first part of the experiment is designed to take into account these two types of thinking.

To study **attention** in general and not only for a specific task, the first part consists of three mental tasks. The first task is a mental arithmetic task, where participants have to solve a series of additions and subtractions consisting of five or six operands. Mental arithmetic requires **convergent thinking** and was previously used to study **concentration** and attention [35, 53]. The second task is an anagram task, where participants have to reorder a set of letters to obtain a valid English word. It was expected that most participants would primarily speak French since the experiment would be advertised primarily at the University of Montreal, hence the English language was chosen to add some difficulty and time required to solve. The anagram task requires divergent thinking since the answer is not unique, and there are no straightforward ways to generate the answer. Anagram task was previously used to study attention [53]. The third task is a digit memorization task, where participants have to memorize a series of seven or eight digits in reverse order. The memorization task requires **convergent thinking** since the answer is straightforward and just needs to be remembered. The memorization task was not used previously in attention research, but previous research suggests that attention is linked with memory [19], which makes this task a good candidate.

Before the start of the first part, participants go through a reference period of a one-minute duration. Data is recorded while participants do nothing. Data collected in this period is used later during analysis.

Figure 3.1 shows the screen that is displayed during the reference phase.

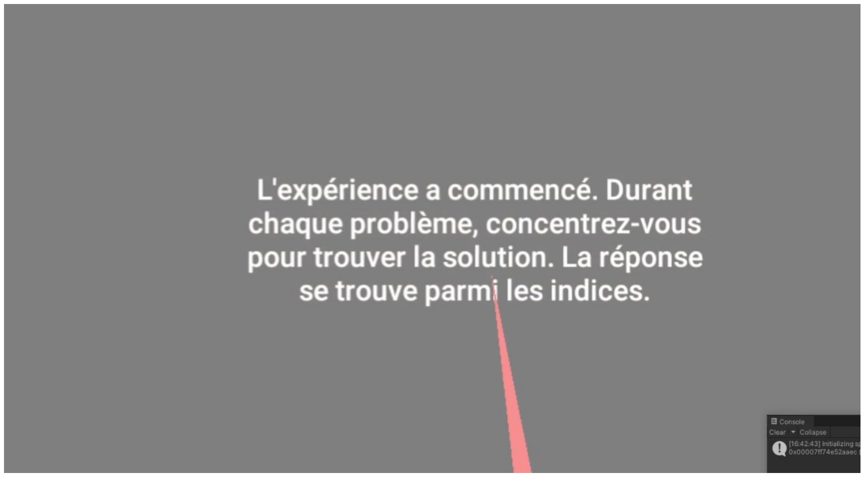

FIGURE 3.1 – Reference phase screen.

Participants complete three types of tasks, mental arithmetic, anagram, and digit memorization, a total of nine times.

Figures 3.2, 3.3, and 3.4 show screen recordings of examples of different types of tasks. The window in the bottom right corner of the screen does not appear in the virtual reality headset and is only helpful for us to know if the experiment is advancing well.

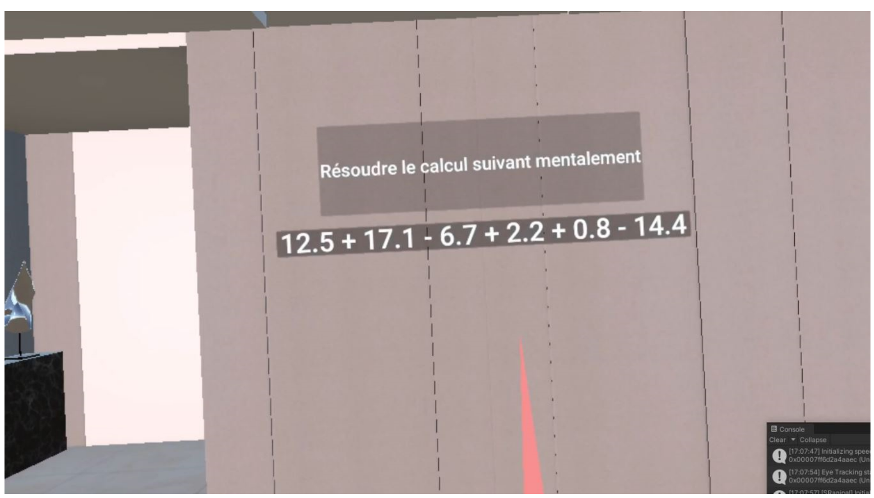

FIGURE 3.2 – Example of Mental Arithmetic task.

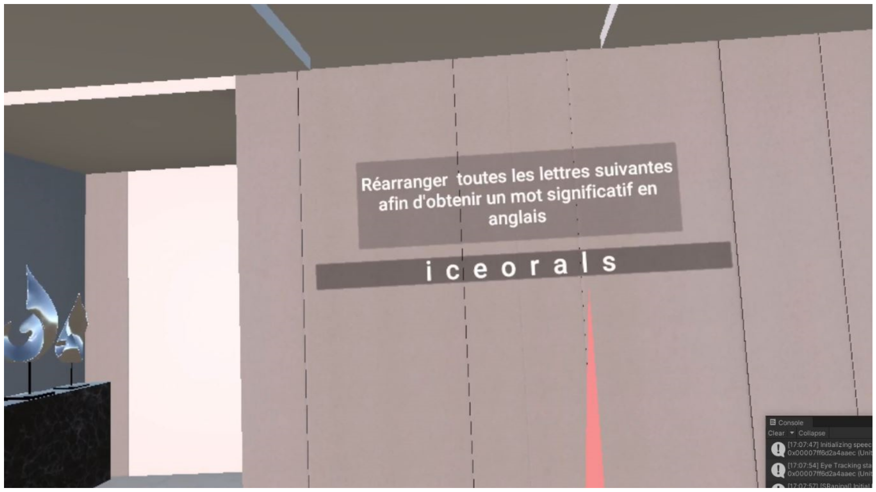

FIGURE 3.3 – Example of Anagram task.

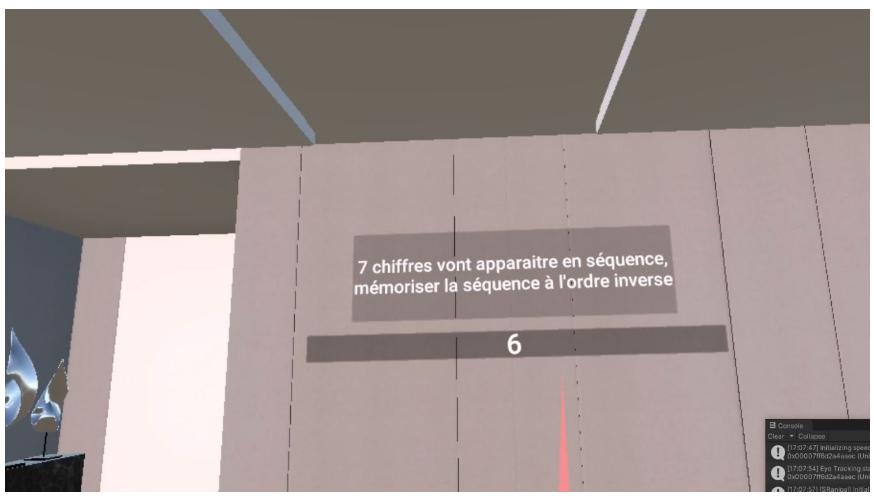

FIGURE 3.4 – Example of Memorization task.

Each task goes as follows, the problem is first presented on the screen, and participants are instructed to solve it. After a fixed time, the problem is hidden and a red window (distractor onset) is displayed over the screen instructing participants to look left to have a clue (hint), and at the same time, two suggestions are presented on the left side of the environment where the participant should be gazing after the onset of the distractor. After a fixed time, the red window disappears, the hints do not disappear, and the problem reappears (except for the memorization task where the problem does not reappear).

After a fixed time, the problem is hidden and a red window is again displayed over the screen instructing participants to look right to have a clue, at the same time another two hints are presented on the right side of the environment. After a fixed time, the red window disappears, the hints do not disappear, and the problem reappears (except for the memorization task where the problem does not reappear).

Figure 3.5 shows the red window that appears at the on-set of distractors. Figure 3.6 and 3.7 show examples of left and right distractors.

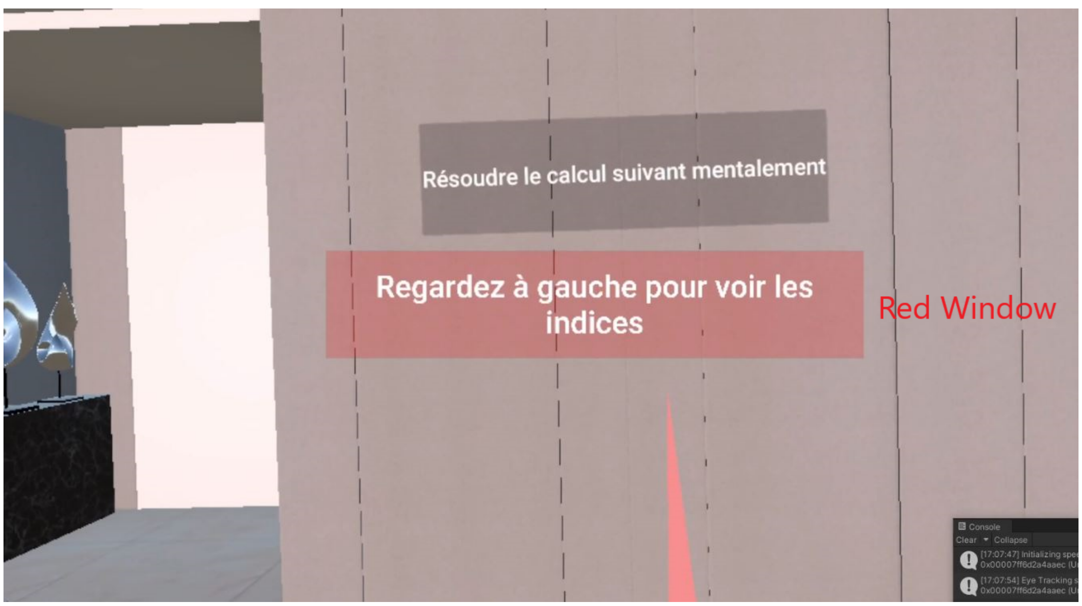

FIGURE 3.5 – Example of the red window displayed at the on-set of distractors.

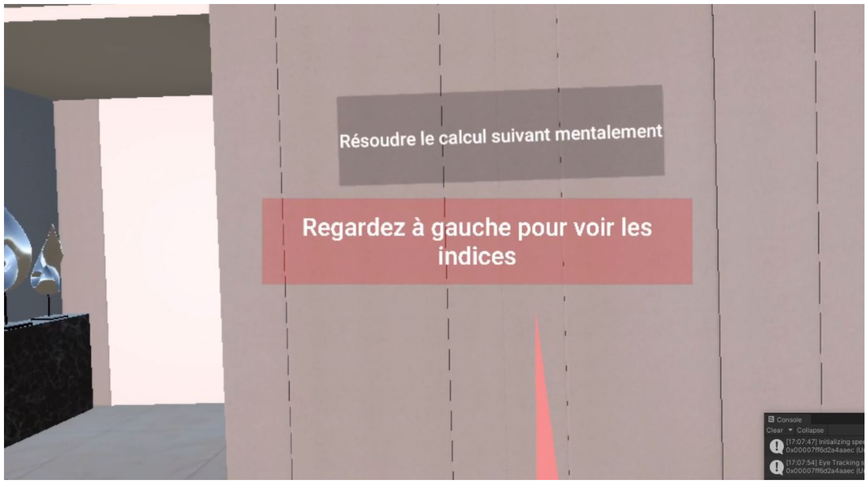

FIGURE 3.6 – Example of left distractor on-set.

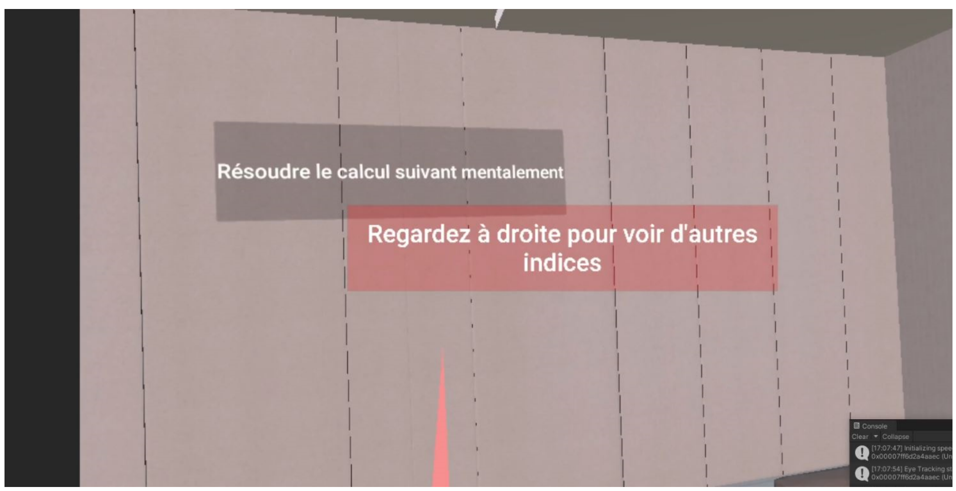

FIGURE 3.7 – Example of right distractor on-set.

Figure 3.8 and 3.9 show examples of left and right hints.

FIGURE 3.8 – Example of left hint.

FIGURE 3.9 – Example of right hint.

A keyboard also appears this time where participants can enter and validate their answers. Participants do not have a time limit and can validate their answer until it is correct. Tasks are separated by in-between task breaks with a fixed duration. Participants first complete three mental arithmetic tasks, followed by three anagram tasks, then three memorization tasks.

Figure 3.10 and 3.11 show keyboards that are used to input and validate answers.

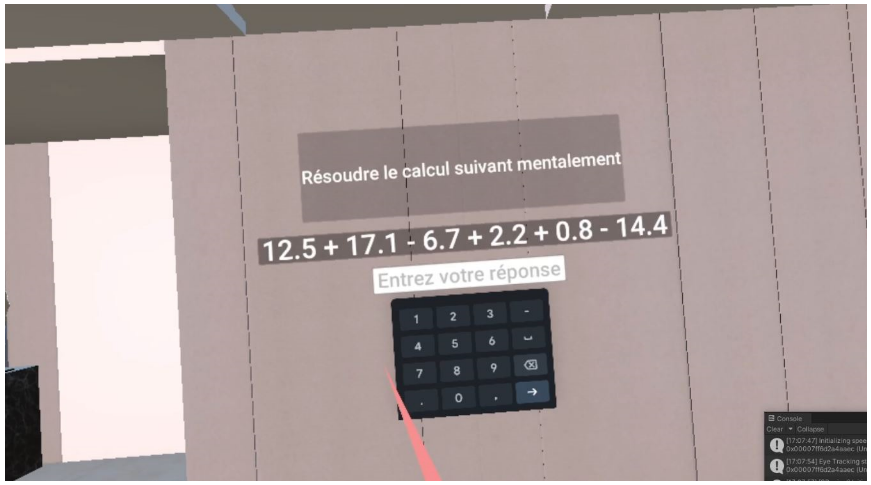

FIGURE 3.10 – The Numerical Keypad used in mental arithmetic task.

