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Enhancing Motor Imagery-Based Brain-Computer Interface Efficacy Using Multisensory Virtual Reality Training

By

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Abstract

The number of stroke survivors suffering from motor impairment and other disabling conditions is on the rise around the globe. The use of motor imagery (MI)-based brain-computer interfaces (BCI) has shown promise as a neurorehabilitation tool for post-stroke rehabilitation therapy. BCIs have been developed to allow users to communicate with the external world by translating brain activity into control signals. MI has been a popular paradigm in BCI control where the user imagines movements of, e.g., their left and right limbs and classifiers are then trained to detect such intent directly from electroencephalography (EEG) signals. For some users, however, it is difficult to elicit patterns in the EEG signal that can be detected with existing features and classifiers. As such, new user control strategies and training paradigms are highly sought-after to help improve motor imagery performance. VR training has emerged as one potential tool where improvements in user engagement and level of immersion have shown to improve BCI accuracy. In this thesis, we take the first steps to explore if multisensory VR training, where not only audio-visual feedback is provided, but also haptic and olfactory, can further improve levels of user experience, and ultimately, improve BCI accuracy. Therefore, as a first step, we explored the influence of multisensory VR experiences on the user's perceived sense of realism, presence, immersion, and engagement, as well as overall quality of the experience. Next, a BCI-embedded VR headset, an off-the-shelf scent diffusion device, and a haptic glove with force feedback were used to develop a training protocol aimed at improving motor imagery detection. Experiments showed that multisensory training boosted MI detection significantly relative to conventional audio-visual VR training. In particular, increased activity in the six common spatial pattern filters used were also observed after the multisensory training phase and peaks in accuracy could be achieved with shorter window duration (6-7 seconds) relative to the optimal durations needed prior to training (8 seconds). Overall, these findings suggest that multisensory immersive training could lead to significantly better motor imagery performance, thus may offer a new paradigm for future MI-BCI studies.

Keywords: Virtual reality, multisensory, immersive media experience, quality of experience, physiological computing

Résumé

Le nombre de survivants d'un accident vasculaire cerebral (AVC) souffrant de déficiences motrices et d'autres troubles invalidants est en augmentation dans le monde entier. L'utilisation d'interfaces cerveau-machine (ICH) basées sur l'imagerie motrice (IM) s'est avérée prometteuse en tant qu'outil de rééducation neurologique pour la thérapie post-AVC. Les ICH ont été développées pour permettre aux utilisateurs de communiquer avec le monde extérieur en traduisant l'activité cérébrale en signaux de contrôle. L'IM est un paradigme courant dans le contrôle des ICH, où l'utilisateur imagine des mouvements, par exemple de son bras gauche ou droit, et où des classificateurs sont ensuite entraînés à détecter cette intention directement à partir des signaux d'électroencéphalographie (EEG). Pour certains utilisateurs, cependant, il est difficile d'obtenir des modèles dans le signal EEG qui peuvent être détectés avec les caractéristiques et les classificateurs existants. C'est pourquoi de nouvelles stratégies de contrôle de l'utilisateur et de nouveaux paradigmes d'apprentissage sont très recherchés pour aider à améliorer les performances d'IM. L'entrainement en réalité virtuelle (RV) est apparue comme un outil potentiel où l'amélioration de l'engagement de l'utilisateur et du niveau d'immersion a permis d'améliorer la précision les ICH. Dans cette thèse, nous prenons les premières mesures pour explorer si la formation RV multisensorielle, où non seulement le feedback audio-visuel est fourni, mais aussi haptique et olfactif, peut encore améliorer les niveaux d'expérience de l'utilisateur, et finalement, améliorer la précision des ICM. Par conséquent, dans un premier temps, nous avons exploré l'influence des expériences RV multisensorielles sur le sentiment de présence, d'immersion, de réalisme et d'engagement perçu par l'utilisateur, ainsi que sur la qualité globale de l'expérience. Ensuite, un casque de RV intégré à un ICH, un dispositif de diffusion d'odeurs et un gant haptique ont été utilisés pour développer un protocole d'entraînement visant à améliorer la détection des IM. Les expériences ont montré que l'entraînement multisensoriel a considérablement amélioré la détection de l'IM par rapport à l'entraînement RV audio-visuel conventionnel. En particulier, une activité accrue dans les six filtres de motifs spatiaux communs utilisés a également été observée après la phase d'entrainement multisensorielle et des pics de précision ont pu être atteints avec une durée de fenêtre plus courte (6-7 secondes) par rapport aux durées optimales nécessaires avant la formation (8 secondes). Dans l'ensemble, ces résultats suggèrent que l'entraînement immersif multisensoriel pourrait conduire à une amélioration significative des performances d'IM, ce qui pourrait offrir un nouveau paradigme pour les futures études ICH-IM.

Mots-clés: Réalité virtuelle, multisensoriel, expérience média immersive, qualité d'expérience, informatique physiologique

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List of Abbreviations

ACR	Absolute category rating
ADL	Activities of daily living
AI	Arousal index
ARAT	Action research arm test
AV	Audio-visual
AVH	Audio-visual-haptic
AVS	Audio-visual-smell
AVSH	Audio-visual-smell-haptic
BB	Biceps brachii
BCI	Brain-computer interface
CV	Consumer version
DK	Development kit
EBR	Eye blink rate
ECG	Electrocardiogram
ECR	Extensor carpi radialis longus
ECU	Extensor carpi ulnaris
EDC	Extensor digitorum comunis
EEG	Electroencephalography
EI	Engagement index
EMG	Electromyography
EOG	Electrooculography
EQ	Embodiment questionnaire
ERD	Event-related desynchronization
ERS	Event-related synchronization
FAA	Frontal alpha asymmetry
FCR	Flexor carpi radialis
FCU	Flexor carpi ulnaris
FES	Functional electrical stimulation
FMA-UE	Fugl–Meyer assessment-upper extremity
fMRI	Functional Magnetic resonance imaging
fNIRS	Functional near-infrared spectroscopy

HIF	Human influential factor
HMD	Head-mounted dsplay
HR	Heart rate
IMEx	Immersive media experiences
IMU	Inertial measuring units
JBI	Joanna Briggs Institute
MAS	Motor assessment scale
MI	Motor imagery
MoCA	Montreal cognitive assessment
MRI	Magnetic resonance imaging
PICOS	Population, intervention, comparison, outcome, and study design
POV	Point of view
PPG	Photoplethysmogram
PQ	Presence questionnaire
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
QoE	Quality of experience
ROB	Risk of bias
ROM	Range of motion
SIS	Stroke impact scale
SSQ	Simulator sickness questionnaire
TB	Triceps brachii
tDCS	Transcranial direct current stimulation
TLX	Task load index
VI	Valence index
VMIQ2	Vividness of movement imagery questionnaire
VO	Visual-only

Synopsis

0.1 Introduction

Des statistiques récentes ont montré qu'une personne sur quatre âgée de plus de 25 ans souffrira d'un accident vasculaire cérébral (AVC) au cours de sa vie, 60% d'entre eux se produisant chez des personnes de moins de 70 ans [2]. Avec plus de 13 millions de nouveaux cas signalés chaque année dans le monde, l'AVC est connu pour causer des handicaps cognitifs et physiques à long terme, affectant ainsi la qualité de vie ce ceux qui y survivent [3]. Pour aider à améliorer les activités de la vie quotidienne, la rééducation physique est recommandée immédiatement ou dans les six mois suivant l'apparition de l'AVC afin de maximiser les chances de réussite [4]. Dans l'ensemble, selon les principes de la théorie de l'apprentissage moteur, la plasticité neuronale peut être modulée davantage si la méthode d'entraînement est répétée intentionnellement avec un nombre suffisant de répétitions [5]. En fait, il a été démontré que la fréquence des séances de rééducation et leur intensité sont les facteurs clés de la récupération [6].