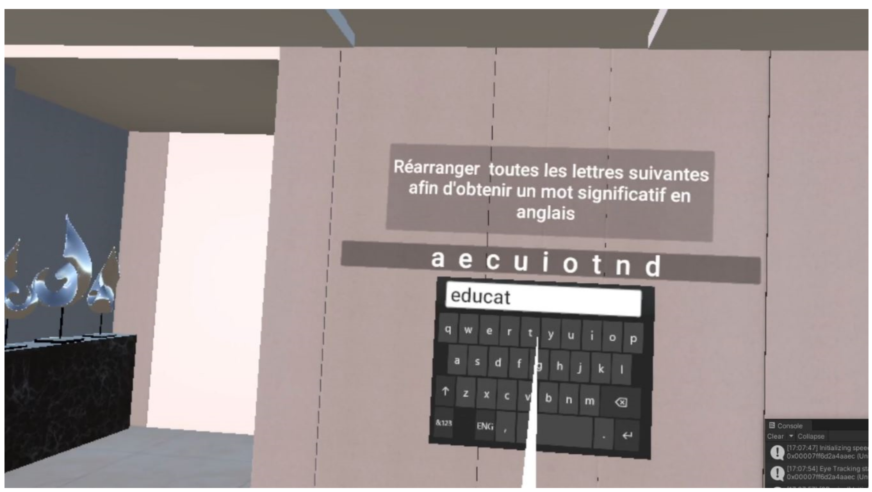

FIGURE 3.11 – The keyboard used in anagram and memorization tasks.

Figure 3.12 shows the screen that is displayed during the short break between two tasks.

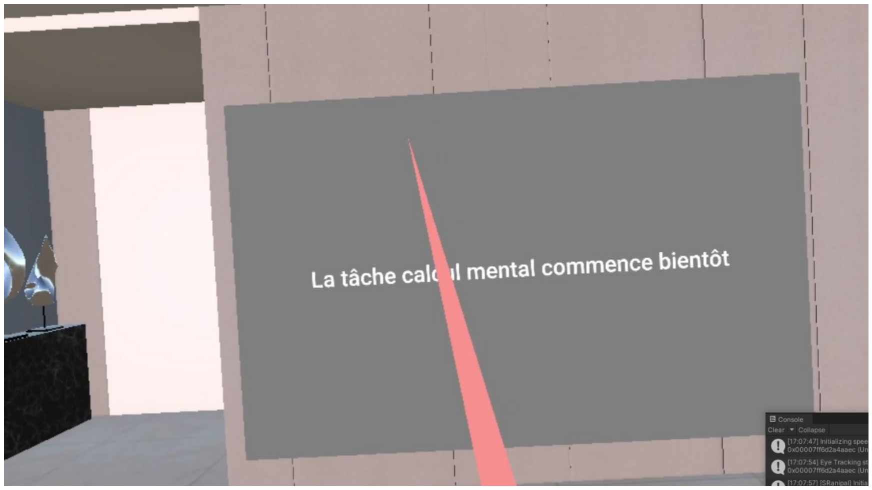

FIGURE 3.12 – Example of in-between task break.

The development of the methodology was iterative and went through many stages. Time duration before the onset of the distractor changed many times, the goal was to give participants just enough time to focus on the tasks, but not enough time to solve them, before the onset of distractors.

The red color of the distractors was also chosen carefully to be attractive to the eyes. To be able to distract participants independently of the position they were gazing at, distractors were displayed at the center of the screen space over everything else and were fixed there. It means, participants would always see distractors when they appeared, and distractors would stay at the center of the screen even if participants rotated or moved their heads.

During early development, at the onset of distractors, the problem was not hidden, and despite the onset of distractors, participants kept looking at the problem trying to solve it. When asked why they all responded they did not want to lose their focus by looking at hints.

In order to remediate this and increase the efficiency of distractors, the experiment was updated, to make the problem statements disappear when distractors appear. This update instantly fixed the problem, as participants could not focus on tasks anymore when they disappeared, and distractors were salient enough to become relevant and attract the participants' attention.

Participants interacted with a keyboard in virtual reality, the keyboard was updated as well. For mental arithmetic and memorization tasks, a numeric virtual pad was presented for participants to enter their answers, whereas an entire virtual keyboard was presented for anagram tasks.

Visual and sound effects were added to notify participants when their answer was correct, and only visual effects were used to notify participants in case of the wrong answers.

In early development, the keyboard was displayed from the start and participants could enter their answers at any moment. Many early testers would type their answer right after looking at the first hints.

In order to push them to concentrate primarily on the process and put their attentional resources on problem-solving, the keyboard was hidden at the start of each task and would only appear after the four hints were displayed and participants had more information. The **distraction** system was also updated throughout development.

In the beginning, for each task, distractions appeared four times. First, a distraction appeared left, then another one appeared right, then left, and finally right. Because of that, tasks were taking too long to be completed. Then the number of distractions was updated to two per task, showing two hints at a time.

The answer is always among hints and participants were informed of that. Each hint is a potential answer and not just guidance to the right answer. They are called hints just for the purpose of simplicity.

Hints in mental arithmetic tasks contain the potential results for the arithmetic problem. Hints in the anagram task contain potential correct arrangements of the letters to form valid words. Hints in the digit memorization task contain the potential correctly ordered digits.

Hints follow a certain logic given by a set of rules. Usually, one of the hints is always very unlikely to be the correct answer. In the mental arithmetic task, absurd numbers are chosen, such as the number 1035 for additions of two-digit numbers. In the anagram task, words containing no letters from the set of letters are chosen, such as the word "porsche" for the set of letters "o,a,r,d". In digit memorization, numbers with only one digit are chosen, such as "1111111" for the numbers unordered number "1217892".

Moreover, two other hints are nearly correct and need **attention** and thinking to be correctly identified as incorrect. In mental arithmetic task, a number with the wrong sign is used, and a number close to the correct answer is utilized. In the anagram task, two valid words that contain all except one or two letters from the set are used. In digit memorization, the number presented in the front order is presented, as well as a number that contains all the correct digits but one or two.

Finally, one hint contains the correct answer to the problem. Correct answers are not always at the same hint placement, each time hints placements are manually randomized.

When hints appear, the system suggests to the participants one hint as a correct answer with the following textual message "this may be the solution" translated in french. The hint targeted with this message is random and can be a wrong answer, as well as a correct answer. Participants are not aware of the hint system but are informed that the correct answer is among hints.

3.1.2 Concentration Improvement

Authors used relaxation in virtual reality by train to study the feasibility of decreasing negative emotions including frustration, anxiety, and apathy [12]. Preliminary results showed a decrease in anxiety and frustration, an increase in memorization performance, and an improvement in cognitive abilities, particularly in attention exercises. Participants also reported a decrease in stress levels after immersion in virtual reality. Moreover, results from [28] suggest that virtual reality environments could help to decrease negative emotions such as frustration and improve memorization abilities.

Previous research suggests that relaxation could help decrease negative emotions and increase memorization abilities and **attention** abilities. In this research, the second part of the experiment used the environment developed in [28] to study the feasibility of improving **concentration** levels and decreasing **distraction** levels using relaxation in virtual reality. We used relaxation to increase the concentration levels of participants and later investigate the effects of relaxation on the **attention** levels of participants.

In the second part, participants first complete a set of cognitive tasks before going for relaxation on a train, then complete another set of cognitive tasks like the first set.

The first task of the second part is a memorization task with two sub-tasks, where participants have to memorize a sequence of four digits in the front order first, then memorize a sequence of three digits in reverse order. In the second task, participants are given a target letter and then have to listen to a sequence of letters and click on the button of the controller each time they hear the target letter. In the third task, participants repeat the same sub-task six times. In every sub-task, images of objects are presented then followed by a set of four letters, and participants have to click on the letter corresponding to the first letter of the presented object. In the fourth task, participants are presented with a sequence of images and sounds of objects, then are presented with an object and asked if the object was seen, heard, or never presented. They answer six questions about the sequence. In the fifth task, a set of circles is presented, and circles are highlighted in a sequence. Participants have to remember the sequence of highlighted circles in the front order. In the sixth task, participants have to remember a sequence of presented objects in the front order, then choose the correct answer among four proposals. This procedure is repeated four times.

Figure 3.13, 3.14, 3.15, 3.16, 3.17, and 3.18 show the different cognitive tasks in the second part of the experiment.

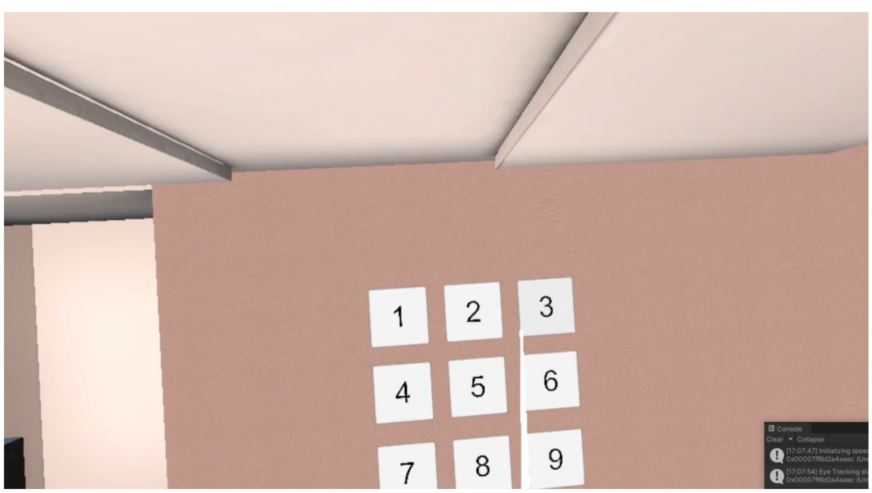

FIGURE 3.13 – Example of task one of the second part.

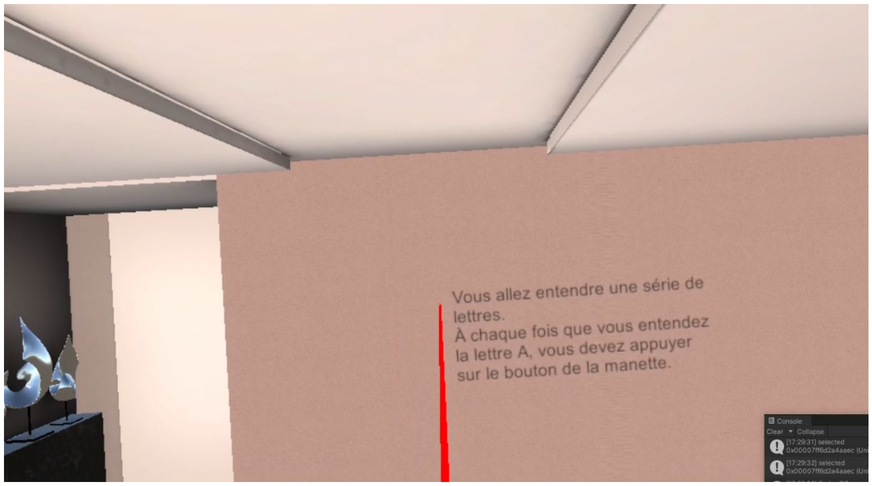

FIGURE 3.14 – Example of task two of the second part.

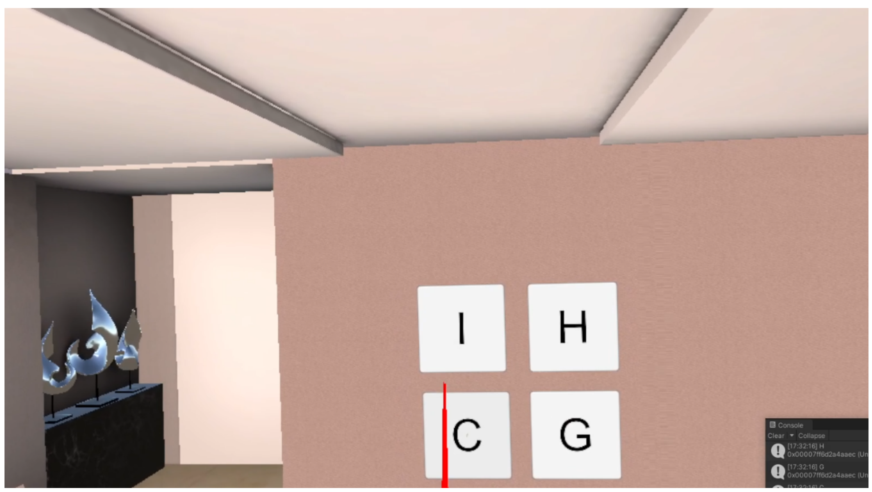

FIGURE 3.15 – Example of task three of the second part.

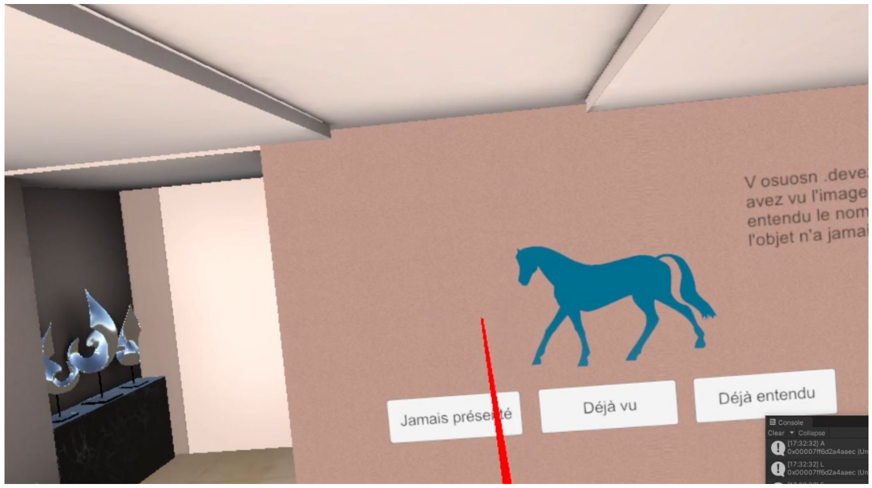

FIGURE 3.16 – Example of task four of the second part.

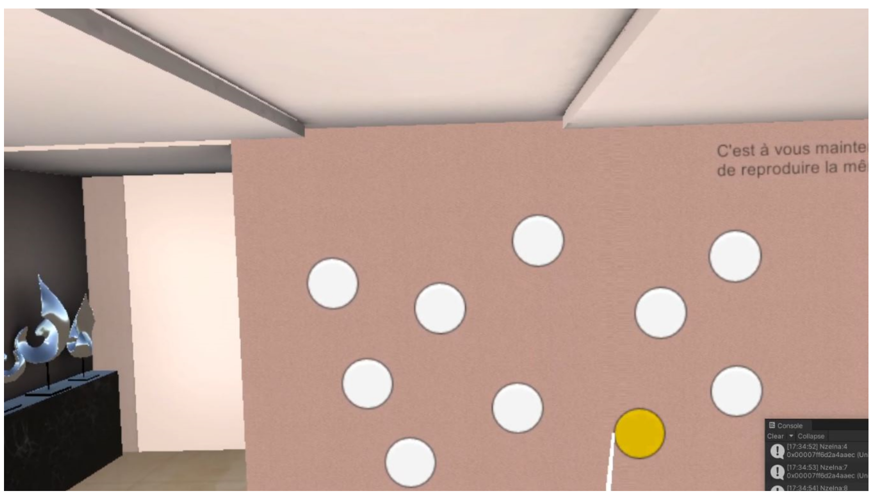

FIGURE 3.17 – Example of task five of the second part.

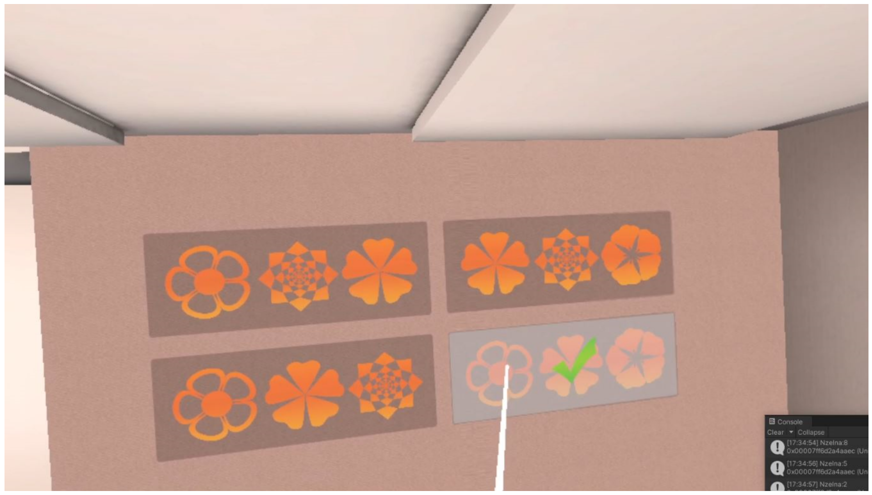

FIGURE 3.18 – Example of task six of the second part.

The relaxation is in virtual reality, participants can look freely around but can not move. Moreover, during relaxation, many elements are added to increase immersion. Participants go for a tour on a train that lasts six minutes approximately. The train moves and participants can hear the sound of the rail wheels as well as relaxing music playing through the sound output system of the VR headset. They can also see other non-player characters on the train, including a family composed of two parents and two children seated next to the player. Participants visit three locations aboard the train, a forest, a frozen mountain, and a desert. The transition between environments is seamless. In all environments, scenery elements, including trees, mountains, deer, cows, and ibex, are added to increase immersion in the virtual environment and improve the experience.

Figure 3.19 shows an example of non-player characters aboard the train. Figures 3.20, 3.21, and 3.22 show the different environments explored during relaxation.

FIGURE 3.19 – Example non-player characters aboard the train during the second part.

FIGURE 3.20 – The first environment of relaxation.

FIGURE 3.21 – The second environment of relaxation.

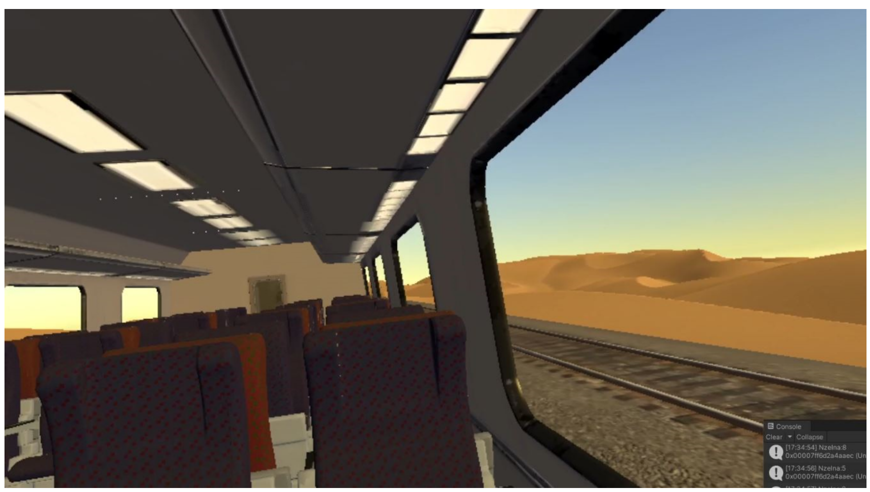

FIGURE 3.22 – The third environment of relaxation.

3.2 Data Analysis

An analysis of the recorded raw EEG data was done in order to select relevant EEG channels and participants' data to keep for further study. Channels with data missing in the majority of participants were dismissed, and participants with many missing channels were dismissed.

3.2.1 Feature extraction

The majority of research on concentration and distraction with EEG used the power spectral density features either as single features [23, 43] or combined in ratios [47, 61]. Electroencephalogram (EEG) power spectral density (PSD) is a quantitative measure that describes the distribution of electrical activity in the brain across different frequencies. It is calculated by applying a mathematical transformation, usually the Fast Fourier Transform (FFT) or other spectral estimation techniques, to the EEG time-domain signal to convert it into the frequency domain. The resulting PSD provides information about the power (amplitude squared) of each frequency component present in the EEG signal [54].

The PSD is particularly useful for analyzing oscillatory brain activity and identifying distinct frequency bands, such as delta (0.5-4 Hz), theta (4-8 Hz), alpha (8-12 Hz), beta (13-30 Hz), and gamma (30-100 Hz) waves. These frequency bands are associated with various cognitive and physiological states and can offer insights into brain function and dysfunction in different contexts [16].

BrainFlow is a library intended to obtain, parse and analyze all kinds of data from biosensors such as EEG [56]. We used Brainflow library for Python programming language to analyze EEG data. Absolute Power Spectral Density (PSD) was computed using the welch method on T-second windows from EEG data. Delta (1 - 4Hz), Theta (4 - 8Hz), Alpha (8 - 13Hz), Beta (13 - 30Hz), and Gamma (30 - 50Hz) bands were used as features for each channel, resulting in a total of 70 features across all EEG channels.

In [37], the feasibility of using a head-mounted display virtual reality to study eye saccades was studied, and results suggested that VIVE Pro Eye could function as an assessment tool of saccadic eye movement. Other eye movement features were not investigated but a recent research concluded that the VIVE Pro Eye VR headset could be used as an eye tracking device with high reliability [66].

The VIVE Eye and Facial Tracking SDK (SRanipal SDK) [2] allow developers to track users' eye and lip movements from VIVE VR devices. The Eye tracking data we collected during the experiments were analyzed manually using the SRanipal SDK. Separate eye data contained a validity column. The validity value is provided by the SRanipal SDK and data is considered valid if the validity value is 31 (i.e. eye openness, gaze origin, gaze direction, pupil diameter and pupil position are all valid), and considered invalid otherwise, as described in the manual of the SDK. Thus, we dropped invalid eye movements for all participants.

Because we manually computed eye movements features, we focused on the most used, and the most important features and statistics according to the literature. saccades, fixations, and blinks were by far the most used features [36, 45, 48]. Pupil diameter and angle of eye vergence (AoEV) were also used in [41].

Eye saccades are rapid, ballistic eye movements that occur when the eyes shift from one fixation point to another. Eye fixations are periods when the eyes remain relatively still and focused on a specific point or object in the visual field.

Saccades and fixations were computed using a velocity-based identification algorithm [64], where we considered eye movements with a velocity higher than 300 degrees per second saccades and eye movements with a velocity lower than 100 degrees per second fixations. these values were considered from previous research [64]. We then extracted saccades count, average saccade amplitude, fixations count, average fixation duration.

Eye blinks are brief, involuntary closures of the eyelids. They were computed using a simple threshold method where eye movements with eye openness lower than 45% were considered blinks and were not considered blinks otherwise. Then, blinks count and average blink duration in a time window of length T were extracted. Blinks were computed with a value of our choice because no details using the VIVE headset could be found in the literature. Our choice was done among many values based on the average number of blinks per minute [25].

Furthermore, other eye movement features were computed. The Vergence angle of the eyes, which is the angle of the convergence or divergence point of the eyes, was calculated using gaze direction vectors. Then, the average angle, and angle variance were computed. The Average pupil diameter and pupil diameter variance were extracted.

In all analyses, only local eye movement data was used, such as gaze directions and gaze origin. The reason for that is that we are more concerned with eye movements in the local space than in the world space since eye movements in the world space are affected by head movements. Also, in order to compute saccades, fixations, blinks, and pupil diameters, the mean data of both eyes were used. In total, 10 features were extracted from eye tracking data.

3.2.2 Investigation of Dataset creation parameters

EEG data from the first part of the experiment was used to create a dataset. For each task, 4 samples with a time window of T seconds each were collected, two samples from the concentration period labeled "concentrated" since tasks are supposed to induce **concentration** within participants at this moment, and two samples that consisted of data of time length T following the appearance of the red window (onset of the distractor) were labeled "distracted" since the distractor is supposed to distract participants, for a total of 36 samples for each participant.

Due to the structure of the experiment used to collect data, we had to choose values for many parameters in order to create samples for the Dataset, as explained above. Before going further in the study, we investigated different parameters in order to choose relevant values.

Two parameters were investigated ; time window T which represents the long duration of data used to create one sample, and the moment from the concentration period where "concentrated" samples are created. T parameter values were investigated first, then the best T value was used to investigate the second parameter.

in order to choose the best parameter values, datasets that were created using different parameter values were evaluated in a classification problem, the leave-p-groups-out-cross-validation (LPGOCV) procedure with p=4 was used. A Random Forest model was trained and tested using the leave-p-groups-out-cross-validation (LPGOCV) method in order to test the model on data from groups never observed during training. Each group corresponded to the data of a participant. Each time, the model was trained on a subset of n-p groups, then tested on a subset of p groups. This procedure was repeated until the model was tested once on all possible combinations of p groups, and the evaluation metrics were averaged. p=1 was used for LPGOCV. F1-score of "distracted" labels were used as a metric to evaluate the performance of the models. The average metric values across LGPOCV were computed.

Datasets for Eye movements and EEG were created and evaluated separately. The best values following the evaluation were used in the rest of the study. This analysis adopted the methodology used in [8].

Figure 3.23 shows an overview of the investigation of dataset parameter values window length T and moment.

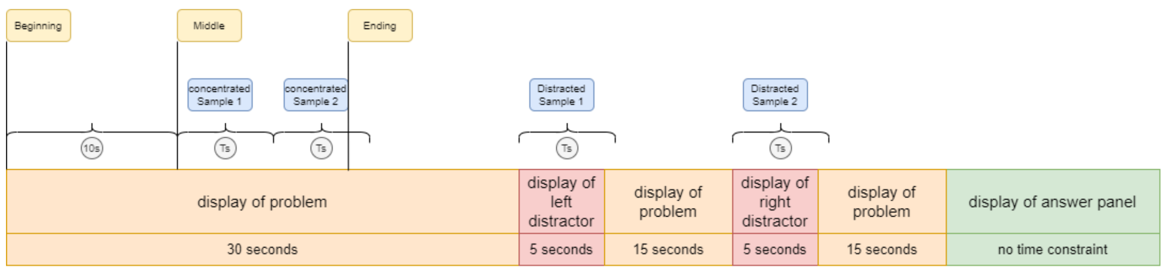

FIGURE 3.23 – Overview of dataset parameters investigation.

3.2.3 Experiment validation

To evaluate our **distraction** method, EEG data from the first part of the experiment were used to create a dataset. For each task, 4 samples with a time window of T seconds each were collected, 2 samples that consisted of the data from second 10 to second 15, and from second 15 to second 20 were labeled "concentrated" since tasks are supposed to induce **concentration** within participants at this moment, and two samples that consisted of data from the T seconds following the appearance of the red window (onset of the distractor) were labeled "distracted" since the distractor is supposed to distract participants, for a total of 36 samples for each participant. The index Beta/Theta ratio which was previously used to assess **attention** levels [43, 46] was computed for all participants and for all EEG channels.

In order to investigate differences between the two groups of data "distracted" and "concentrated", for each participant, the index average was calculated. Values of the index of the two groups of data were compared to each other for each participant using a hypothesis testing method.

Wilcoxon Signed-Rank test was used to investigate differences in the two groups of data "concentrated" and "distracted". The Wilcoxon Signed-Rank test is a nonparametric test designed to evaluate the difference between two treatments or conditions where the samples are correlated, and the null hypothesis asserts that the medians of the two samples are identical. The Wilcoxon Signed-Rank test was used instead of the Student t-test to investigate differences between the two groups because data did not respect the normality assumption, but conditions to use the Wilcoxon Signed-Rank test were met.

3.2.4 Distraction and Concentration Detection

The power band ratio Beta/Theta was previously referenced and used as an indicator of **attention** levels [43, 46]. It was also used in this study to validate the distraction method. The same set of data used for validation was considered here.

EEG signals are different from subject to subject, thus subject-dependent data transformation is necessary to make a meaningful comparison between participants. Thus, samples were created using data from the reference period; the reference period lasted one minute, and produced 12 samples. For each participant, a "MinMax" scaler was fit with samples of the reference period, then was used to scale original samples of the participant.

LDA is a statistical method used for classification and dimensionality reduction that tries to maximize the deviation between the classes' samples and reduce the deviation within the classes' samples.

LDA Assumes we have a set of size n of D-dimensional samples $X = \{x^{(1)}, x^{(2)}, ...x^{(n)}\}$. n_1 samples belong to class 1 and n_2 samples belong to class 2 such that $n_1 + n_2 = n$. We also assume the mean vector of each class is :

$$\mu_k = \frac{1}{n_k} \sum_{i \in C_k} x^{(i)} \qquad \text{where} \qquad k = 1,2$$

LDA produces a line y such that : $y = \theta^T X$. The mean values of each class of the projection are then :

$$\hat{\mu}_k = \frac{1}{n_k}\sum_{i\in C_k} y^{(i)} = \frac{1}{n_k}\sum_{i\in C_k} \theta^T x^{(i)} = \theta^T \mu_k \qquad \text{where} \qquad k = 1,2$$

The objective of LDA is to find θ that maximizes the deviation between classes and minimizes the deviation within classes.

The deviation between classes can be represented by the distance between the projected means :

$$\hat{\mu}_2 - \hat{\mu}_2 = \theta^T(\mu_2 - \mu_1)$$

And the deviation within classes can be represented using the variance of each class :

$$\hat{s}_k^2 = \sum_{i\in C_k} (y^{(i)} - \hat{\mu}_k)^2 \qquad \text{where} \qquad k = 1,2$$

Then, to maximize the deviation between classes and minimize the deviation within classes, the objective function $J(\theta)$ can be defined as :

$$J(\theta) = max_\theta \frac{\hat{\mu}_2 - \hat{\mu}_1}{\hat{s}_1 + \hat{s}_2}$$

The objective can be rewritten as :

$$J(\theta) = max_\theta \frac{\theta^T S_B \theta}{\theta^T S_W \theta}$$

Where $S_B = (\mu_2 - \mu_1)(\mu_2 - \mu_1)^T$ is the between-class scatter matrix and $S_W = S_1 + S2$ is the inter-class scatter matrix. There are multiple ways to solve this problem.

The line defined by the equation $y = 0$ separates the two classes in the projected space, and the projections can be calculated using the equation $y^{(i)} = \theta^T x^{(i)}$

The linear Discriminant Analysis (LDA) model was used to reduce to one, the dimensionality of the data, and to discriminate between the two states, according to the two-state labels “concentrated” and “not concentrated” (previously labeled “distracted”). LDA model from the Scikit-learn package with “solver” parameter set to “svd” was used. To make predictions and to have an indicator of the concentration levels for a sample, we used the trained LDA model to compute the probability of the sample being labeled "concentrated" ; where higher values indicated higher **concentration** levels and vice versa. The decision boundary of the model is linear, and the decision threshold is always zero when using "svd" solver since the data are centered using the overall mean when projected onto the resulting dimension. A value greater than zero for the indicator signified the label was "concentrated", whereas a value lower than zero signified the label was "not concentrated".

To evaluate the produced model in a classification problem, the leave-p-groups-out-cross-validation (LPGOCV) procedure with p=4 was used. The model was trained and tested using the leave-p-groups-out-cross-validation (LPGOCV) method in order to test the model on data from groups never observed during training. Each group corresponded to the data of a participant. Each time, the model was trained on a subset of n-p groups, then tested on a subset of p groups. This procedure was repeated until the model was tested once on all possible combinations of p groups, and the evaluation metrics were averaged. The maximal value p=4 (80% data for training and 20% for testing) was used, as the largest values required significantly more time to validate. F1-score, Recall, and Precision of "distracted" labels were used as metrics to evaluate the performance of the model. The average scores and standard deviations of metrics values across LGPOCV were computed.

Figure 3.24 shows details on how the concentration indicator computation methodology.

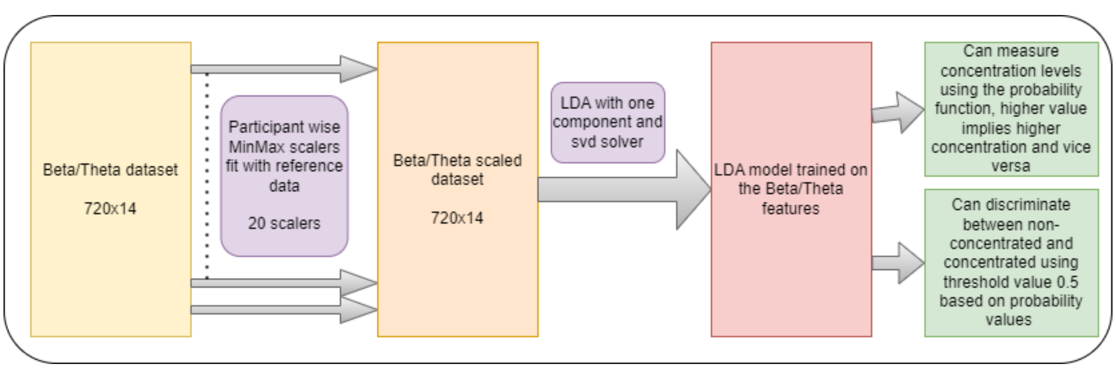

FIGURE 3.24 – Methodology for computing concentration levels indicator.