Cependant, dans beaucoup d'endroits dans le monde, l'accès plusieurs fois par semaine à des professionnels de la santé spécialisés dans la rééducation n'est pas possible en raison du coût élevé, de la disponibilité du personnel ou de la couverture d'assurance, pour ne citer que quelques facteurs. Ainsi, les séances de rééducation de routine sont rarement réalisées [7]. Pour surmonter cette limitation, des outils de rééducation à domicile ont été explorées par le biais de médiation technologique. La réalité virtuelle (RV) est donc apparue comme une option peu coûteuse, engageante, interactive, efficace, et qui a montré une amélioration des résultats fonctionnels tout en diminuait les niveaux de dépression [8].

Récemment, la RV combinée à un exosquelette ou à des outils informatiques physiologiques a été proposée pour améliorer la rééducation des membres supérieurs/inférieurs, le contrôle de l'équilibre, la marche ainsi que les performances de la démarche [9; 10; 11; 12; 13; 14; 15; 16]. Les environnements virtuels dynamiques et personnalisés peuvent alors être facilement mis à jour pour s'adapter aux interventions spécifiques de l'utilisateur. C'est à dire qu'ils peuvent être adaptés à un plan de rééducation spécifique pour un patient, de permettent de suivre automatiquement la progression du patient et d'ajuster la tâche en conséquence. Des dispositifs d'acquisition de données

et peu coûteux pour monitorer l'électroencéphalographie (EEG), l'électromyographie (EMG) et l'électrooculographie (EOG) ont donc été étudiés dans le cadre de nouvelles interventions.

Les interventions basées sur la RV reposent sur l'interaction du patient avec des objets virtuels par le biais de mouvements actifs de la main ou de mouvements imaginaires détectés par une interface cerveau-machine (ICM) [17; 18; 19] ou par biofeedback [20]. Des recherches récentes ont montré que la modulation de la neuroplasticité par la RV peut améliorer la fonction motrice et la force musculaire des survivants d'un AVC [21]. Le paradigme de l'imagerie motrice (IM), par exemple, a montré qu'il engageait les mêmes circuits neuronaux sous-jacents associés aux actions imaginées et exécutées [22]. Par conséquent, les tâches d'IM sont largement utilisées pour explorer la plasticité et le contrôle neuronaux chez les individus sains et les patients [17]. Ainsi, les tâches d'IM ont été principalement appliquées à différentes fins, telles que l'amélioration des niveaux d'attention [23], la réduction du trouble de stress post-traumatique chronique [24], et la rééducation après un AVC [25].

Avec les systèmes de visiocasque (HMD-VR), le sentiment de réalisme et l'immersion perçue jouent un rôle clé dans la rééducation [26; 27]. Les environnements réalistes peuvent offrir un contenu plus attrayant et inciter les survivants d'un AVC à utiliser ces systèmes plus fréquemment afin d'améliorations leur qualité de vie [28]. La majorité de ces applications n'exploitent toutefois que deux sens : l'audio et le visuel. La richesse de l'expérience, au contraire, pourrait être améliorée si d'autres sens étaient stimulés [29]. Les innovations récentes en matière de dispositifs portables, notamment ceux adaptés aux applications de RV, ont permis l'émergence de ces expériences multisensorielles [30]. Par exemple, des combinaisons, des gilets, des gants et des manches haptiques font leur apparition sur le marché, offrant aux utilisateurs un retour haptique synchronisé avec l'expérience (par exemple, sentir un tir à la poitrine dans un jeu de tir). En outre, des dispositifs de diffusion d'odeurs fixés aux casques de RV peuvent fournir aux utilisateurs des senteurs en temps réel de différents arômes (par exemple, des applications de méditation avec des odeurs de lavande pour augmenter la relaxation), rendant les expériences plus réalistes et immersives. Toutefois, comme le souligne [31], le succès des nouvelles applications immersives dépendra de l'expérience qu'elles offrent à l'utilisateur et non de la technologie utilisée. À ce titre, la mesure de la qualité de l'expérience (QoE) est devenue cruciale.

0.1.1 Objectifs et contributions de la thèse

L'utilisation de HMD-VR avec les biosignaux pour des fins de rééducation est en plein essor [32]. Dans le cadre des interventions basées sur la RV, les facteurs dits d'influence humaine (FHI) jouent un rôle crucial dans l'expérience médiatique immersive perçue (IMEx). Alors que deux personnes peuvent utiliser le même casque de RV, jouer au même jeu au même endroit et avoir les mêmes objectifs, ces deux personnes peuvent avoir des expériences très différentes, avec des perceptions variables de l'immersion, de la présence, du réalisme, de l'engagement et du cybermalaise (s'apparentent aux malaises dus au mal des transports mais dans la RV). Par conséquent, les résultats cliniques et non-cliniques des interventions basées sur la RV sont fortement corrélés avec la QoE et les FHIs [33].

Cela peut être particulièrement vrai dans les expériences immersives multisensorielles où, en plus des stimuli audio-visuels, le feedback olfactif et haptique peut être utilisé pour améliorer le QoE [30]. Par conséquent, la caractérisation de ces expériences sera cruciale pour le succès des technologies multisensorielles émergentes.

Par conséquent, la première étape de cette thèse, comme discuté dans le chapitre 2, a été d'examiner systématiquement la littérature existante sur les aspects technologiques des systèmes de visiocasque, les applications de biosignaux, et les dispositifs portables qui ont été utilisés à des fins de rééducation. Cependant, l'amélioration de l'efficacité d'un tel système est liée à la fois à la qualité de l'expérience de RV et à de nouvelles stratégies de contrôle de l'utilisateur, ainsi qu'à de nouveaux paradigmes d'entrainement qui sont essentiels pour améliorer les performances des ICM.

Par conséquent, notre objectif initial était d'explorer l'impact de l'inclusion d'odeurs, d'haptiques et de la combinaison d'odeurs et d'haptiques sur la qualité d'expérience perçue et le comportement de l'utilisateur, en mettant l'accent sur la corrélation entre les mesures neurophysiologiques et les évaluations subjectives. Par conséquent, comme décrit dans le chapitre 3, nous avons mis en œuvre un environnement VR multisensoriel interactif avec l'inclusion de modalités audio-visuelles, olfactives et haptiques. Enfin, nous avons proposé un paradigme d'entraînement multisensoriel en RV pour améliorer les performances de l'ICM-IM, ainsi que ses aspects de qualité d'expérience explorés dans le chapitre 4. Nous avons discuté de l'influence de l'entrainement immersive multisensorielle sur les performances de l'IM dans le chapitre 5.

0.2 Contexte

0.2.1 Expériences immersives multisensorielles

Le concept d"immersion sensorielle" fait référence au fait d'être complètement entouré par une représentation multisensorielle du monde réel, mais dans un cadre virtuel [34]. Les expériences multisensorielles s'efforcent d'améliorer la qualité de l'expérience en renforçant le sentiment d'immersion, de présence et de réalisme de l'utilisateur, en favorisant un plus grand engagement, ainsi qu'en réduisant potentiellement les cybermalaises. Liée à l'immersion, la "présence" tourne autour des illusions de lieu et de plausibilité et indique le sentiment d'être physiquement présent dans l'environnement virtuel [35]. Le réalisme, quant à lui, fait référence à la présentation d'objets virtuels, aux graphismes et aux animations qui correspondent étroitement à ceux vus dans le monde réel [36]. L'engagement, ensuite, reflète le degré d'interaction des utilisateurs avec l'environnement virtuel [37]. Et enfin, le cybermalaise résulte du conflit entre les entrées sensorielles au cerveau, qui sont connues pour entraîner un inconfort (léger ou sévère) en termes de maux de tête, de vertiges et de nausées [38].