To study the feasibility of detecting **distraction** using eye tracking, we created a set of data with eye movement features and time window T, we included “concentrated” samples and “distracted” samples as described above. The set of data gathered 36 samples for each participant ; 18 “concentrated” samples and 18 “distracted” samples. Scikit-learn python library was used to train and validate the models. Before each training, training data were fit to a robust scaler that centers and scales data using their median and interquartile range, this scaler was later used to transform test data before testing. Many scalers were tested, and the robust scaler gave the best results among others. Various models were trained and tested using the leave-p-groups-out-cross-validation (LPGOCV) method such as before. We also created a random classifier that would predict the two states with equal probability and evaluated it using the same procedure.

3.2.5 Concentration improvement

We defined in the first chapter Attention Restoration Theory (ART) as a psychological framework suggesting that exposure to natural environments facilitates the restoration of voluntary attention capacity, reducing mental fatigue and enhancing cognitive functioning [39].

In the second part of the experiment, we used the environment developed in [12, 28] to study the feasibility of improving **concentration** and decreasing **distraction** levels using relaxation in Virtual Reality. Participants were invited to travel in a virtual train which has proven to reduce negative emotions. Participants first completed a set of 6 cognitive tasks before going for relaxation in the virtual train, then completed another set of the same cognitive tasks with the same difficulty.

We used the same set of cognitive tasks and kept the same difficulty before and after relaxation to have the relaxation procedure as the only variable able to affect the concentration and distraction levels of the participants. The relaxation procedure was a tour on a virtual train that went through three natural environments ; a forest, a frozen mountain, and a desert. Such environments were previously used to decrease the negative emotions and improve attention of individuals [12, 29].

To compare the attentional state of the participants before and after relaxation, we used the tools we developed earlier to monitor retrospectively the concentration and distraction levels of the participants during the entirety of the second part of the experiment. We split the entirety of data from the second part into T-second segments and created samples from EEG data and Eye Tracking data, where the choice of T was based on 3.2.2.

We used the LDA concentration indicator we developed in 3.2.4 to assign to each sample of the EEG data samples a real value that represented the probability of the sample being labeled “concentrated”. The LDA model we used was trained on the dataset from 3.2.2 with parameters T=6 and moment=middle.

The Eye Tracking data samples were classified using a Logistic Regression model trained on the dataset from 3.2.2 with parameters T=3 and moment=middle with either label “0” if not distracted or label “1” if distracted.

Following the above computations, we averaged both the concentration indicators and distractions labels for each task, for each participant, and for each phase (before relaxation, and after relaxation). This method of retrospective monitoring was used in [41] to assess the concentration of learners. We also computed the scores of participants in the six cognitive tasks both before and after relaxations in order to make a score based comparison between participants, and to make a comparison between the different metrics we calculated : concentration, distraction, and scores.

3.3 Summary

In this chapter, details on the methodology used to collect EEG and Eye Tracking data, as well as analyses carried out in this study, were reported.

The purpose of the study was to develop means to measure **attention**, **concentration**, and **distraction** levels, as well as to improve the concentration levels, of participants while completing cognitive tasks in virtual reality.

To achieve the first goal, participants performed a series of cognitive tasks, while their levels of **attention** were manipulated using distractors. Distractors were visual items that appeared in the field of view of participants and aimed to divert their visual attention from the main task.

Collected data were first used to create a set of data. To do that, two parameters relevant to dataset creation were investigated, sample window length T, and sample moment. Many datasets using different parameter values were compared in a classification task, and the best parameters were used in the rest of the study.

Next, in order to validate the **distraction** method presented in this study, the levels of **attention** of participants were compared between concentration periods and distraction periods using an indicator of attention from previous research.

Finally, the datasets created before were used to develop means to detect and measure **attention**, **concentration**, and **distraction** levels. EEG dataset was used to create a real-valued indicator of concentration levels, while the Eye Movements dataset was used to create a distraction detection model. The EEG concentration indicator model could also be used to detect concentration in a binary setting.

To achieve the second goal, participants completed two sets of cognitive tasks, before and after relaxation. To investigate the effects of the proposed **concentration** improvement strategy, the concentration indicator developed before was used to compare participants before and after relaxation.

CHAPITRE 4

EXPERIMENT

The experiment consists of two parts. The first part was designed to study the first research question ; the feasibility of detecting and monitoring **distraction** and **concentration** using EEG and Eye Tracking. The second experiment targeted the second research question ; the feasibility of increasing the concentration levels of participants and decreasing their distraction using relaxation. In this chapter, for each part, the tools used to create the experiment, the experiment creation process, The hardware tools used in this study, and the data collection method are detailed.

In section 4.1, the hardware tools used to perform the experiment, as well as the tools used to record data are listed. In section 4.2, the software tools used to develop the experiment are listed, and the developement process is detailed. In section 4.3, we list the files recorded for each participants, their content, and how they are created and updated. In section 4.4, we show the course of the experiments.

Before diving into the chapter, we will try to draw a line to separate the work done by the student from the work provided at the beginning of the study. Aside from the room where the cognitive tasks occurred (which was an aesthetic element that did not intend to implement any concept of attention theory), the student developed entirely the first part of the experiment using Unity. The first part was used to find means to detect and measure attention levels. The second part of the experiment which focused on the study of relaxation was provided from another study and the student did not participate in its development.

All hardware used in this study including the VR and EEG headsets were entirely setup and maintained by the student during the development of the virtual environment and during the experiments with the participants. All the data recording procedure except the “Log file of the second part” file was implemented by the student 4.3. The student also recruited, prepared, and supervised all the participants during the experiment. All the analyses done in this study were carried out by the student.

During the theoretical design of the experiment, the student received a very useful idea about how to induce distraction and was used by the student subsequently.

The room aesthetic used in the first part of the experiment was provided. Also, the entire environment of the second part of the experiment was provided and ready to use in VR [12]. The file “Log file of the second part” was also provided 4.3.

4.1 Hardware tools

To record EEG data, OpenBCI CYTON bio amplifier board with a DAISY module to record EEG from 16 channels. It is a scientifically validated tool to record EEG data and was extensively used in research. The OpenBCI bio amplifier comes with a dongle to receive data via Bluetooth at a frequency of 125 Hz. Different electrodes were used depending on the location. FRI (Florida Research Instruments Inc., Cocoa Beach, Florida USA) reusable wet EEG electrodes TDE-201 were used at placements Fp1 and Fp2. FRI reusable dry EEG electrodes TDE-200 were used at placements F7 and F8. 5 mm spike reusable dry EEG Electrodes TDE-210 were used for the rest of the placements. Electrodes were inserted in a 19 Channel EEG cap from FRI.

All EEG electrode placements in this study followed the 10-20 standard. The 10-20 system of electrode placement is an internationally recognized method to describe the location of EEG Electrodes, each electrode placement site has a letter to identify the lobe or area of the cerebrum it is reading from ; pre-frontal (Fp), frontal (F), temporal (T), parietal (P), occipital (O), and central (C) even though there is no “central lobe” ; due to their placement, and depending on the individual, the “C” electrodes can exhibit/represent EEG activity more typical of frontal, temporal, and some parietal-occipital activity. There are also (Z) sites ; a “Z” (zero) refers to an electrode placed on the midline sagittal plane of the skull, (FpZ, Fz, Cz, Oz) and is present mostly for reference/measurement points and does not represent either hemisphere adequately. “Z” electrodes are often utilized as grounds or references.

The experiment took place in a virtual reality environment and must be completed wearing a VR headset. In this study, HTC VIVE Pro Eye VR headset with only one right controller and one base was used. The VR headset has a field of view of 110 degrees and a refresh rate of 90 Hz. It comes with many features including integrated headphones, a microphone, and a gyroscope. The VR headset came with an integrated eye tracking system that could track eye movements at a maximal frequency of 120 Hz and accuracy between 0.5 degrees and 1.1 degrees. The integrated Eye Tracker was used to record Eye movement data.

4.2 Experiment Creation

Unity engine was used to develop the entire experiment. Unity is a popular game development engine that uses C Sharp programming language. The first part of the experiment was created in this study, while the second part of the experiment was developed earlier [12]. The first part of the virtual reality experiment takes place in a room. The room is illuminated and scenery elements inside it include two sofas on the right and left sides, a plant on the left rear side, and babies and animals' frames on the left and right walls. At the center of the room, a chair is present, and a camera is positioned right above the chair, facing the front wall. The camera represents the player, who can look around freely but can't move.

The three tasks of the first part, mental arithmetic, anagram, and digit memorization were all presented on the front wall. Each task consists of several components :

- Problem statement : Text field containing the statement of the problem.
- Object of the problem : Text field containing the anagram unordered letters, the digits to memorize, or the arithmetic formula.
- Hints : Text field containing suggestions and possible correct answers.
- Answer of participant : Input field containing the answer entered by the participant.
- Virtual keyboard : Set of buttons that simulates the behavior of a keyboard used to interact with the environment by answering problems.
- Distractor : Red Text field that notifies participants of the presence of hints.

The different components were created using C Sharp programming language, and Unity Editor tools to facilitate development and free assets from Unity Asset Store. Unity Asset Store is a platform where third-party tools to simplify development using Unity are available. In this part of the experiment, two free assets were used. The first asset provided a ready-to-use virtual keyboard. The second asset is the room where the experiment takes place.

Figures 4.1 and 4.2 show the different components of each task in the first part of the experiment.

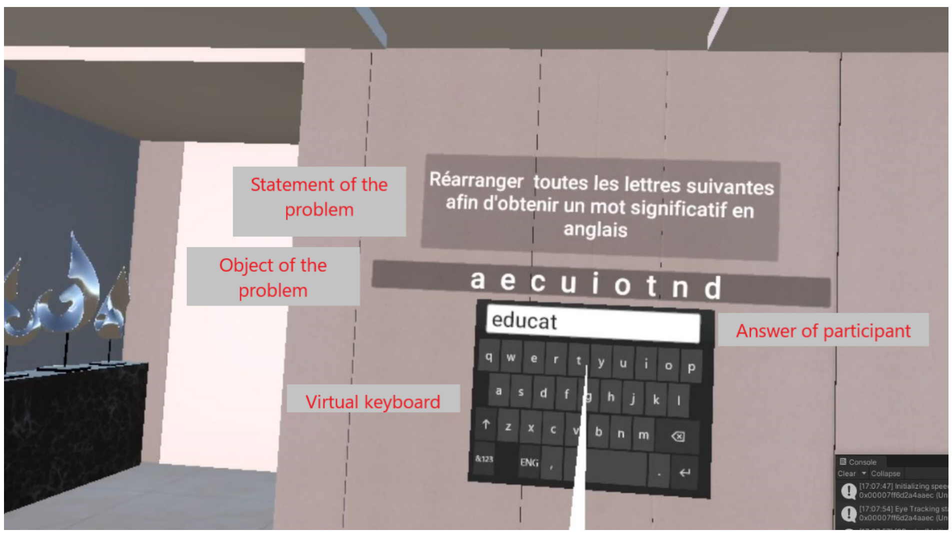

FIGURE 4.1 – Part 1 of different components of a task.

FIGURE 4.2 – Part 2 of different components of a task

To avoid unpredictable effects during the first part of the experiment. A demonstration version of the experiment containing only one task of each type (three tasks in total) was created and destined to be completed before completing the complete version.

The second part of the experiment used the same room as the first part but with different lighting for cognitive tasks before and after relaxation aboard the train. Each cognitive task is accompanied by written and vocal instructions. Before each task starts, an example is given for better comprehension. The interaction system is fundamentally different in the second part compared to the first part. All interactions in the first part are done using a virtual keyboard or keypad, an input field, and a validation button. In the second part, there is no input field and no validation button.

The entirety of the experiment was first developed for the mouse and keyboard. The mouse was used to rotate the camera and click on interactable objects, whereas the keyboard was only used to input letters and numbers. Then, the experiment was modified to work on Virtual Reality using "Unity XR Interaction Toolkit" package.

In the VR version of the experiment, to interact with the virtual environment, such as to input answers, participants had a controller to interact with a virtual keyboard inside the environment. A pink line indicated where the controller is pointing and turned white when the object pointing at was interactable. Figure 4.3 shows how the controller pointing indicator looks when it is directed toward a non-interactable surface.

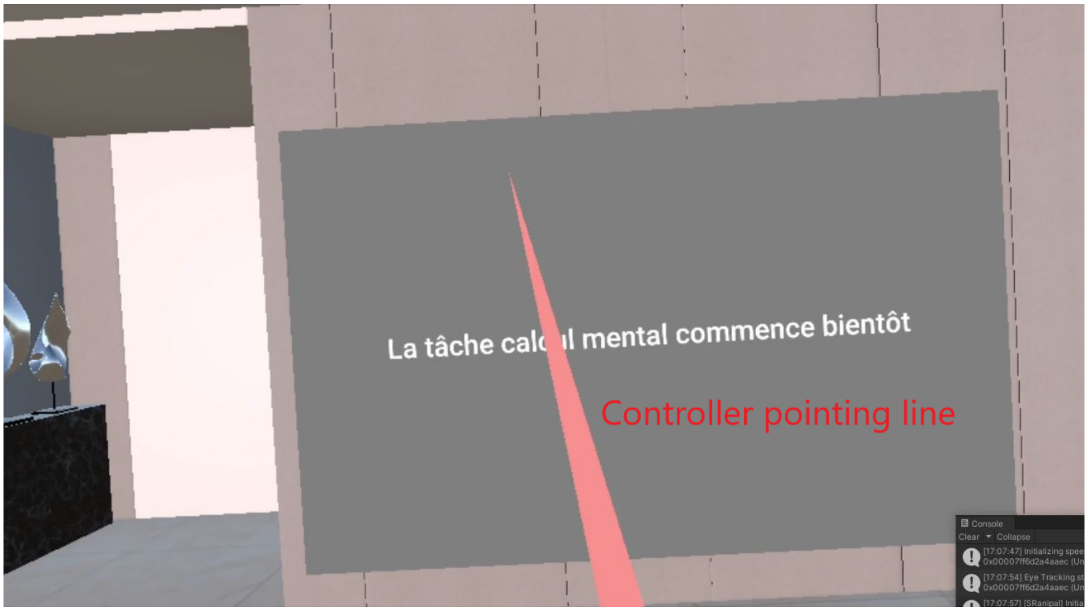

FIGURE 4.3 – Indication of where the controller is pointing using a pink/white line.

4.3 Data Recording

Recorded data consisted of six files : video recording, comments, log of the first part, log of the second part, EEG data, and Eye movements data.

Video recording : Video recording of the entire experiment. The virtual experiment in the virtual reality headset was cast on the monitor screen of the computer used to perform the experiment. The monitor screen was recorded using OBS Studio software during the entirety of the experiment for each participant in the MKV video format. The length of the videos was 40 minutes and weighed more than one gigabyte on average. Video files were used later to investigate the behaviors of participants.

Comments : Text file created manually containing comments and answers of participants after performing the experiment. The answers of participants included their judgment about the **distraction** method and relaxation method.

Log file of the first part : CSV file created manually and containing information updates through time of the first part of the experiment while performed by participants. The CSV file was created using a C Sharp script and was updated every 100 milliseconds on average. It contained six data columns :

- Time : Contains local computer times.
- Timestamp : Contains the Unix milliseconds times of the current local times in UTC format.
- Num Task : Contains the task numbers from 0 to 8 for the nine tasks.
- Type Task : Contains types of tasks which can be “mental arithmetic”, “anagram”, or “memorization”.
- Game Event : Contains current events happening during the experiment, including the beginning of the task, the onset of the distractor, and the offset of the distractor.
- User Input : Contains the last character entry in the input field “answer of participant”.

Log file of the second part : CSV file created manually and containing information updates through time of the second part of the experiment while performed by participants. The CSV file was created using a C Sharp script and was updated three times per second on average. It contained nine data columns :

- Time : Contains local computer times. These times were later converted to Unix times to be synchronized with EEG data and Eye movements data.
- idScene : Id of the current scene in Unity, used to differentiate between tasks of the second part as each task happened in a different scene.
- EventDesc : Contains description of events happening currently. An event is a sub-task of the current task.
- EventAction : Contains action performed by the user currently.
- ScoreEvent : Contains the player’s score in the current event.
- ScoreExercice : Contains the player’s score in the current task.

- ScoreGlobal : Contains the global score throughout the second part of the experiment.
- TempsDeReponse : Contains the response time of the participant to the current event.
- ExerciceDuration : Empty column, did not contain any information.

EEG data : CSV file containing data recorded from EEG headset. Data were obtained via a dongle connected to the computer with USB and connected to the EEG headset with Bluetooth. Data were recorded using BrainFlow for Python, a library intended to obtain, parse and analyze data from biosensors including EEG. EEG data were recorded 125 times per second and followed the library's default format. Data from each EEG headset channel were recorded in a column. With indexes starting from 0, columns from index 1 to 16 contained respectively EEG data of channels Fp1, Fp2, P7, P8, O1, O2, F7, F8, F3, F4, T7, T8, P3, P4. The column with index 30 contained times of data recording in Unix milliseconds format. The format contained other data that were not relevant and thus not used in this study.

Eye movements data : CSV file containing data recorded from the Eye tracker integrated into the VR headset. Eye movement data were obtained using HTC VIVE SRanipal SDK for Unity in a C Sharp script. Data could be recorded at a refresh rate of 120 Hz using an alternative thread in Unity, but a transformation of data using Unity's main thread compelled us to record data at a rate of 90 Hz in 48 data columns. Data in columns included :

- Unix Time column : Contains local times in Unix milliseconds format.
- Single eye validity : Contains validity of data of single eye movements, a value of 31 signifies all eye movements are valid.
- Single eye openness : Contains a normalized value representing how open the eye is.
- Single eye pupil diameter : Contains the diameter of a single eye pupil in millimeters.

- Single eye pos : 2D values containing the normalized position of a single eye in the sensor area.
- Single eye gaze origin : 3D values containing the local point in the eye from which the gaze ray originates.
- Single eye gaze direction : 3D values containing the local normalized gaze direction of the eye.
- Single eye world gaze origin : 3D values containing the world point in the eye from which the gaze ray originates.
- Single eye world gaze direction : 3D values containing the world normalized gaze direction of the eye.

All eye movement data were obtained from the attribute $ViveSR.anipal.Eye.EyeData_v2.verbose_data$. Gaze origin and gaze direction data were represented using a right-handed coordinate system whereas the Unity engine uses a left-handed coordinate system, thus data were transformed accordingly.

4.4 The course of experiments

Experiments needed two computers to be completed due to a lack of computational power. On the first computer, a virtual reality experiment was completed by participants, and data recorded included video recording, comments, log of the first part, log of the second part, and Eye movements data. EEG data were recorded on a second computer. The two computers synchronized their times with the server manually before the start of each experiment. In addition, during early tests, the virtual reality environment would freeze permanently. To remediate this, the Eye movements data recording start was delayed to three seconds after the launch of the virtual environment.

The specs of the first computer were : Windows 10 Pro, Intel Core i7-6820HK CPU @ 2.70 Ghz 2.70Ghz processor, 16 GB of RAM, and a GTX 1060 GPU. The first computer was an MSI VR One backpack.

The specs of the second computer were : Windows 10, Intel Core i5-9300H CPU @

2.40Ghz 2.40 Ghz processor, 8 GB of RAM, and a GTX 1650 Max-Q GPU with 4 GB of memory. The second computer was an MSI gaming laptop.

When participants were ready for the experiment, they started by wearing the EEG headset with an adjustable chinstrap for better skin contact, reference and ground electrodes were then attached to earlobes. Next, an additional tight cap was added for more skin contact, followed by the virtual reality headset. Participants put on an empty school bag, where the case containing the EEG board as well as the batteries was stored. Then they did eye tracking calibration using VIVE calibration tool, and time was synchronized between the two computers before the experiment started. 4.4 shows how the EEG and eye tracking headsets were set up.

FIGURE 4.4 – Setup of the EEG and eye tracking headsets.

Before the start of the first part, participants went through a reference period of one-minute duration. Data was recorded while participants were doing nothing. Data collected in this period were used later during analysis.

During the first part, participants completed three types of tasks, mental arithmetic, anagram, and digit memorization, a total of nine times. Each task went as follows, the problem was first presented on the screen, and participants were instructed to solve it. After 30 seconds, the problem was hidden and a red window (distractor onset) was displayed over the screen instructing participants to look left to have a clue (hint), and at the same time, two suggestions were presented on the left side of the environment where the participant should be gazing after the onset of the distractor. After five seconds, the red window disappeared, the hints did not disappear, and the problem reappeared (except for the memorization task where the problem did not reappear). After 15 seconds, the problem was hidden and a red window was again displayed over the screen instructing participants to look right to have a clue, at the same time another two hints were presented on the right side of the environment. After five seconds, the red window disappeared, the hints did not disappear, and the problem reappeared (except for the memorization task where the problem did not reappear). A keyboard also appeared this time where participants could enter and validate their answers. Participants did not have a time limit and could validate their answer until it was correct. Tasks were separated by in-between task breaks with five seconds duration. Participants first completed three mental arithmetic tasks, followed by three anagram tasks, then three memorization tasks.

Figure 4.5 shows an overview of the different phases of a task in the first part of the experiment.

display of problem	display of left distractor	display of problem	display of right distractor	display of problem	display of answer panel
30 seconds	5 seconds	15 seconds	5 seconds	15 seconds	no time constraint

FIGURE 4.5 – Different phases of a task in the first part of the experiment.

During the second part of the experiment, participants first completed a set of cognitive tasks before going for relaxation on a train, then completed another set of cognitive tasks like the first set. Cognitive tasks in the second part had different time durations. During relaxation, participants went for a tour on a train that lasted six minutes approximately. The train was moving, and they could hear the sound of the rail wheel as well as relaxing music playing through the sound output system of the VR headset. They could also see other nonplayer characters on the train including a family that was seated next to the player. Participants visited three locations aboard the train, a forest, a frozen mountain, and a desert.

Figure 4.6 shows an overview of the entire experiment.

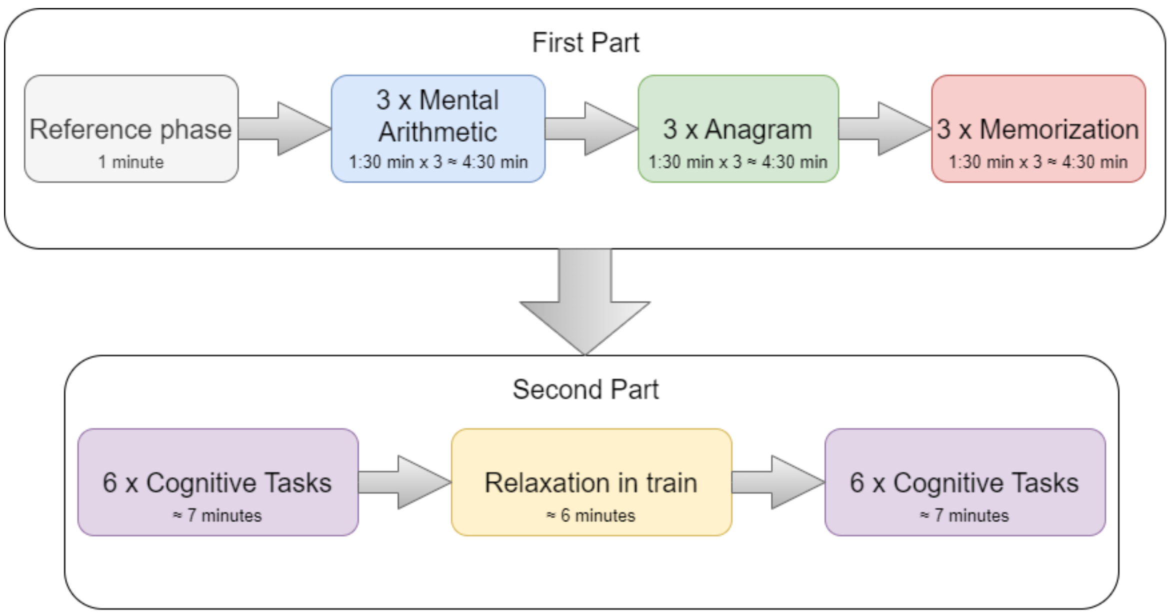

FIGURE 4.6 – Overview of the experiment.

31 participants (M = 15, F = 16) aged between 17 and 44 (mean = 23, std = 5) undertook the experiment at BMU (Beam Me Up Labs Inc., Montréal, Quebec, Canada). The average duration of the experiment across all participants was 40 minutes.

4.5 Summary

In this chapter, details on how the experiment was implemented, how the data were recorded, and how experiments were carried out were shown.

The first part of the experiment was implemented using the Unity engine and C Sharp programming language. The development was iterative, and feedback from early testers helped gradually improve the experiment. The second part of the experiment was also implemented using the same tools but was already finished before starting this study.

Six different files contained data from each experiment. EEG data and Eye Tracking data were recorded in separate files and in data columns. EEG data were recorded using the BrainFlow library for Python while Eye Tracking data were recorded manually in a CSV file with 48 columns using C Sharp. Data in different files were synchronized using the Unix Time column present in all files.

One computer was not enough to perform the experiment in Virtual Reality, due to high resource demand. Instead, the virtual reality experiment, as well as the Eye Tracking recording was done on a computer, while EEG data recording was done on another computer.

CHAPITRE 5

RESULTS AND DISCUSSION

We put forward two hypotheses in this study : 1) it is possible to detect and monitor the different **concentration** and **distraction** levels of the participants using EEG and Eye Tracking in VR while completing cognitive tasks. 2) The concentration of the participants will increase and their distraction will decrease after relaxation compared to before the relaxation period.

During experiments in virtual reality, data from eye tracking and EEG headsets were collected. The experiment consisted of two parts. The first part was designed to verify the first hypothesis ; the feasibility of detecting and monitoring **distraction** and **concentration** using EEG and Eye Tracking. The second experiment was designed to investigate the second hypothesis ; the feasibility of improving the concentration of participants and decreasing their distraction using relaxation.

In this chapter, the main findings following the analysis of data are presented. In section 5.1, dataset creation parameters are investigated in order to choose the best parameters and maximize performance in the rest of the analysis. Next, in section 5.2, validation of the **distraction** method is done using EEG data. Then in section 5.3, the first hypothesis is investigated using both EEG and Eye Tracking data. Finally in section 5.4, previous results are used to compare participants' **attention** levels before and after relaxation. We conclude the chapter with a discussion over the main findings of this research in section 5.5

5.1 Investigation of Dataset creation parameters

An analysis of the recorded raw EEG data was done in order to select relevant EEG channels and participants' data to keep for further study. Channels with data missing in the majority of participants were dismissed, and participants with many missing channels were dismissed. It resulted in two channels being dismissed (C3, C4) and 14 channels kept (Fp1, Fp2, P7, P8, O1, O2, F7, F8, F3, F4, T7, T8, P3, P4), and in 11 participants dismissed, and 20 participants kept for further study.

In order to select relevant parameters for the rest of the study, two parameters were investigated ; time window T which represents the length duration of data used to create one sample, and the moment from the concentration period where "concentrated" samples are created. For T, we tried values of the set $S_t = \{1,2,3,4,5,6,7,8,9,10,15,30\}$. For the moment of creation of "concentrated" samples, we tried three moments. The first moment was the moment when the task started (labeled "beginning"), and The second moment was ten seconds after the task started (labeled "middle"). The final moment was 20 seconds after the task started (labeled "ending"). T parameter values were investigated first, then the best T value was used to investigate the second parameter.

Figure 5.1 shows results of F1-scores for different T values, for EEG datasets as well as Eye movements datasets. The window length values 3 and 6 gave the highest F1-scores, 91% and 89% respectively. For EEG data, The window length values 6 and 5 gave the highest F1-scores, 75% and 73% respectively.

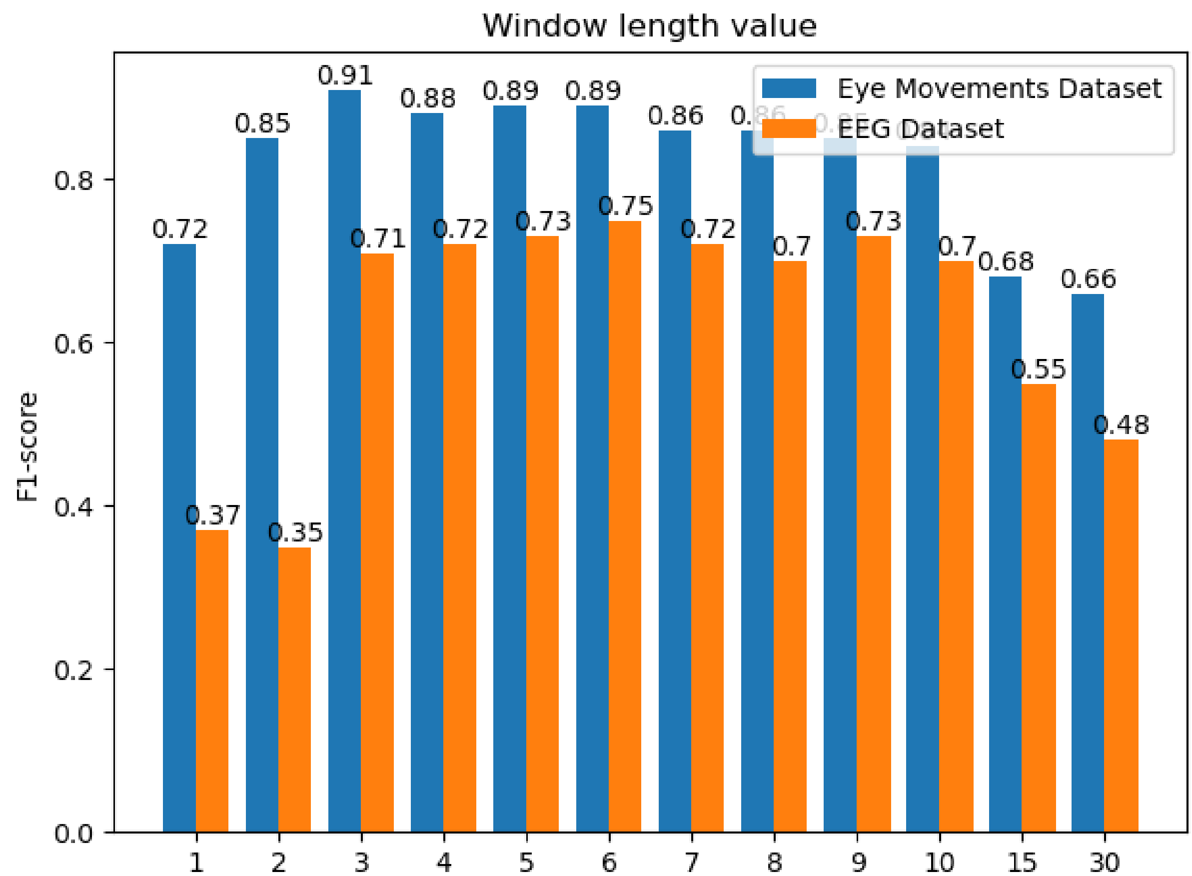

FIGURE 5.1 – F1-scores of different data length values.

Window length value 6 had the highest average F1-score across EEG and Eye movements dataset, thus it was used for the next analysis.