Les applications RV existantes s'appuient généralement sur des vidéos à 360 degrés et du son 3D pour permettre à l'utilisateur de se sentir immergé dans l'environnement. En tant qu'êtres humains, nous sommes habitués à faire l'expérience du monde en utilisant nos cinq sens, et pas seulement deux. Pour améliorer encore l'expérience et accroître le sentiment de présence et d'immersion de l'utilisateur, des études récentes ont exploré l'inclusion de différentes modalités sensorielles. Par exemple, des stimuli tactiles et somatosensoriels ont été incorporés par le biais de vibrations [39; 40], de changements de température [41], et de flux d'air [42], tandis que les diffuseurs d'odeurs ont été utilisés pour fournir des stimuli olfactifs [43; 44], et la stimulation électrique de la langue pour fournir un sens virtuel du goût [45]. La stimulation de différents sens humains crée une expérience utilisateur personnalisée et améliorée [46; 47; 48]. Dans [29], par exemple, un sentiment de présence accru a été signalé lorsque les utilisateurs étaient exposés à des stimuli olfactifs, thermiques et de flux d'air, même dans des scénarios passifs où les utilisateurs n'avaient pas à interagir avec l'environnement. De plus, il a été démontré que la rétroaction vibrotactile influence les niveaux d'engagement, améliorant l'interaction avec l'environnement virtuel [49]. Dans le domaine de la RV, l'interaction avec les objets 3D se fait généralement à l'aide de contrôleurs manuels ou de systèmes de suivi des mains. Des travaux récents ont toutefois montré les avantages de l'utilisation d'exosquelettes/gants haptiques pour fournir des indices supplémentaires sur la rigidité et la texture des objets (par exemple, [40; 50; 51]), notamment en ce qui concerne l'amélioration de l'exécution des tâches. Cependant, comme le souligne le document [30], moins de 2% des études multisensorielles publiées se sont appuyées sur plus de trois sens stimulés. On sait donc peu de choses sur l'impact des différents stimuli multisensoriels sur les FHI, ainsi que sur leur impact global sur la qualité d'expérience.

0.2.2 Mesure de la qualité d'expérience

Mesurer la qualité d'expérience des expériences multisensorielles peut toutefois s'avérer difficile. Alors que la qualité d'expérience des médias immersifs est généralement mesurée à l'aide de ce que l'on appelle les facteurs d'influence technologiques et contextuels [52], les facteurs humaines (également appelées FHI) jouent un rôle crucial dans les expériences multisensorielles. Par exemple, certaines odeurs qui peuvent être agréables pour certains peuvent être désagréables pour d'autres. De plus, pour certains, le retour haptique peut rendre la scène plus réaliste et améliorer le sentiment de présence et d'immersion, tandis que pour d'autres, il peut perturber l'engagement et dégrader l'expérience globale. Il est donc important de mesurer ces facteurs individualisés (appelés ici sous-échelles ou sous-facteurs de qualité d'expérience) en temps réel pendant que l'utilisateur est immergé, car cela permet d'adapter les stimuli sensoriels pour maximiser la qualité d'expérience. La mesure des FHI et de leur influence sur la QoE de l'IMEx peut suivre trois principes : questionnaires, analyse des données comportementales et psychophysiologiques [52]. Par conséquent, les mesures de la qualité d'expérience reposent sur des évaluations subjectives et/ou des mesures objectives pour évaluer les avantages des expériences immersives.

0.2.2.1 Évaluation subjective de la qualité d'expérience

Les questionnaires sont les plus courants et plusieurs d'entre eux ont été rapportés dans la littérature pour cibler certains aspects, comme le sentiment de présence, le niveau d'engagement et des cybermalaises pour n'en citer que quelques-uns: [53; 54; 37]. Alors que la plupart des questionnaires ciblent un seul facteur, ce n'est que récemment qu'un questionnaire unifié sur l'expérience utilisateur a été proposé, contenant 10 sous-échelles pour mesurer la présence, l'engagement, l'immersion, le flux, la convivialité, les compétences, les émotions, les conséquences de l'expérience, le jugement et l'adoption de la technologie [55]. Cependant, l'utilisation d'enquêtes papier-crayon pourrait interrompre l'expérience de l'utilisateur virtuel, en particulier celles basées sur des visiocasques (HMD). En fait, plusieurs études basées sur des HMD ont rapporté que les expérimentateurs lisaient à haute voix les questions aux participants une fois que certaines conditions de l'expérience étaient remplies afin d'éviter de rompre l'immersion en retirant le casque (par exemple, [56]). Par ailleurs, dans certains travaux, les participants remplissent les questionnaires à la fin de la session. Bien que cette méthode permette d'éviter le problème de la déconnexion de l'immersion, elle repose sur la mémoire humaine qui, dans les expériences multi-conditionnelles, s'est avérée très sensible aux erreurs [57]. Des questionnaires intégrés dans l'environnement virtuel ont donc été développés pour surmonter le problème de la déconnexion de l'immersion et des erreurs de mémoire [58; 59].

De plus, les questionnaires peuvent prêter à confusion, en particulier ceux qui portent sur les états émotionnels humains, en raison, par exemple, de l'ambiguïté des mots utilisés ou des différences dans les expressions utilisées selon les langues et les cultures [60; 61]. C'est pourquoi les approches graphiques d'auto-évaluation ont été largement utilisées [62; 63; 64]. Ces outils associent intuitivement des éléments graphiques iconiques aux émotions ressenties. Récemment, l'EmojiGrid a exploité la capacité d'utiliser des emojis pour caractériser les émotions évoquées après avoir exposé les utilisateurs à des vidéos VR 360°, montrant certains avantages par rapport à d'autres questionnaires conventionnels [65]. Néanmoins, les questionnaires ne permettent pas un suivi en temps réel des FHI, c'est pourquoi des innovations dans les analyses comportementales et psychophysiologiques ont fait l'objet de recherches plus récentes.

0.2.2.2 Évaluation objective de la qualité d'expérience

Malgré l'utilisation répandue de questionnaires, les évaluations subjectives ne permettent pas d'évaluer en temps réel l'expérience spécifique de l'utilisateur, c'est pourquoi le monitorage et l'analyse des signaux neurophysiologiques sont apparues comme une alternative prometteuse.

Avec l'évaluation de la qualité d'expérience basée sur les biosignaux, des outils/technologies supplémentaires doivent être portés par l'utilisateur, tels que des montres intélligentes pour mesurer la fréquence cardiaque [66], ou des bandeaux pour mesurer les signaux cérébraux. Les signaux du photopléthysmogramme (PPG), par exemple, ont été utilisés pour suivre les changements dans

les niveaux de stress [67], tandis que les électro-oculogrammes (EOG) ont été utilisés pour révéler des détails sur l'attention en utilisant les mouvements oculaires [68]. De plus, les mesures de la fréquence cardiaque acquises à partir des électrocardiogrammes (ECG) ont été liées au stress et qui peut entraîner de mauvaises expériences [69]. Les signaux EEG, à leur tour, ont été proposés pour dévoiler l'association entre l'état mental et les niveaux d'engagement des utilisateurs, et leur impact sur l'expérience de RV [70]. Il a également été démontré que la charge mentale a un effet sur l'expérience globale de l'utilisateur [71], ainsi les mesures en temps réel de la charge de travail (par exemple, la puissance de la bande thêta frontale, 4-8 Hz) pourraient être utiles pour les expériences multisensorielles [72]. En outre, l'EEG a été utilisé pour monitorer les indices arousal et valence de l'utilisateur [73], tandis que certaines puissances spectrales de sous-bandes de l'EEG (par exemple, la bande bêta, 12-30 Hz) ont été liées à différents processus émotionnels dans le cerveau [74], ainsi qu'à l'exploration de jeux immersifs (bande thêta) [75]. L'asymétrie alpha frontale (FAA) a été proposée comme un corrélat du plaisir et de la satisfaction de l'utilisateur [76], ainsi que pour signifier le sentiment de présence et d'immersion dans la RV [75; 77]. Enfin, les mouvements de la tête pourraient également fournir des informations sur l'expérience, qu'il s'agisse d'états émotionnels [78] ou de cybermalaise [79]. De plus, l'analyse des orientations de la tête pourrait fournir une approximation du champ d'attention de l'utilisateur, ce qui a un lien avec l'expérience globale [80].