To investigate moment values, a window length value 6 was used. Figure 5.2 shows the results of F1-scores for different moment values. Both EEG data and Eye movements data extracted from the middle of the concentration phase had the highest F1-score values.

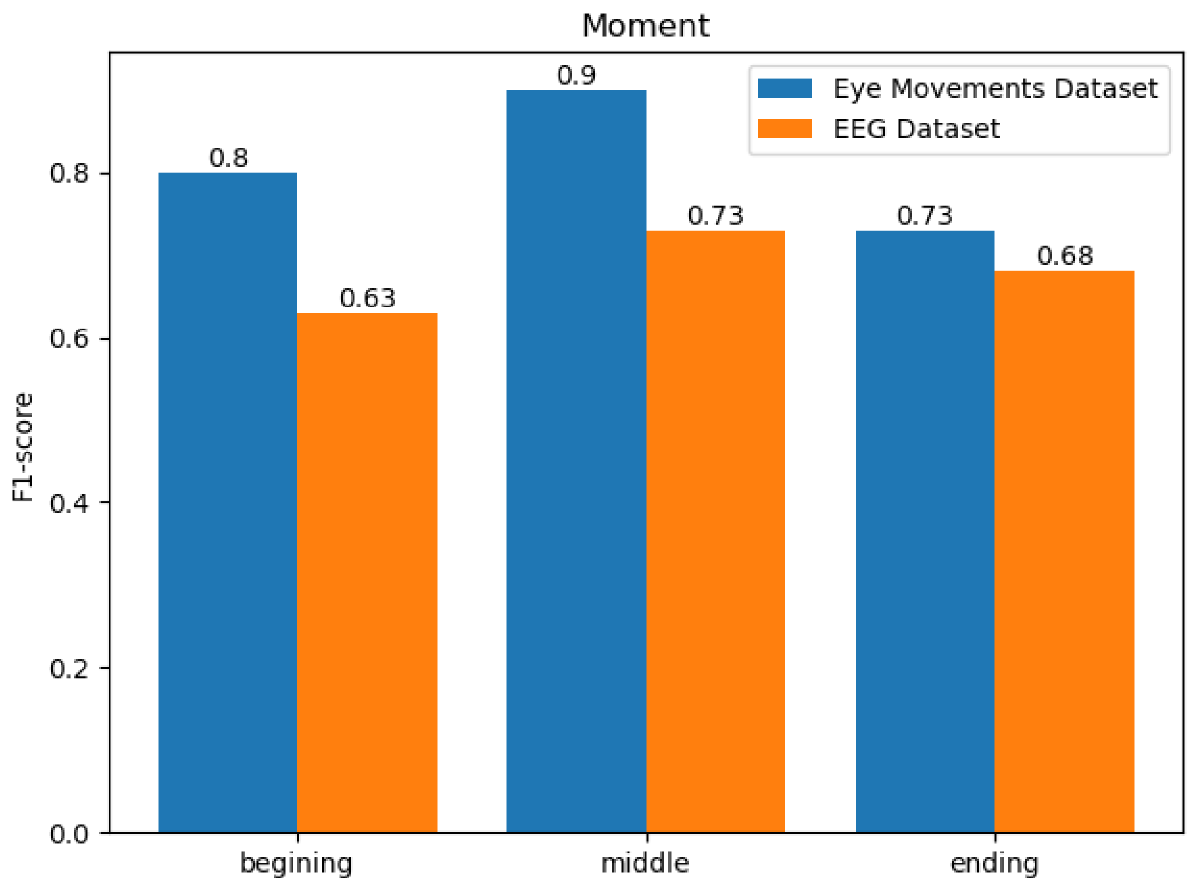

FIGURE 5.2 – F1-scores of different moment values.

In further analysis, parameter moment with value "middle", and a window length value of 6 seconds was used.

5.2 Experiment Validation

In order to verify the effects of the **distraction** method used in this study, an indicator of **attention** levels used in previous studies was used to compare the attention levels of participants during both concentration and distraction periods. Beta/Theta ratio Indicator values were computed using EEG data.

For each participant, the indicator average was calculated separately using the data of the two groups "concentrated" and "distracted". Figure 5.3 shows the average value of Beta/Theta ratio for all participants at EEG channel P4. On average, the index value decreased by 35% during distraction periods compared to concentration periods. In order to validate the differences between the two groups, a Wilcoxon signed-rank test was carried out for all participants using the indicator average values across all EEG channels with the alternative hypothesis that the indicator values are significantly higher during concentration periods than distraction periods for all participants. The Scikit-learn python package [57] was used for this test.

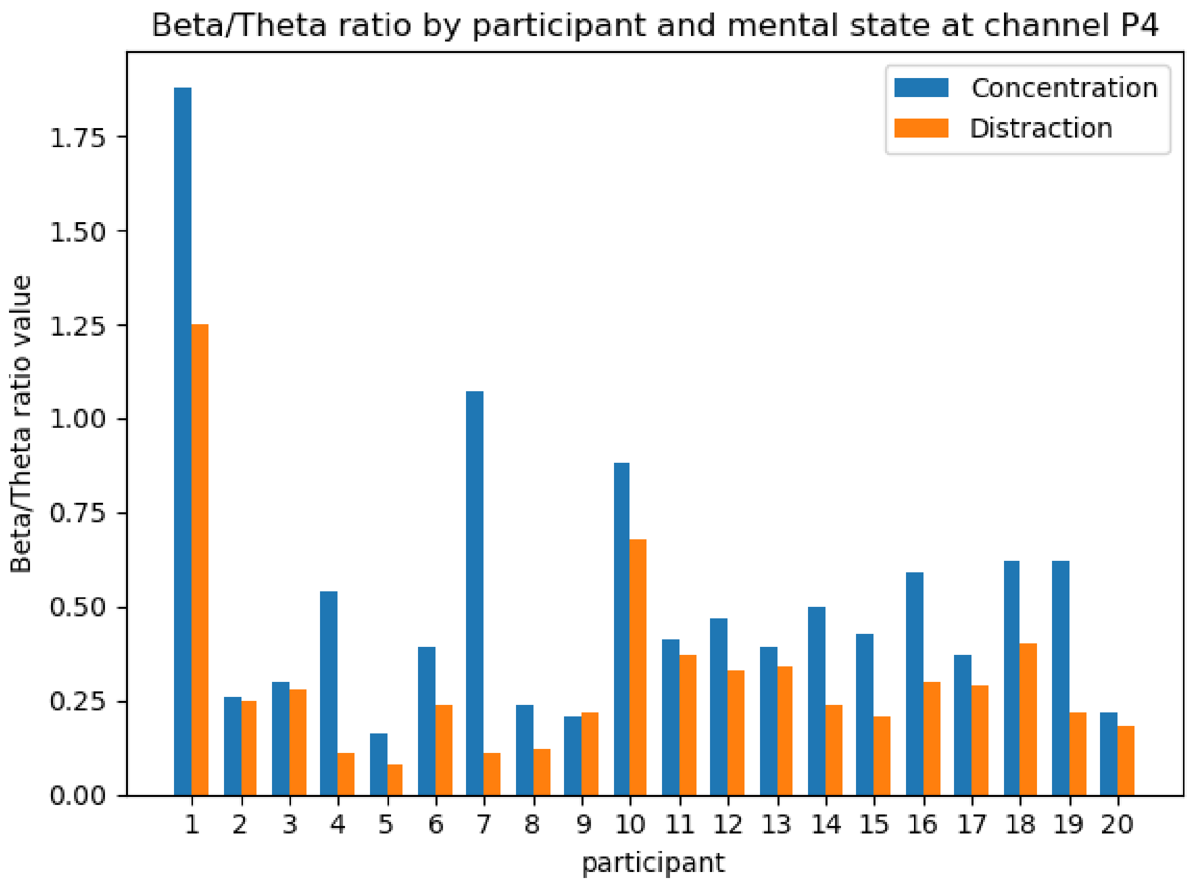

FIGURE 5.3 – Beta/Theta ratio value by participant and mental state at EEG channel P4.

Table 5.I shows the results of the analysis. The null hypothesis could be rejected under a confidence level of 95% for all channels except Fp1 where p-value is higher than 0.1. These results suggest that values of the Beta/Theta index during distraction

periods are significantly lower than during concentration periods in 14 EEG channels except for one channel, which is Fp1. Following that, it can be accepted that the method used to generate **distraction** in this study is valid.

Indicator	Channel	p-value
Beta/Theta	Fp1	< 0.001
	Fp2	< 0.001
	P7	< 0.001
	P8	< 0.001
	O1	< 0.001
	O2	< 0.001
	F7	< 0.001
	F8	< 0.001
	F3	< 0.001
	F4	< 0.001
	T7	< 0.001
	T8	< 0.001
	P3	< 0.001
	P4	< 0.001

TABLE 5.I – Results of Wilcoxon signed-rank test by EEG channel.

5.3 Concentration and Distraction Detection

EEG data were used to detect **concentration** using an LDA model, while Eye Movements data were used to detect **distraction** using multiple models.

The average scores and standard deviations of metrics values across LGPOCV were computed for the LDA model. The mean F1-score of the "concentrated" state was 73.99%, with a standard deviation of 5.93%. The average recall of the "concentrated" state was 78.12%, and the average precision was 71.37%.

A comparison between Eye movements models for **distraction** detection was carried out. Table 5.II shows the average scores as well as standard deviations after evaluating the models using LPGOCV with p=4. Logistic Regression and Random Forest achieved the highest F1-score of 89% for correctly detecting distraction, while K-Nearest Neighbors (KNN) and Naive Bayes achieved the lowest F1-score of 86%. Results suggest it is possible to effectively discriminate between "distracted" state and "concentrated" state using these models, even for data of new participants never seen before.

Model	F1 Distraction Mean, Std	Recall Distraction Mean, Std	Precision Distraction Mean, Std
KNN	0.86, 0.03	0.89, 0.05	0.83, 0.06
Logistic Regression	0.89, 0.02	0.9, 0.04	0.88, 0.04
RBF SVM	0.88, 0.03	0.86, 0.06	0.9, 0.04
Random Forest	0.89, 0.03	0.88, 0.06	0.9, 0.04
Naive Bayes	0.86, 0.04	0.85, 0.07	0.87, 0.05
Multilayer Perceptron	0.89, 0.03	0.89, 0.05	0.89, 0.05
Random Baseline	0.49, 0.04	0.49, 0.05	0.49, 0.04

TABLE 5.II – Results of model evaluation using LPGOCV with p=4 on Eye Movements dataset.

5.4 Concentration improvement

To compare the attentional state of the participants before and after relaxation, we used the tools we developed earlier to monitor retrospectively the concentration and distraction levels of the participants during the entirety of the second part of the experiment in T-second segments using the tools we developed in 3.2.4 and 3.2.2.

Figure 5.4 shows the average concentration levels by participant and phase (before relaxation and after relaxation). Levels of **concentration** after relaxation decreased on average by 18% across all participants and was higher before relaxation for 16 participants. Figure 5.5 shows the average concentration levels by task and phase. The average level of concentration in the first three tasks was 28% lower after relaxation compared to to before relaxation.

A one-tailed Wilcoxon Signed-Rank test was performed to compare the levels of concentration of participants before relaxation and after relaxation. The results from pre-relaxation ($M = 0.17$, $SD = 0.05$) and post-relaxation ($M = 0.12$, $SD = 0.06$) indicate that the relaxation in Virtual Reality resulted in a decrease in concentration levels ; $z = 192.0$, $p = .0002$.

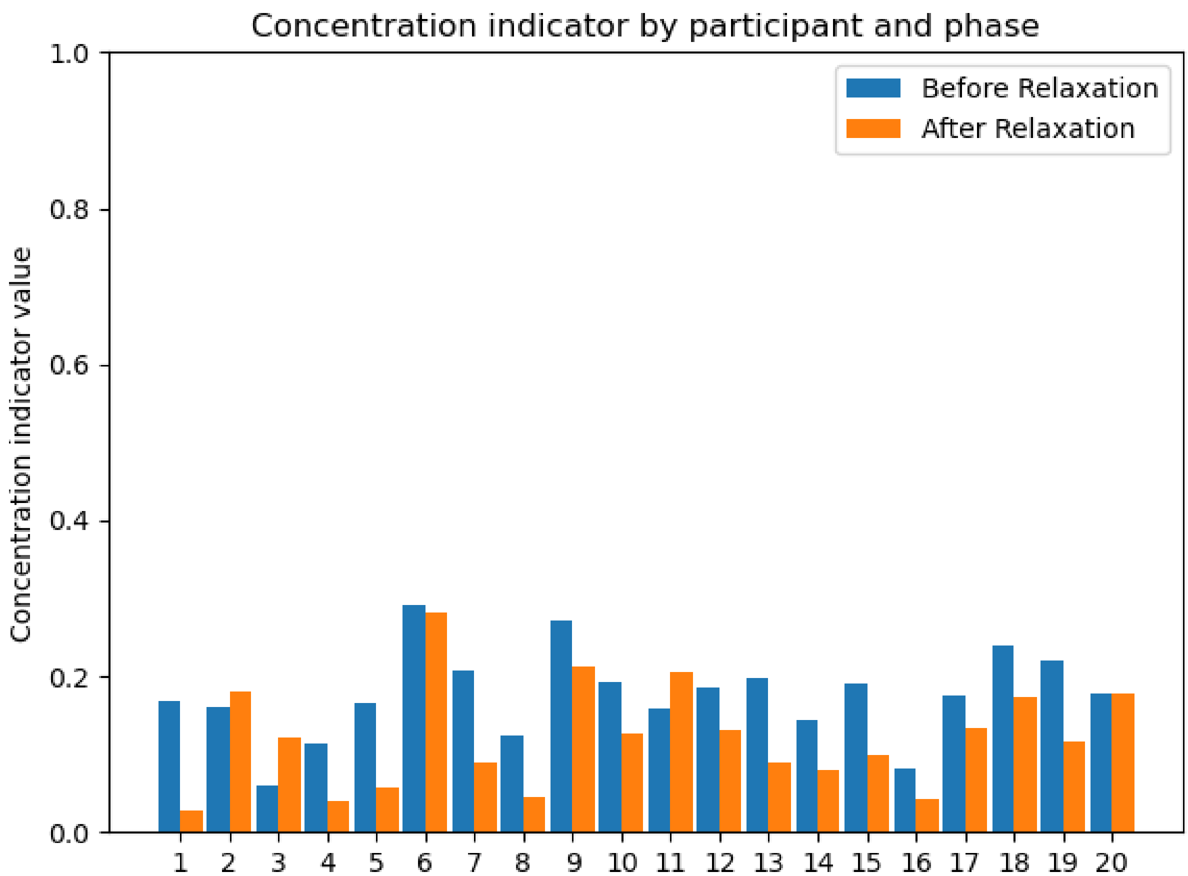

FIGURE 5.4 – Concentration indicator levels by participant and phase.

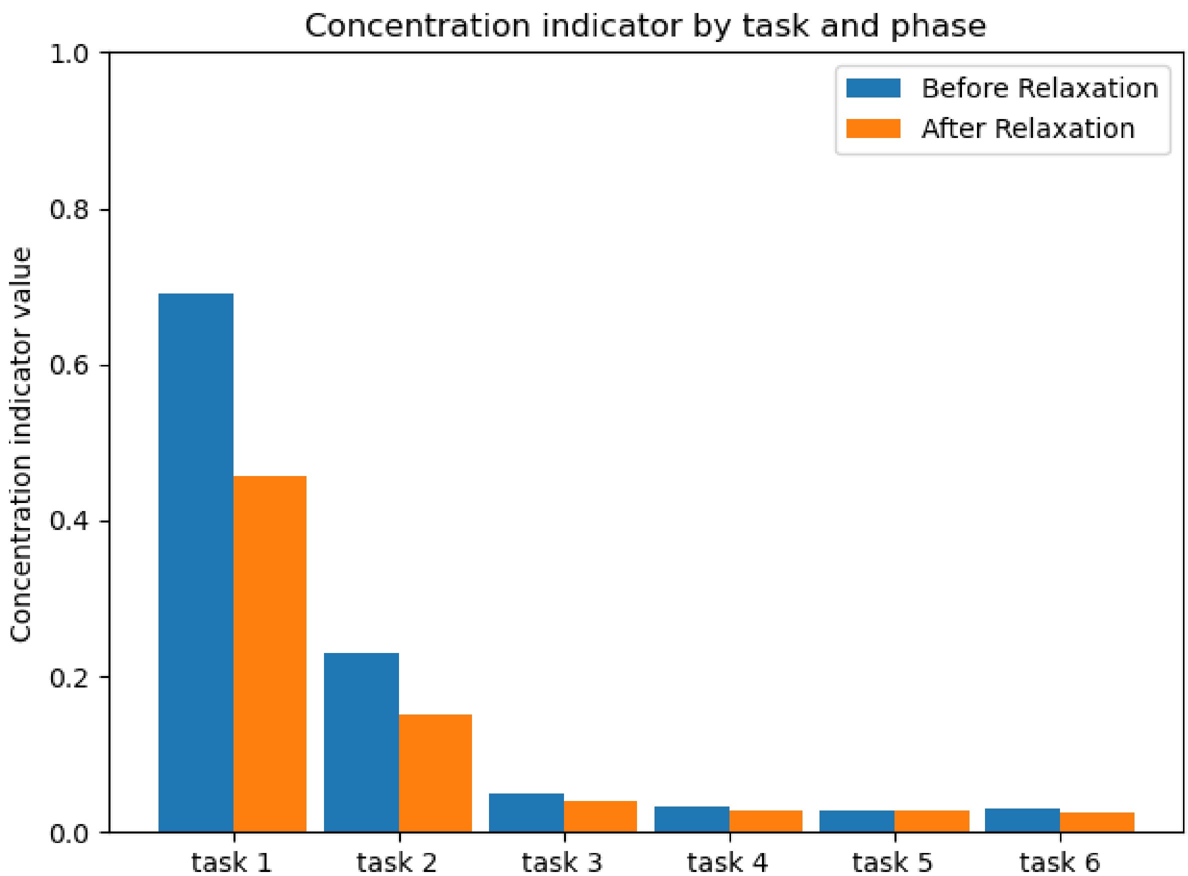

FIGURE 5.5 – Concentration indicator levels by task and phase.

Figure 5.6 shows the average distraction levels by participant and phase (before relaxation and after relaxation). Levels of **distraction** after relaxation decreased on average by 15% across all participants and was higher before relaxation for 14 participants. Figure 5.7 shows the average distraction levels by task and phase. The levels of distraction decreased the most after relaxation in tasks 3, 6, and 4 in this order.

A one-tailed Wilcoxon Signed-Rank test was performed to compare the levels of distraction of participants before relaxation and after relaxation. The results from pre-relaxation (M = 0.32, SD = 0.09) and post-relaxation (M = 0.27, SD = 0.07) indicate that the relaxation in Virtual Reality resulted in a decrease in distraction levels ; z = 21.0, p = .01.

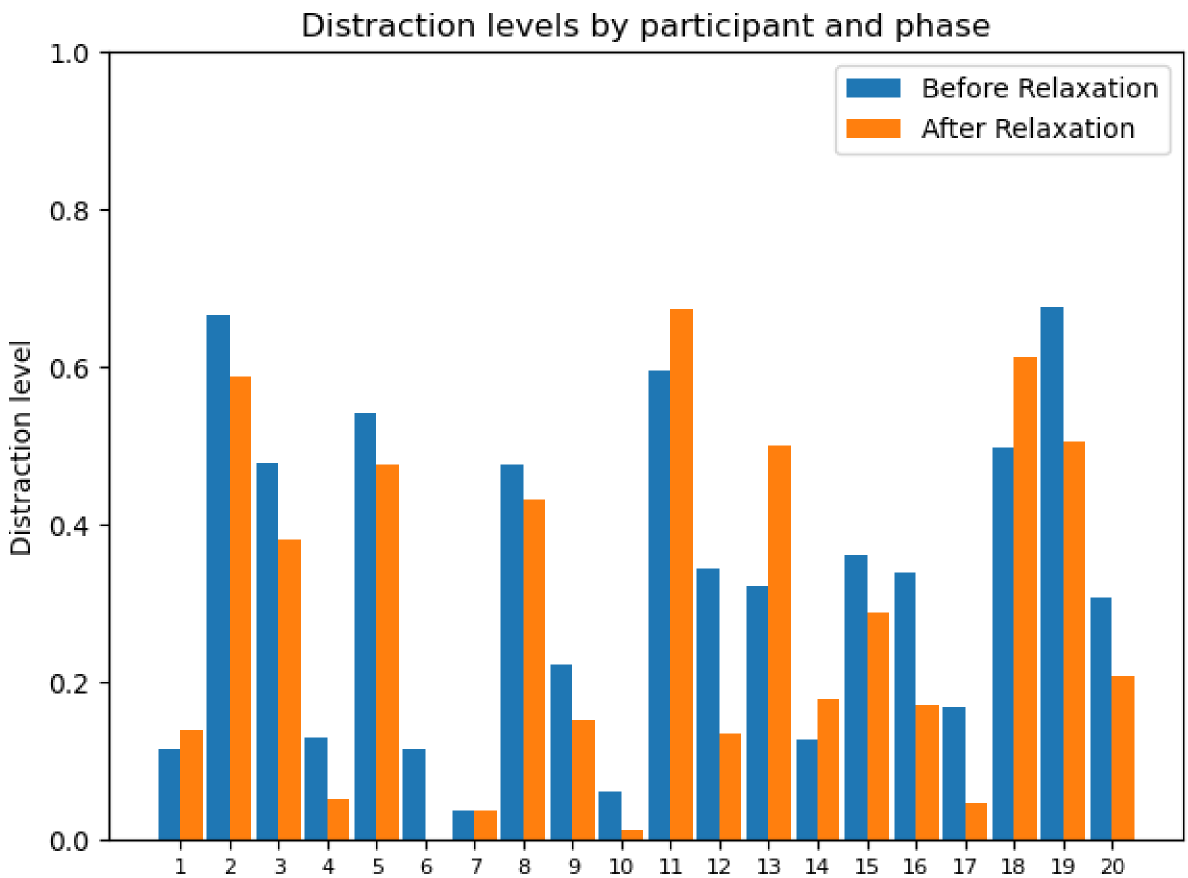

FIGURE 5.6 – Distraction levels by participant and phase.

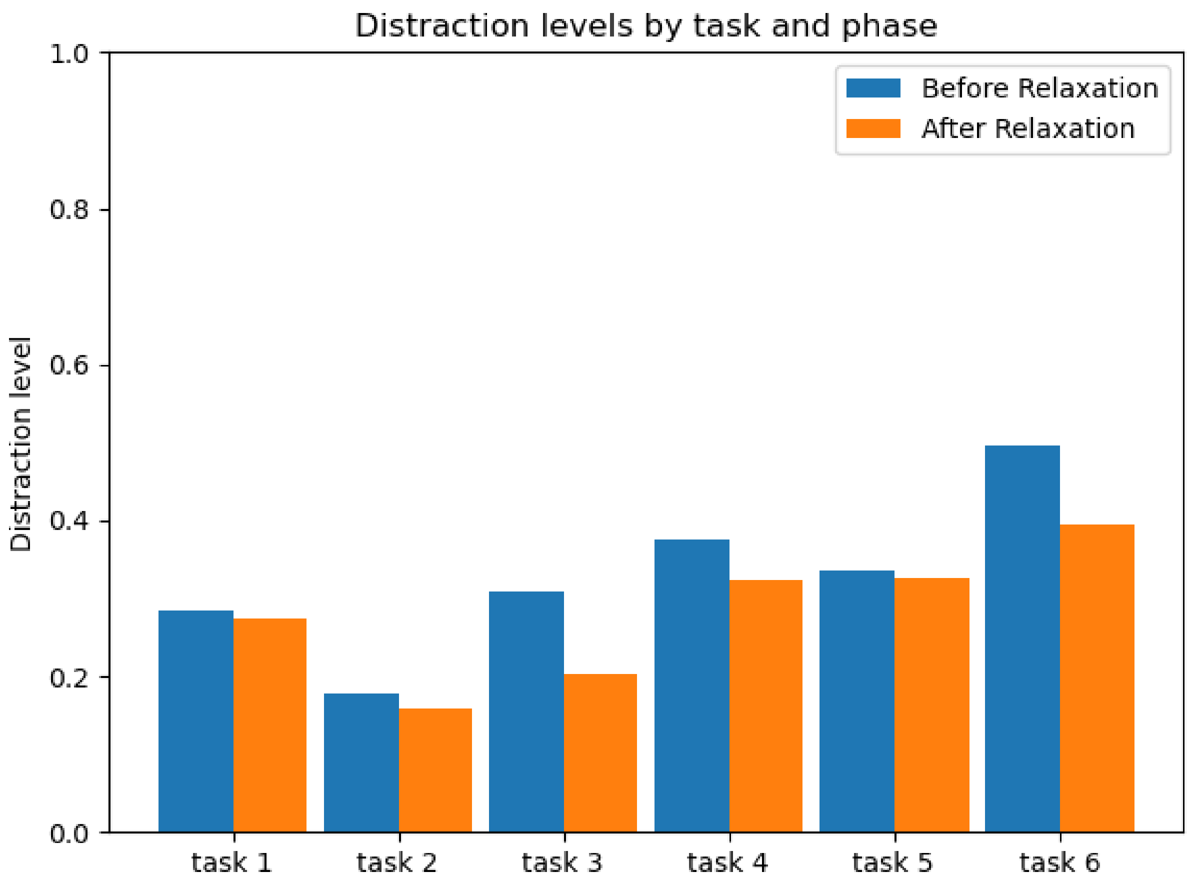

FIGURE 5.7 – Distraction levels levels by task and phase.

Figure 5.8 shows the average normalized scores across the tasks for all the participants. The scores of the participants decreased by 7% on average after relaxation compared to before relaxation and was higher before relaxation for 14 participants. Figure 5.9 shows the average normalized scores across the participants for all the tasks. The decrease in scores after relaxation was most significant in tasks 4, 1, and 6 in this order.

A one-tailed Wilcoxon Signed-Rank test was performed to compare the scores of participants before relaxation and after relaxation. The results from pre-relaxation (M = 0.84, SD = 0.27) and post-relaxation (M = 0.78, SD = 0.31) indicate that the relaxation in Virtual Reality resulted in a decrease in the scores of participants ; $z = 153.0$, $p = .03$.

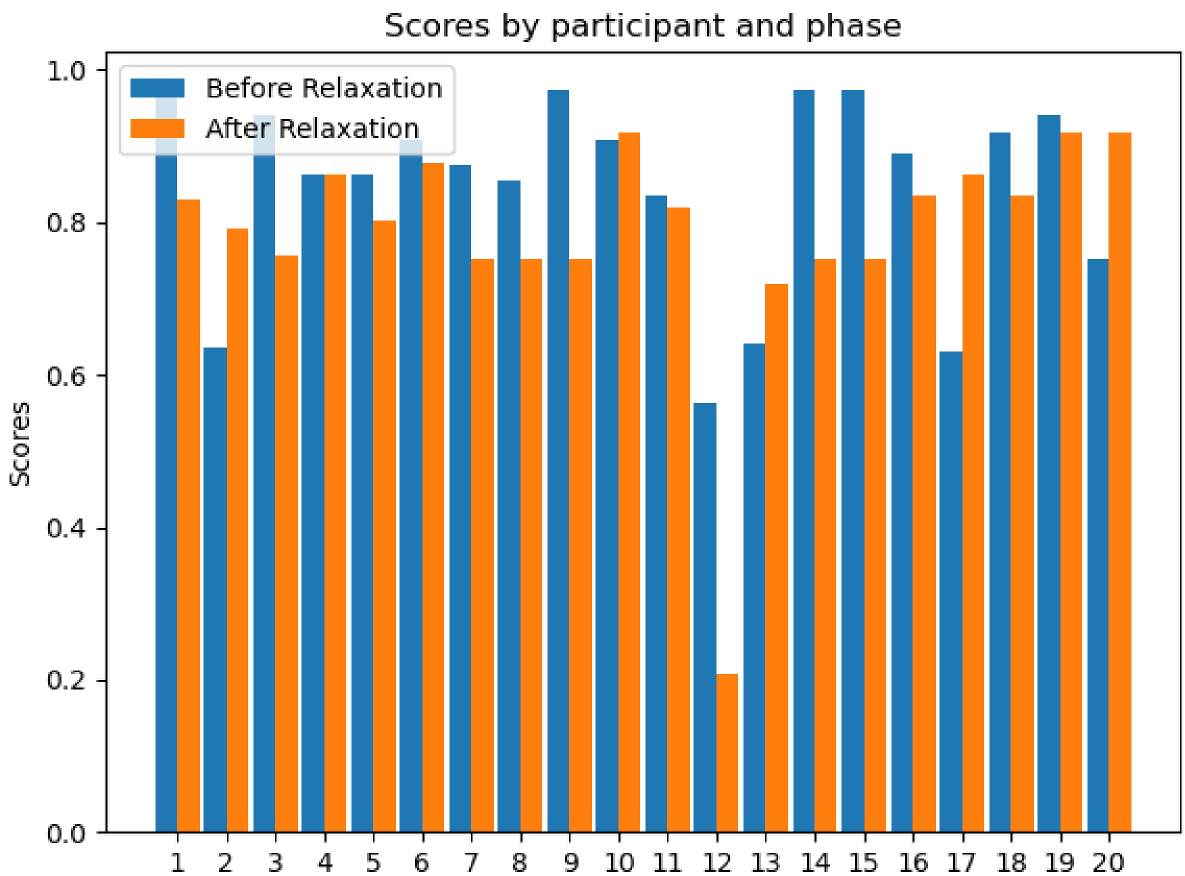

FIGURE 5.8 – Normalized scores per participant and phase.

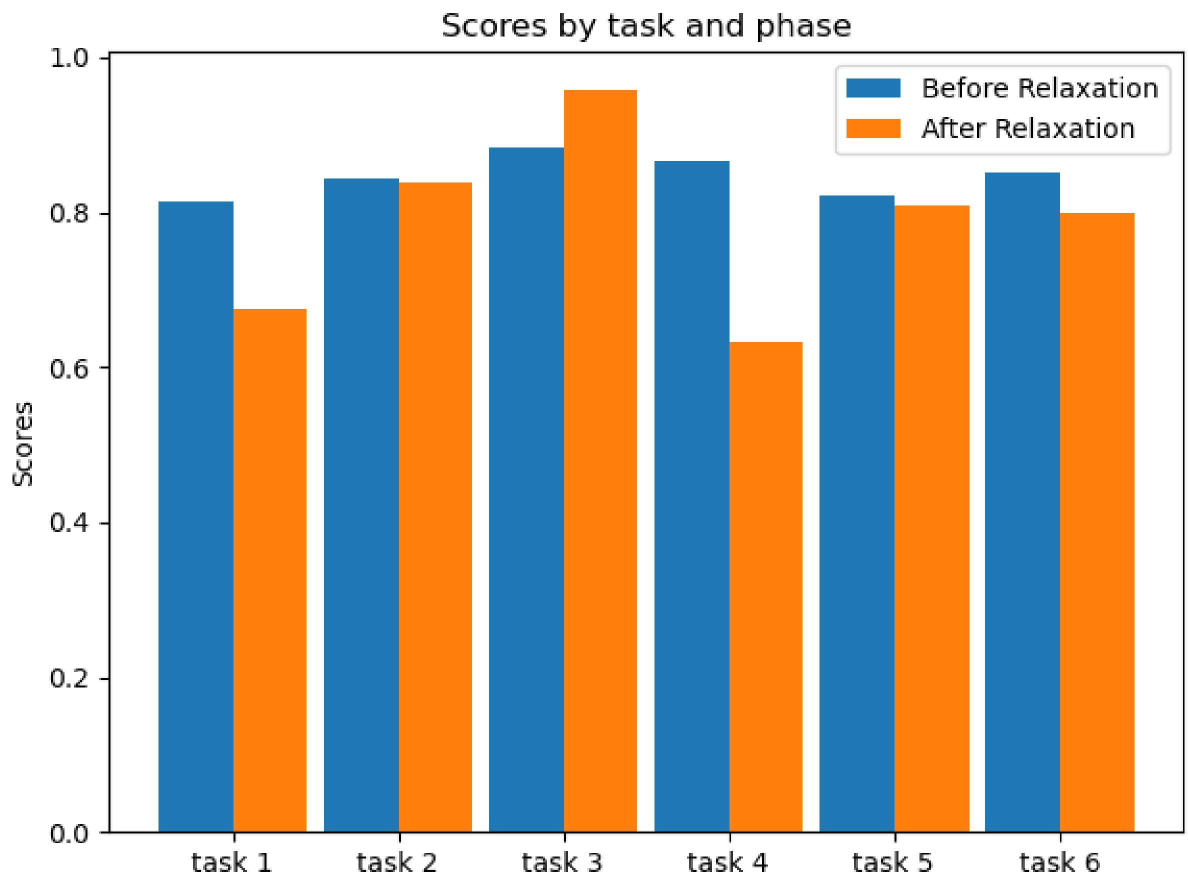

FIGURE 5.9 – Normalized scores per participant and phase.