En général, pour l'évaluation neurophysiologique de la qualité de l'expérience, on utilise des dispositifs portables disponibles dans le commerce. Une telle approche peut présenter plusieurs inconvénients, notamment un inconfort, une interférence avec la tâche, ainsi qu'une interférence avec la collecte des signaux, ce qui limite le plein potentiel de la méthodologie. Par exemple, les montres intélligentes ou les capteurs qu'on positionne sur les doigts (par exemple, la réponse galvanique de la peau) peuvent interférer avec le placement de gants/exosquelettes haptiques, tandis que les sangles HMD peuvent interférer avec le placement de certaines électrodes EEG dans des régions stratégiques du cerveau. Néanmoins, les progrès récents en matière de bioamplificateurs portables et d'interfaces cerveau-machine (ICM) portables ont permis de placer des capteurs directement dans le visiocasque, ce qui permet de calculer ces mesures en temps réel pendant que l'utilisateur est immergé dans une expérience multisensorielle sans affecter l'expérience elle-même [81].

0.2.3 Revue systématique des systèmes multimodaux basés sur les HMD

Une recherche sur les articles de journaux en langue anglaise évalués par des pairs a été menée dans cinq bases de données, dont Scopus, IEEE, Web of Science, PubMed et Science Direct, entre les années janvier 2015 et décembre 2021. Les mots-clés suivants ont été utilisés : *(electro* OR respiration OR "galvanic skin") AND "stroke rehabilitation" AND "virtual reality"*. Les mots-clés ont été recherchés dans le titre ou le résumé des articles. Sur les 218 articles identifiés, 46 provenaient de PubMed, 16 de ScienceDirect, 59 de IEEEXplore, 38 de Web of Science et 59 de Scopus. Après sélection des articles, 12 articles portant sur le HMD-VR, les signaux physiologique multimodaux et la rééducation motrice après un AVC ont été inclus dans cette étude.

0.2.3.1 Environnement Virtuel

Le moteur de jeu Unity3D a été défini comme étant le plus courant pour la conception d'environnements virtuels, le contrôle de système haptiques et l'intégration de dispositifs externes (par exemple, des systèmes d'acquisition de signaux biologiques) dans le déroulement du jeu. Les HMD portables, qui offrent une expérience stéréoscopique proche de la réalité et une perception accrue de la profondeur et de l'immersion, ont été largement utilisés. En particulier, trois études ont utilisé le casque HTC Vive (Valve Washington, Washington, États-Unis), [82; 83; 84], tandis que les autres ont utilisé un Oculus (Oculus VR, Irvine, Californie, États-Unis), probablement en raison de son accessibilité aux SDK et de son prix inférieur. Les études ont fait état de taux de rafraîchissement d'affichage variables, allant de 60 à 90 Hz.

Pour fournir un contenu ciblé axé sur la rééducation, des environnements personnalisés ont généralement été développés, bien que deux études se soient appuyées sur des jeux pré-développés [85; 86]. Par exemple, deux études ont mis en œuvre un thérapeute virtuel pour présenter des exercices dans un environnement virtuel [87; 82]. Néanmoins, une seule étude a fourni des informations détaillées sur le processus de conception de l'environnement virtuel, y compris les propriétés des différents objets et l'ajustement de l'intensité du feedback [83]. Les autres articles examinés n'ont pas réussi à fournir des informations complètes sur les concepts centrée sur l'humain, notamment la cartographie et les modèles conceptuels [88].

0.2.3.2 Calculs physiologiques

L'informatique physiologique est apparue comme un outil puissant dans l'interaction homme-machine, permettant l'analyse en temps réel des signaux physiologiques et des informations comportementales pour améliorer l'interaction en transmettant à la machine des informations sur l'état cognitif/mental/affectif de l'utilisateur, ainsi que des informations en temps réel sur les mouvements du patient, améliorant ainsi le sentiment de personnification. En outre, les données physiologiques/comportementales peuvent donner un aperçu des processus conscients et inconscients et peuvent donc également transmettre des informations sur les états de motivations et d'intentions de l'utilisateur.

EEG Comme le montre le tableau 2.2, sept articles se sont appuyés sur des méthodes de calcul physiologique basées sur l'EEG dans leurs études de rééducation en RV. Comme l'objectif principal des études concerne l'amélioration de la motricité, la plupart des études ont acquis des signaux EEG à partir d'électrodes situées au-dessus du cortex moteur, correspondant aux positions FC3, FC4, C3, C4, C5, C6, CP3 et CP4 des électrodes du système de positionnement international 10-20. En termes de paradigmes ICM, six études se sont appuyées sur l'imagerie motrice (MI) [87; 89; 86; 90; 91; 92]. L'hypothèse sous-jacente à l'IM est que les illusions de mouvement et une forte

sensation de personnification pourraient améliorer la plasticité neuronale nécessaire à la rééducation, l'informatique physiologique et le retour d'information en temps réel contribuant à une meilleure personnification. Les patients victimes d'un accident vasculaire cérébral subaigu, par exemple, qui ont utilisé des paradigmes basés sur l'IM pourraient alors améliorer leurs résultats fonctionnels [93]. Une désynchronisation plus forte dans les bandes EEG alpha (7-13 Hz) et bêta (13-30 Hz) de l'hémisphère ipsilésionnel, par exemple, a été démontrée [94]. De plus, une asymétrie hémisphérique accrue a été mise en évidence dans les séances d'IM avec rétroaction, ce qui suggère une amélioration de la performance des tâches de motricité et une modification de l'apprentissage moteur [95; 96]. En fait, des différences dans l'asymétrie interhémisphérique chez les patients victimes d'un AVC ont été signalées par rapport à un groupe témoin [97], ce qui suggère que les biosignaux pourrait être utilisée non seulement pour personnaliser l'environnement, mais aussi pour suivre la progression et le succès de l'intervention [98]. L'impact de la rééducation basée sur le HMD a également été quantifié au moyen de comparaisons post-hoc basées sur la synchronisation/désynchronisation liée aux événements ERS/ERD [89], la cohérence corticomusculaire (c'est-à-dire, synchronisation entre les signaux EEG et EMG) [99], le rythme alpha à l'état de repos [86], et les analyses spectrales de puissance du rythme EEG [90; 91; 92].

Malgré les avantages que présente l'utilisation des ICM basées sur l'IM, des études ont signalé que la détection des tâches d'imagerie motrice à l'aide d'outils de neuroimagerie standard peut être difficile pour 15 à 20% de la population. Les études antérieures parlaient d'"analphabétisme en matière d'ICM", ce qui laisse entendre que le problème se situe au niveau de l'utilisateur. Plus récemment, la terminologie "inefficacité de l'ICM" [100] a été intégrée car elle combine les facteurs liés à l'utilisateur avec les limites du matériel (par exemple, les systèmes d'acquisition du signal et la qualité du signal) et du logiciel (par exemple, la précision des algorithmes de classification) [101]. Pour surmonter ce problème, les recherches récentes se sont concentrées sur le développement de nouvelles méthodes de filtrage, de techniques d'extraction de caractéristiques et d'algorithmes d'apprentissage automatique plus récents et plus complexes (par exemple, [102; 103; 104; 105]) pour s'attaquer à l'aspect logiciel. En outre, des améliorations des bioamplificateurs et des électrodes (secs ou à base de gel ; actifs ou passifs) ont été étudiées pour résoudre les problèmes matériels [106].

EMG L'EMG fournit des informations sur l'activité électrique des muscles. L'emplacement des électrodes est généralement déterminé en fonction de l'objectif de l'étude, c'est-à-dire l'amélioration de la fonction du membre supérieur ou inférieur. L'étude des membres supérieurs peut porter sur les muscles de la main, du poignet, du coude et de l'arrière/avant-bras, tandis que celle des membres inférieurs peut porter sur le pied, la cheville, le genou, la cuisse et la hanche. Comme le montre le tableau 2.2, seulement cinq des douze études reposaient sur des signaux EMG, deux d'entre eux ont utilisé un système sans fil Delsys Trigno (Delsys Incorporated, Natick, USA) [99; 89], deux ont utilisé des brassards Myo (Thalmic Labs) [84], et un a utilisé un bioamplificateur OpenBCI [84]. Ces systèmes fonctionnaient à des taux d'échantillonnage de 2000, 100 et 125 Hz, respectivement. En plus des analyses EMG post-hoc pour surveiller l'amélioration physique due à la rééducation

(par exemple, l'amplitude EMG, la détection de l'état de repos/actif), trois études se sont appuyées sur les signaux EMG pour cartographier le bras/la main du patient dans l'environnement RV afin d'améliorer le sentiment de personnification [99; 82; 84].

0.2.3.3 Modalité de retour d'information

Le retour d'information (feedback) est connu pour améliorer le sens de personnification et pour favoriser la plasticité cérébrale. Il est donc largement utilisé en neuro-rééducation. Les modalités de retour d'information visuelles et auditives sont la forme la plus classique de rétroaction, mais des études plus récentes ont exploré l'utilisation du retour haptique (par exemple, par les contrôleurs, comme mentionné ci-dessus) pour améliorer le sentiment d'immersion et de présence. Le retour haptique ajoute le sens du toucher à l'expérience virtuelle et augmente le sentiment d'immersion [107]. Des gants, des contrôleurs, des brassards ou même des exosquelettes peuvent être utilisés pour fournir un retour haptique [108]. Comme le montre le tableau 2.1, cinq études s'appuient sur le retour haptique, dont trois utilisent les contrôleurs du système RV pour fournir un retour par vibration [89; 83; 82], une propose un dispositif personnalisé basé sur des moteurs vibrants [86], et une utilise le dispositif UnlimitedHand (H2L Inc, Tokyo, Japon) pour fournir un retour de stimulation électrotactile [92]. Le retour haptique était principalement utilisée dans ces études pour informer le sujet de la fin d'une tâche et/ou en réponse à une interaction avec un objet spécifique dans l'environnement virtuel.

0.2.3.4 Résultats rapportés

Des outils de calcul physiologique post-hoc ont été exploités pour extraire les changements dans les biosignaux mesurés. Par exemple, [91] a signalé des différences dans l'activité EEG de l'imagerie motrice dans des environnements virtuels par rapport à l'imagerie régulière. En effet, le test ANOVA avec correction de Greenhouse-Geisser et le test du rang signé de Wilcoxon par paire ont montré un résultat statistiquement significatif dans la bande alpha ($F_{(2{,}524,\ 20{,}191)} = 4{,}800$, $p < 0.05$), entre "exécution motrice et VR (VRMP)" par rapport à la condition de contrôle. Dans la bande thêta (4-7 Hz), la différence se reflétait entre l'exécution motrice et la VRMP ($F_{(1.874,\ 14.990)} = 7.615$, $p < 0.05$). Dans plusieurs études, on a également observé que l'interaction interhémisphérique était affectée par le feedback visuel, audio ou haptique [91; 86; 89; 92]. [86] a calculé l'ERD/ERS ipsilatéral de la bande bêta en utilisant les électrodes C3 et C4. Par la suite, en effectuant un test t, une différence statistiquement significative a été observée entre la première et la dernière session ($t(199) = -16{,}921$, $p < 0.001$). De plus, il est connu que les traitements dont le niveau d'engagement est plus élevé maintiennent les patients motivés et donnent de meilleurs résultats [109]. Étant donné qu'il existe une relation directe entre l'engagement et l'attention [110] et que les déficits d'attention peuvent résulter d'accidents vasculaires cérébraux [111], l'utilisation d'outils de RV pour accroître la concentration des patients pourrait être très bénéfique. Certains rythmes (par exemple, les bandes alpha et bêta sur la

région pariétale pour le stimulus visuel), ont été liés à l'attention [112; 113; 114; 115] et associés à la fonction motrice [116].

À cette fin, [91] a trouvé une relation entre la capacité à réaliser une imagerie kinesthésique et la modulation de la bande alpha-bêta (ρ= 0,50, p < .05) et, donc, indiquant potentiellement une amélioration des niveaux d'attention. En outre, [92] a noté des niveaux d'attention plus élevés dans la stimulation visuelle-électrotactile par rapport à la condition visuelle seule, et les niveaux d'attention plus élevés se sont également avérés être corrélés avec le retour haptique et l'utilisation de l'exosquelette [117]. Néanmoins, [89] a noté que les patients présentant des déficiences plus sévères ont montré l'amélioration la plus significative en utilisant des paradigmes basés sur l'imagerie motrice dans un cadre de RV, tandis que le feedback basé sur l'EMG s'est avéré plus prometteur pour les patients présentant des déficiences légères.

Les solutions basées sur la RV s'appuient généralement sur leur sens amélioré du réalisme [118], de l'immersion et de la présence [119], et de la personnification [120] pour stimuler les performances de rééducation [121]. Pour atteindre ces objectifs, [89], par exemple, a personnalisé les modèles de main dans l'environnement virtuel pour qu'ils correspondent au teint et au sexe du patient et [82] a fourni des animations proches de la réalité d'exercices en extérieur. [90], à son tour, a exploité la régression linéaire pour examiner la relation entre la performance du neurofeedback et la personnification globale et a signalé une relation significative dans la condition expérimentale HMD-VR ($F_{(1,\ 10)}$= 8,293, p= 0,016, R^2= 0,399).

0.3 Explorer l'influence de l'expérience multisensorielle de la RV sur les utilisateurs

Au vu des résultats de la revue de la littérature, une intervention multimodale/multisensorielle basée sur le HMD, telle que la formation ICM-IM pourrait potentiellement améliorer les résultats cliniques. Cependant, nous avons d'abord tenté d'explorer le rôle de l'expérience multisensorielle de la RV sur la qualité d'expérience et le comportement de l'utilisateur, avant de proposer de nouveaux paradigmes d'apprentissage avec un retour alterné (par exemple, vibrotactile, olfactif et auditif) pour le ICM-IM. Dans cette section, un jeu VR a été développé pour combiner les retours audio-visuels, olfactifs et haptiques. Après le jeu, les participants ont été interrogés sur leur IMEx à sur cinq catégories : le réalisme, l'immersion, la présence, l'engagement et la qualité globale de l'expérience (QoE). En outre, à l'aide d'un casque VR instrumenté, nous mesurons les signaux EEG, ECG et EOG et calculons plusieurs mesures instrumentales des facteurs d'influence humains.

0.3.1 Matériels et méthodes

0.3.1.1 Participant

Les données ont été recueillies auprès de 11 participants (deux femmes, âge moyen de 25,4 ans ± 2,3 ans). Des mesures de sécurité ont été prises pour minimiser les risques liés au COVID-19, notamment en maintenant une distance sociale et en désinfectant le matériel à l'aide d'une chambre UV-C et de tampons d'alcool.