We used the Wilcoxon Signed Rank test to validate the results similarly to 3.2.3. The Wilcoxon Signed-Rank test was used instead of the Student t-test to investigate differences between the two groups because data did not respect the normality assumption, but conditions to use the Wilcoxon Signed-Rank test were met.

5.5 Discussion

The purpose of this study was to find a means to detect and monitor **concentration**, and **distraction**, and to find methods to improve the attention of individuals while completing cognitive tasks in a Virtual Reality environment using EEG and Eye Tracking technologies. In order to do that, we designed an experiment in two steps. In the first step, we manipulated participants' attention levels experimentally using cognitive tasks and distractors. In the second step, participants completed a set of cognitive tasks before trying relaxation to improve their concentration and decrease their distraction, then completed another set of cognitive tasks. We hypothesized that : 1) it is possible to detect and monitor the concentration and distraction levels using EEG and Eye Tracking. 2) Concentration of participants will improve after relaxation and their distraction will decrease compared to before the relaxation period.

First, we verified the **attention** levels of participants using data from EEG. The Beta/Theta ratio was previously used as an indicator of attention levels ; other indicators have also been used previously, including the Beta/Alpha ratio and Theta/Alpha ratio. After computing the Beta/Theta ratio, results indicated levels of attention of participants when solving the tasks were higher than the levels of attention of participants when distractors appeared on the screen, suggesting that participants were able to focus on the tasks and that participants were distracted by the objects appearing on-screen. Since the data did not follow a normal distribution, and since the variance of the two groups of data (distracted and concentrated) was not homogeneous, we could not validate these results using paired t-test. Instead, results were validated using Wilcoxon signed-rank test.

Next, means to detect the participants' **concentration** and **distraction** were computed using data from the first part. For EEG, a real-valued indicator was computed using Beta/Theta values at 14 channels. We used LDA to produce an indicator that is easy to understand and interpret as the probability of being concentrated. The channels F8, P4, O2, and F7 in this order had the highest absolute weights, which is in accordance with the literature to some extent [18, 46], about frontal and parietal lobes being relevant for measuring **attention** levels. The EEG indicator could also be used to discriminate between "concentrated" and "not concentrated" states. The model achieved an F1-score of 73% on a participant-independent setting with LPGOCV, which is significantly above the 50% chance level.

The best model to discriminate between "distracted" and "not distracted" states using eye features used Logistic Regression and achieved an 89% F1-score when evaluated in the manner of the EEG model. The features that contributed the most were the number of saccades, and the number of fixations in this order, while the features least relevant were the average pupil diameter and the average angle of eye vergence. Surprisingly, the number of blinks was not the least relevant feature as the window length was six seconds, hence blinking was not likely in this short window. Saccades and fixations were computed using a simple velocity-based algorithm [64]. Eye features were all computed manually using methods from literature and were not the focus of the study, suggesting that the performance of detection of **distraction** could be significantly improved using specialized libraries.

The choice of the window length for dataset samples was based on the trial. We tried numerous values (1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 15, and 30) for EEG data as well as eye tracking data and tested the corresponding sets on our classification problem. Eye tracking classification was significantly more robust to window length change than EEG classification. Window length 6 produced the best results. We tried different sampling techniques, similarly to [8]. We also tried choosing "concentrated" samples at different moments of the "concentrated" period; we tried three alternatives. We tried choosing samples at the beginning of the "concentrated" period, at 10 seconds, and at 20 seconds. The best alternative was 10 seconds and was used in this study.

To investigate the second hypothesis, we used the **concentration** indicator and the **distraction** detection model developed before to monitor retrospectively the concentration and distraction levels before and after going through relaxation, we also computed the scores of the participants in each cognitive task before and after relaxation.

Results revealed lower concentration levels after relaxation, suggesting our method to restore attention and increase concentration was not effective. These results correlate with the scores of the participants where the scores after relaxation were lower compared to before relaxation. Together, these results are in conflict with previous findings where relaxation improved the performance of participants in **attention** tasks [12, 28].

Our attention restoration method might not have worked for many reasons. The experiments in this study (40 minutes) lasted significantly longer than the experiments of Hamdi et al. (20 minutes) [12], double the duration on average. Moreover, before starting the experiment, the participants had to wear an EEG cap, a chinstrap, another cap, and an Eye tracking headset 4.4, which represents a significant load over the head of their head. Because of these reasons, many participants reported pain at the middle of the experiment (starting of the second part of the experiment) due the Eye Tracking headset pressing the comb EEG electrodes. in [52], the authors summarize clinical and preclinical research on the effects of pain on cognitive function. They found that pain can impair attention, memory, and executive function, leading to reduced concentration. Pain might be the cause why the relaxation did not lead to the expected outcome.

Furthermore, the long duration of the study may have induced a mental fatigue state, as many participants reported. In [14], the authors reviewed the effects of mental fatigue on cognitive performance, highlighting that fatigue can impair attention, decision-making, and response inhibition. These cognitive declines can result in reduced concentration and overall task performance. Finally, Reports of the participants in our study also included boredom during relaxation due to repetitive and long process. The boredom could also be another reason why the relaxation was not effective.

Results from the monitoring using the Eye Tracking suggest the distraction of the participants decreased after relaxation compared to before relaxation, which is in conflict with the findings that the concentration, as well as the tasks' scores, decreased after relaxation. Many alternatives could be considered. The relaxation might have really been effective at the visual level of attention, which could have lead to a decrease in distraction levels since the distraction detector uses Eye Tracking data, but we believe this might not be the reason. A more likely explanation for this phenomenon could be the mental fatigue mentioned before. We did not intentionally include any distractors in the second part of the experiment and the participants did not report any factor that could have drawn their attention away from the main tasks, thus, they were only focused on the tasks. Therefore, the decrease in distraction levels could be a direct consequence of the decrease of the cognitive resources due to mental fatigue [14]. Our distraction detection tool relies on the fact that there are more eye movements and there are more saccades during distraction periods, and mental fatigue could affected those indicators.

5.6 Summary

In this chapter, details on the results of the analyses carried out in this study are shown.

The purpose of the study was to develop means to measure **attention**, **concentration**, and **distraction** levels, as well as to improve the concentration levels of participants while completing cognitive tasks in virtual reality.

Collected data were first used to create a set of data. To do that, two parameters relevant to dataset creation were investigated, sample window length T and sample moment. T=6 and sample moment middle yielded the highest F1-score and were thus used in subsequent analyses.

Next, the levels of **attention** of participants were compared between **concentration** periods and **distraction** periods using the Beta/Theta indicator of attention, and results showed that the levels of attention of participants were higher during concentration compared to during distraction.

Finally, the datasets created before were used to develop means to detect and monitor **concentration** and **distraction** levels. The EEG dataset was used to create a real-valued indicator of concentration levels, while the Eye Movements dataset was used to create multiple distraction detection models that achieved 89% F1-score. The EEG concentration indicator model was also used to detect concentration in a binary setting and achieved a 73% F1-score. EEG and Eye Tracking models were evaluated using LPGOCV with p=4.

To achieve the second goal, participants completed two sets of cognitive tasks before and after relaxation. Comparison using the **concentration** indicator developed before suggested that relaxation did not improve participants' concentration levels but decreased them.

CHAPITRE 6

CONCLUSION

The first purpose of this study is to develop a means to assess the attentional state of individuals using EEG and Eye Tracking technologies while completing cognitive tasks in a Virtual Reality environment, and use it as a monitoring tool. The second purpose is to find methods to improve the attention levels. We hypothesized that levels of concentration, and distraction of participants could be detected and monitored, and that relaxation would increase the concentration levels of participants, and decrease their distraction.

In order to collect data and investigate the two hypotheses, an experiment in Virtual Reality was developed. It was divided into two parts. The first part was used to investigate the first hypothesis, while the second part was used to investigate the second hypothesis.

In the following sections, the main findings in each chapter are summarized. Novelty in **concentration** methodology and experimentation paradigm is presented. Then, the main findings during the analysis are presented, as well as the results.

6.1 Experiment development

The experiment was developed using Unity, a popular game engine. It was divided into two parts. The first part was used to investigate the first question ; detection of **concentration** and **distraction**, while the second part was used to study the effects of relaxation on concentration and distraction levels. The entire experiment was completed in VR.

The first part consisted of three tasks. Mental arithmetic is a convergent thinking **attention** task. Anagram, a divergent thinking attention task. Digit memorization, convergent thinking, memory task. Tasks were either used in previous research on attention or supported by attention theory.

A distraction system was added in order to avert participants' attention from the main task and induce distraction.

The second part consisted of two sets of cognitive tasks before and after relaxation. The implementation was already provided for this study, and we only had to integrate it into the first part of the experiment.

The development of the experiment was iterative. Each time, feedback and behavior of early version testers during the experiment served for the next version.

6.2 Dataset Creation parameters

In order to maximize the performance of our models, datasets with different sample window lengths and sample moments were compared, and the best parameters were used for the rest of the study.

While Eye movements datasets were robust to parameter changes, EEG datasets were very sensitive to parameter changes for high and low values. EEG and Eye movement datasets performance changes relative to parameters were mostly correlated; i.e., EEG datasets performance was highest when Eye Movements datasets performance was also highest, and vice versa.

6.3 Feature Extraction

To study **attention**, data from two biosensors were obtained, EEG and Eye Tracking, while participants completed cognitive tasks in a virtual reality environment.

The EEG headset used dry electrodes, and The Eye tracking system was integrated into the virtual reality headset. Previous studies have already validated these tools for research.

Absolute power spectral density was computed from recorded EEG data and power bands Delta, Theta, Alpha, Beta, and Gamma were extracted from 14 EEG channels resulting in 70 features. Feature extraction was done using BrainFlow library.

Feature extraction from Eye movements data was done manually. Saccades and fixations were computed using a velocity-based algorithm from previous research. Features also included blinks, eye vergence, and pupil diameters.

6.4 Experiment Validation

In order to validate our **distraction** method, an indicator of **attention** levels from previous research was used to compare the attention levels of participants while concentrating and while being distracted. Results showed that the attention levels of participants were significantly higher during **concentration** periods than during distraction periods.

Results were validated using the Wilcoxon Signed-Rank test, showing that using distractors to divert the visual attention of participants away from the cognitive tasks decreased the attention levels of participants.

6.5 Detection and Monitoring of Concentration and Distraction

In order to answer the first research question and investigate the first hypothesis, extracted features from EEG and Eye Tracking were separately used to create two sets of data.

The EEG dataset was used to measure and detect the **concentration** state. We successfully created a real-valued indicator of concentration. moreover, while testing the indicator in a binary classification task with “concentrated” and “not concentrated” states, the model performed significantly better than the chance level, suggesting the indicator could be used to assess concentration levels.

The eye Movements dataset was used to detect the **distraction** state. Multiple machine learning models for binary classification tasks with “distracted” and “concentrated” states were trained and tested. All models performed significantly higher than the chance level and outperformed the far EEG classification model.

While distraction detection models using Eye Tracking performed significantly better than concentration detection models using EEG, data from EEG could be used to produce a real-valued indicator of the concentration levels of participants.

The resulting models were used later to create tools to monitor retrospectively the concentration and distraction levels of participants during the second part of the experiment.

6.6 Improving Attention levels using Relaxation

To answer the second research question and investigate the second hypothesis, extracted features from EEG and Eye Tracking were separately used to create two sets of data. The models we developed earlier were used to create tools to monitor retrospectively the concentration and distraction levels of participants during the second part of the experiment.

Relaxation had positive effects on the **attention** levels of participants in previous research. In order to Answer the second question, we used the **concentration** levels indicator and the **distraction** detection tool to compare participants' data before and after going through relaxation.

Results did not suggest improvement in concentration levels, for any participant. Furthermore, results showed that the concentration levels of all participants decreased after relaxation, which was in contrast with previous research. Thus, our method to improve the concentration levels of participants was not effective and did not show promise. On the other hand, the distraction levels of the participants using eye movements decreased after relaxation.

6.7 Limitations

This study used three technologies : Virtual Reality, EEG, and Eye Tracking. Considering that all three tools needed a lot of resources, the experiments were done using two computers. Hence eye tracking data and EEG data were collected on different computers, and the time between the two computers was synchronized manually with another time server before starting each experiment. This method resulted in a time lag of no more than half a second between time annotations of eye tracking data and EEG data. Eye tracking data were recorded in the same computer as the VR experiment, which implies eye tracking data were perfectly synchronized with the experiment, whereas EEG data were recorded in a different computer than the VR experiment, which implies EEG data were not perfectly synchronized with the experiment and a time lag of less than half a second existed between EEG data and the VR experiment. Much research on EEG related to this study uses analysis methods highly sensitive to time, such as N100, which is observed approximately 100 milliseconds after the onset of a stimulus. As a result, many important EEG analyses methods such as Event-related potentials (ERPs) are out of the scope of this study and could be an exciting direction for future research.

6.8 Future Directions

As cited in section 6.7, this study did not make use of all well known and used EEG features. Event-related potentials (ERPs) have been widely used in attention research, thus, including such new features can greatly improve the detection and quantification capabilities of concentration models.

Eye tracking in Virtual Reality is relatively new and still maturing, thus, specialized tool to compute eye movements from the VIVE Pro Eye VR HMD are still either nonexistent, or very expensive. Due to that, eye Movements features were computed manually in this study, and were limited to 10 features. Virtual Reality is rapidly developing and gaining popularity. Therefore, providing an open source feature extraction tool that works for VR HMDs equipped with eye tracking technology could accelerate the advance in attention research, and in other field.

In this study, our method to increase concentration did not work and even the scores of the participants decreased after relaxation which contradicts [12]. A difference between the two studies, is that in our study prior to the relaxation part, the participants completed other cognitive tasks for 20 minutes. Therefore, the participants were in a state of mental fatigue and most likely needed a longer relaxation to restore their resources. The scenario in our study is most likely to happen in real life, one will not rest or relax until he is tired, which is more likely to happen after at least one or several hours. Therefore, we recommend future research on the restoration of attention to induce a mental fatigue state before doing the relaxation procedure, and ensure that the relaxation is long enough for the participants to recuperate.

Another report we had from the participants was the boredom during relaxation due to the length of the train travel which was six minutes approximately. Six minutes is not supposed to be a long period of time, but the fact that the participants could not move, but just rotate in the virtual environment, made it seem like it was a long period of time. This study was not the only ART study in VR where the participants were not able to move as it is common practice. One of the reasons why the open spaces where the most relaxing in [29] is the fact that they give one a sense of freedom and belonging to the environment, which is not present in current ART studies that uses VR. Giving the possibility of moving and interacting with the environment to the participants is essential to improve the effects of relaxation and diminish the gap between the experiences in natural environments and virtual ones.

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