0.3.1.2 Hardware

Différents matériels ont été nécessaires pour cette expérience, notamment : (1) un casque VR, (2) un bioamplificateur pour recueillir les signaux psychophysiologiques, (3) une unité de diffusion d'odeur (scentware), et (4) des manchons haptiques. Des dispositifs abordables ont été sélectionnés pour augmenter la reproductibilité et l'accessibilité. En particulier, un Oculus Quest a été utilisé pour présenter le contenu virtuel et un bioamplificateur OpenBCI (Cyton et Daisy) a été utilisés pour enregistrer 16 canaux d'EEG, d'EOG et d'ECG à une fréquence d'échantillonnage de 125 Hz. Nous avons suivi les directives publiées sur la manière d'instrumenter les HMD-VR disponibles sur [122]. Profitant de l'emplacement des sangles du casque VR, les signaux EEG ont été recueillis dans trois régions à l'aide de 11 électrodes sèches argent/chlorure d'argent (Ag/AgCl), à savoir : frontale (Fp1, Fpz et Fp2), centrale (F3, F4, FCz, C3 et C4) et occipitale (O1, Oz et O2). Deux électrodes horizontales et deux électrodes verticales placées dans la mousse frontale du casque VR ont été utilisées pour enregistrer les signaux EOG. Deux électrodes ont été placées sur les mastoïdes comme référence, et une électrode jetable sur la clavicule gauche a été utilisée pour enregistrer l'ECG. Le bioamplificateur OpenBCI a été placé dans une boîte imprimée en 3D et montés sur la sangle supérieure du casque.

Un dispositif olfactif ION2 a été monté sur le casque et utilisé pour diffuser des senteurs à proximité du nez pendant que l'utilisateur interagit avec l'environnement virtuel. La figure 3.1 montre le casque, les électrodes ExG montées et le dispositif olfactif fixé. Enfin, un manchon haptique de bHaptics a été utilisé pour fournir un retour haptique. Un visuel des manchons, ainsi que des autres matériels utilisés, est présenté dans la Fig. 3.2c.

0.3.1.3 L'environnement de jeu

L'environnement virtuel du jeu a été mis en œuvre dans Unity3D 2021.3.25f1 et représente une forêt d'oranges dans laquelle les joueurs doivent collecter le plus d'oranges possible (voir Fig. reffig:timing2). Dans la condition impliquant les odeurs, des odeurs de fond, telles que l'herbe, les fleurs et la forêt, étaient toujours présentes pour simuler l'odeur de l'environnement. Lorsque des

oranges étaient saisies, un nuage de brume apparaissait, un “pouf” auditif était présenté dans la condition impliquant l’audio, et l’orange disparaissait pendant 3,5 secondes avant de réapparaître. Dans les conditions impliquant des odeurs, une explosion d’agrumes était également produite en synchronisation avec le contenu audio-visuel. Dans les conditions impliquant l’haptique, des vibrations dans le manchon haptique se produisaient lorsque les oranges étaient saisies avec succès. Les utilisateurs ont été invités à explorer l’environnement, à s’approcher des arbres et à ramasser autant d’oranges que possible pendant deux minutes à l’aide des contrôleurs Oculus. À la fin du jeu, alors qu’ils étaient encore dans la RV, les utilisateurs ont été invités à évaluer le niveau de présence, d’immersion, de réalisme, d’engagement et d’expérience globale qu’ils percevaient à l’aide de l’évaluation par catégorie absolue (ACR) en 5 points [123]. La boîte à outils décrite dans [124] a été utilisée pour créer l’environnement et la Fig. 3.2 montre une capture d’écran du questionnaire.

0.3.1.4 Conception de l’expérience

Afin d’explorer l’impact de l’introduction d’entrées haptiques et olfactives sur la qualité d’expérience globale de l’IMEx multisensorielle, cinq conditions ont été testées, à savoir : visuel uniquement (VO), audio-visuel (AV), audio-visuel-odeur (AVS), audio-visuel-haptique (AVH) et audio-visuel-odeur-haptique (AVSH). Pour éviter les biais, l’ordre des conditions était contrebalancé entre les participants. L’expérience s’est ensuite déroulée avec l’ordre aléatoire des cinq conditions. Comme leurs noms l’indiquent, les conditions VO ne présentaient à l’utilisateur que les éléments visuels, y compris la brume lorsqu’il réussissait à tirer sur une orange. La condition AV incluait les “poufs” supplémentaires alignés dans le temps avec les visuels du nuage de brume. Dans la condition AVS, les odeurs de fond et les éclats d’orange étaient présentés, tandis que dans la condition AVH, les manches vibraient lors du tir d’une orange. Enfin, la condition AVSH comprenait tous les stimuli sensoriels susmentionnés alignés dans le temps. À la fin, les participants ont été invités à donner leur avis sur les différentes conditions, dans le but d’obtenir des informations permettant d’améliorer les itérations futures de l’expérience.

0.3.1.5 Analyse des données

Extraction des caractéristiques Pour traiter les signaux EEG, la boîte à outils EEGLAB pour MATLAB a été utilisée. Pour le prétraitement, un filtre passe-bande entre 0,5 et 45 Hz a été appliqué, suivi d’une normalisation de la moyenne zéro. L’algorithme de reconstruction du sous-espace des artefacts a ensuite été appliqué pour éliminer les artefacts liés au mouvement. Les puissances spectrales des sous-bandes EEG ont été calculées pour les cinq bandes conventionnelles, à savoir : delta (0-4HZ), thêta (4-8Hz), alpha (8-12Hz), bêta (12-30Hz) et gamma (30-80Hz) pour chaque canal EEG. Ces valeurs ont ensuite été utilisées pour calculer un indice d’engagement (EI), un indice d’arousal (AI), un indice de valence (VI) et un FAA. L’EI est calculé sur la base du rapport des bandes de puissance bêta / (alpha + thêta), dont la moyenne est calculée sur toutes les électrodes

[125]. AI et VI, à leur tour, sont calculés sur la base des puissances des sous-bandes d'électrodes spécifiques, conformément à [126], dans l'équation 3.1. À partir de l'EEG, la FAA est calculée en soustrayant le log-puissance de la bande alpha de l'électrode F4 du log-puissance de la bande alpha de l'électrode F3. De plus, la charge mentale a été quantifiée en calculant l'activité moyenne de la bande de puissance thêta de l'EEG sur les électrodes Fp1, Fpz, Fp2, F3, F4 et FCz [72]. À partir des signaux EOG, la boîte à outils Blinker a été utilisée pour extraire la caractéristique EBR [127]. À partir du signal ECG, le paquet python BioSPPy a été utilisé pour extraire la HR [128].

Statistiques Pour analyser l'impact des différents stimuli sensoriels sur les évaluations subjectives, un test ANOVA à mesures répétées avec correction de Greenhouse-Geisser a été réalisée à l'aide d'IBM SPSS 20 avec un test de signification à l'intervalle de confiance de 95%.

0.3.2 Results and Discussion

0.3.2.1 Analyse subjective

La figure 3.4 représente les diagrammes à barres des notes moyennes attribuées par les 11 participants pour chaque sous-catégorie FHI et la qualité globale pour chacune des cinq conditions expérimentales. Dans le graphique, les différences significatives au niveau de 95% sont représentées par un astérisque, au niveau de 99% par deux et au niveau de 99,9% par trois astérisques. Comme on peut le voir, les trois conditions multisensorielles (AVS, AVH, AVSH) ont augmenté le réalisme, la présence, l'immersion, l'engagement et l'expérience globale par rapport aux conditions VO et AV. L'inclusion de stimuli haptiques et olfactifs a permis d'améliorer de manière significative le sentiment de présence par rapport à l'utilisation individuelle des entrées sensorielles supplémentaires, ainsi que l'engagement par rapport à la condition AVS. Il est intéressant de noter que l'incorporation de stimuli haptiques ou olfactifs a donné lieu à des évaluations de réalisme et d'immersion similaires et que la condition combinée AVSH n'a montré qu'une légère augmentation de l'immersion par rapport aux conditions AVS et AVH, une saturation ayant pu se produire. La condition AVH, cependant, a entraîné une augmentation du sentiment de présence, de l'engagement et de l'expérience globale, par rapport à la condition AVS, ce qui suggère un impact plus important du retour haptique sur ces FHI. Dans les cinq conditions, l'analyse statistique a révélé une différence significative pour l'expérience globale ($F_{(2.201,\ 22.013)}$= 12.564, p .001), le réalisme ($F_{(1.718,\ 17.180)}$= 4.915, p= .024), la présence ($F_{(1.792,\ 17.918)}$ = 7.953, p= .004), immersion ($F_{(2.293,\ 22.930)}$= 3.351, p= .047), et engagement ($F_{(2.875,\ 28.746)}$= 9.349, $p \leq .001$).

0.3.2.2 Analyse des mesures instrumentales

Le tableau 3.1 montre l'impact que les différentes conditions expérimentales ont sur les six caractéristiques psychophysiologiques extraites. L'analyse statistique suggère que seul l'AI présente une différence significative ($F(4, 40)= 3.000$, $p= .030$) entre AVS et VO ($p= .021$), AVSH et VO ($p= .013$), et AVS et AVH ($p= .049$). Dans l'ensemble, l'AVS a montré l'AI le plus élevé, ce qui suggère que cette condition était la plus excitante pour les participants. En ce qui concerne le FAA, les valeurs positives indiquent une plus grande tendance à l'approche (oscillation de l'hémisphère gauche plus élevée), tandis que les valeurs négatives sont associées à une tendance au retrait (oscillation de l'hémisphère droit élevée) [129]. Les résultats de la FAA ont montré une tendance à l'augmentation, à mesure que les modalités étaient ajoutées, suggérant ainsi un plus grand désir de continuer à payer et des motivations accrues, comme le plaisir. Les commentaires spontanés des participants après l'expérience corroborent cette hypothèse. Enfin, l'EBR a montré des valeurs accrues lorsque des entrées sensorielles supplémentaires étaient fournies, corroborant ainsi les résultats de l'étude [130] qui montrait un lien entre l'EBR et la présence. De plus, une augmentation de la bande de puissance thêta moyenne, en tant que mesure de la charge mentale, a été observée de AV (M= 4,16, ET= 1,74) à AVSH (M= 4,91, ET= 2,43), suggérant un traitement d'ordre supérieur pour la tâche multisensorielle [131]. En fait, les augmentations de la puissance thêta et de la charge mentale pourraient être liées aux augmentations combinées de l'engagement et de l'attention, comme cela a été rapporté dans [71] et montré dans [132] avec des stimuli olfactifs.

0.4 Formation multisensorielle en RV : Augmenter les performances du MI

Les ICM ont été développées pour permettre aux utilisateurs de communiquer avec le monde extérieur en traduisant l'activité cérébrale en signaux de commande. L'imagerie motrice (IM) est un paradigme populaire dans le contrôle des ICM, où l'utilisateur imagine des mouvements, par exemple de ses membres gauche et droit, et où les classificateurs sont ensuite entraînés à détecter cette intention directement à partir des signaux EEG. Pour certains utilisateurs, cependant, il est difficile d'obtenir des modèles dans le signal EEG qui peuvent être détectés avec les caractéristiques et les classificateurs existants. Ainsi, de nouvelles stratégies de contrôle de l'utilisateur et de nouveaux paradigmes d'entraînement sont très recherchés pour aider à améliorer les performances de l'imagerie motrice. L'entrainement en RV est apparue comme un outil potentiel où les améliorations de l'engagement de l'utilisateur et du niveau d'immersion ont montré qu'elles amélioraient la précision de l'ICM. Dans cette section, nous faisons les premiers pas pour explorer si la formation RV multisensorielle, où non seulement le feedback audio-visuel est fourni, mais aussi haptique et olfactif, peut encore améliorer les niveaux d'engagement et le sentiment de présence, et finalement, améliorer la précision de l'ICM.

Nous décrivons ici un jeu VR multisensoriel interactif qui a été développé avec l'inclusion de modalités de retour audio-visuel, olfactif et haptique pour comparer l'entrainement VR multisensorielle à l'entrainement VR audio-visuelle conventionnelle. À cette fin, une version améliorée de l'expérience décrite dans la section précédente, avec un nouvel ensemble de feedback, un nouvel environnement RV et un nouveau matériel, a été utilisée. Après avoir joué au jeu, les utilisateurs ont fait part de leur perception du réalisme, de la présence, de l'immersion et de l'engagement dans le jeu, ainsi que de leur niveau de cybermalaise. Pour évaluer plus précisément leur état émotionnel, l'outil graphique d'auto-évaluation EmojiGrid a été utilisé pour contrôler le sentiment de plaisir (valence) et le niveau d'arousal (excitation) de l'expérience. Pour suivre ces facteurs en temps réel, un casque VR équipé de biocapteurs a été mis au point. Des capteurs EEG, EOG et PPG ont été intégrés directement dans le casque afin d'éviter que les participants aient à porter des technologies supplémentaires. Les utilisateurs ont subi une séance d'IM avant et après avoir été exposés aux conditions expérimentales, afin d'évaluer plus précisément l'impact de la formation multisensorielle en RV sur les performances de l'IM. Les aspects de la qualité de l'expérience susmentionnée sont décrits en détail dans le chapitre 4 et l'influence de la formation immersive multisensorielle sur les performances de l'IM est rapportée dans le chapitre 5. Cependant, nous avons représenté ici le résumé de ces chapitres.

0.4.1 Matériaux et Méthodes

0.4.1.1 Participants

Onze participants (trois femmes, 25,81 ± 3,88 ans) ont été recrutés pour participer à cette étude. Le protocole de l'expérience a été revu et approuvé par le comité d'éthique de l'Institut national de la recherche scientifique (INRS), Université du Québec (numéro : CER-22-663). Pendant la collecte des données, des précautions sanitaires liées au COVID-19 ont été prises en compte etmises en place. Tous les participants sont considérés comme des utilisateurs novices de BCI, et c'était la première fois qu'ils exécutaient une tâche d'imagerie motrice. Il est important de souligner que les données d'un sujet ont été considérées comme trop bruyantes pour être analysées, et sont donc écartées de l'analyse.

0.4.1.2 Intégration des équipements et des données

Dans cette étude, un VR-HMD a été couplé à des gants haptiques à retour de force, à un brassard à électromyogramme (EMG), à un dispositif de diffusion d'odeurs et à un système BCI sans fil (ci-après dénommé "BCI-HMD") intégré directement dans le casque selon les directives décrites par [122]. Une illustration des différents composants du système est présentée à la Fig. 4.1a, outre qu'un visuel d'un utilisateur les portant à la Fig. 4.1b. De plus, un jeu VR a été créé et synchronisé avec le matériel. Plus de détails sur le HMD instrumenté sont donnés ci-après.

Casque Instrumenté: BCI-HMD Un HMD Meta Quest2 (écran LCD d'une résolution de 1920×1832, taux de rafraîchissement de 72 Hz et champ de vision de 89°) a été utilisé. Trois modalités de signaux physiologiques, dont l'électroencéphalographie (EEG), l'électro-oculographie (EOG) et la photo-pléthysmographie (PPG), ont été intégrées dans la mousse faciale et les sangles de tête du casque VR et directement connectées à un bio-amplificateur OpenBCI encastré dans une boîte imprimée en 3D et placé sur le dessus des sangles du HMD (voir Fig. 4.1b). Selon le système international 10-20 [133], les bio-amplificateurs OpenBCI Cyton et Daisy (OpenBCI, États-Unis) ont été utilisés pour capturer 11 canaux EEG des régions frontales (Fp1, Fpz, Fp2, F3, F4, Fz, Fc1, Fc2) et centrales (C3, C4, Cz) à une fréquence d'échantillonnage de 125 Hz. Afin d'assurer le confort des participants, des électrodes EEG sèches et souples softPulse^{TM} (Datwyler, Suisse) ont été utilisés. Un capteur PPG a été utilisé pour surveiller la fréquence cardiaque et a été intégré dans la plaque frontale du HMD, ainsi que deux paires d'électrodes EOG verticales et horizontales. En outre, une paire de brassards Myo à 8 canaux (Thalmic labs, Canada) a été placée sur les avant-bras des participants afin de capturer les signaux d'électromyographie (EMG) à une fréquence de 200 Hz à l'aide d'électrodes sèches. Les différentes modalités et entrées de signaux ont été synchronisées et enregistrées à l'aide de lab streaming layer (LSL).

Retour Multisensoriel Une paire de gants haptiques Novaa^{TM} (SenseGlove, Pays-Bas) a été utilisée pour fournir un retour de force précis à chaque doigt. Les gants peuvent également suivre les mouvements du poignet, de la main et des doigts en utilisant les capteurs de l'unité de mesure inertielle (IMU). Profitant des actionneurs résonnants linéaires sur le pouce et l'index, les participants peuvent percevoir la texture et la rigidité d'un objet 3D dans un environnement virtuel. Le montage des contrôleurs Meta Quest2 sur les gants a permis de cartographier en 3D l'emplacement des mains dans l'espace virtuel, comme le montre la Fig. 4.1b. En outre, un dispositif olfactif OVR ION2 (OVR Technologies, États-Unis) a été connecté au BCI-HMD pour fournir une rétroaction olfactive en dispersant des arômes près du nez de l'utilisateur.

Environnement Virtuel Développé Un environnement virtuel personnalisé a été conçu dans Unity3D 2021. Comme l'illustre la Fig. 4.2a, cinq oranges sont placées sur chacune des six assiettes disposées sur une table. Le participant est assis au centre et trois assiettes à gauche ettrois à droite du participant ont été stratégiquement positionnées à trois distances différentes (trois niveaux). Les assiettes les plus proches (niveau 1) sont placées à une distance relative à 20 cm du sujet dans le monde réel, tandis que les assiettes les plus éloignées (niveau 3) sont situées à 60 cm ; les assiettes du milieu sont placées à 40 cm (niveau 2). L'environnement et la distance sont conçus de manière à ce que même les oranges placées sur l'assiette la plus éloignée soient accessibles par une extension complète du bras, sans nécessiter de mouvement supplémentaire du corps.

0.4.1.3 Conception Expérimentale

Nous avons suivi un plan expérimental à mesures répétées (appelé protocole expérimental intrasujet) dans lequel tous les participants ont été soumis aux mêmes conditions expérimentales (avec un ordre contrebalancé). La Figure 4.3 illustre la chronologie du protocole et les blocs expérimentaux, étape par étape. Au cours de la phase de préexpérimentation, les participants ont d'abord été évalués afin de déterminer s'ils avaient le mal de transports ou une sensibilité aux odeurs, et s'ils étaient à l'aise avec le BCI-HMD et les gants haptiques. Chaque participant a ensuite reçu verbalement des instructions complètes avant de porter les brassards Myo et la BCI-HMD. Ensuite, tous les systèmes ont été calibrés, la qualité du signal a été vérifiée et les ajustements nécessaires ont été effectués pour améliorer la qualité du signal. Enfin, les participants ont reçu un entraînement en jeu avec et sans une rétroaction multisensoriel.

Au courant de la deuxième étape, on a demandé aux participants d'exécuter une tâche mondaine de BCI-MI en imaginant qu'ils saisissent une orange en utilisant leur main gauche ou droite [134]. Durant cette séance d'IM, l'utilisateur est signalé à imaginer la manipulation de l'orange qui est devenue rouge pendant une durée de 10 secondes. Les oranges sont aléatoirement transformées en rouges entre les côtés gauches et droits, comme le montre la Fig. 4.2b. Pendant les 10 secondes, les participants ont été invités à imaginer qu'ils devaient empoigner l'orange choisie, la déplacer au milieu de la table et la presser sur la cuvette centrale. Ensuite, l'orange disparaît pour une période de repos de 5 secondes, après quoi une autre orange surgit et la procédure est répétée jusqu'à ce que les 30 oranges (5 oranges × 6 assiettes) aient été pressées, que toutes les assiettes soient vides et que la cuvette centrale soit remplie de jus d'orange, comme le montre la Fig. 4.2c).

Après cette première tâche d'imagerie motrice, les participants ont été invités à jouer deux autres fois, une fois avec la seule rétroaction audiovisuelle et une fois avec les stimuli multisensoriels. Un ordre contrebalancé des conditions a été appliqué à tous les sujets afin d'éliminer tout biais. Dans ces conditions expérimentales, similaires à celles des sessions MI, une orange assignée au hasard était transformée en rouge et les utilisateurs devaient l'empoigner (Fig. 4.2d), la déplacer au-dessus de la cuvette centrale et la presser jusqu'à ce que tout le jus en soit extrait, ce qui faisait éclater et disparaître l'orange et augmenter le niveau de jus dans la cuvette (Fig. 4.2e). Le mouvement de la main des participants dans le monde réel était reproduit sur les modèles de main virtuels (représentés par des mains bleues dans les figures) avec une fréquence de rafraîchissement de 100 Hz. Dans la condition avec uniquement un retour audiovisuel, l'action de presser une orange est suivie d'un effet sonore "squish" synchronisé avec une animation sans appliquer aucun retour de force physique. Dans la condition multisensorielle, en revanche, les utilisateurs ont pu sentir la forme et la texture 3D des oranges dans l'environnement virtuel et ont dû appliquer une force pour réussir à presser et extraire le jus d'orange. Dans cette condition, le retour audiovisuel était également synchronisé avec un éclat d'agrumes présenté pendant 3 secondes. Les participants étaient autorisés à interagir avec l'environnement virtuel à leur propre rythme, assis sur une chaise pivotante. L'expérience s'est terminée lorsque toutes les oranges ont été pressées et que tout le jus a été extrait.

Une fois les deux conditions contrebalancées réalisées, les utilisateurs ont été soumis à une deuxième tâche d'imagerie motrice en suivant les mêmes instructions et la même procédure que la première session décrite ci-dessus. Une fois les conditions expérimentales terminées, les participants ont répondu à plusieurs questionnaires apparaissant directement dans l'environnement du jeu (plus de détails dans la section suivante) ainsi qu'à l'EmojiGrid, un outil graphique permettant de mesurer les émotions des utilisateurs. À la fin, les participants ont répondu à un questionnaire de comparaison post-expérience et ont passé un entretien à questions ouvert.

0.4.1.4 Évalautions Subjective

Un ensemble de questionnaires liés à la qualité d'expérience a été exploité après chaque condition expérimentale, y compris des questions relatives à l'intensité perçue de la présence, à l'immersion, au réalisme, à l'interaction et à l'expérience entière à l'aide de l'échelle d'évaluation par catégorie absolue (ACR) à 5 points [123], adaptée à l'intérieur du jeu à l'aide d'une boîte à outils développée par [124]. Pour le cybersickness, une échelle à 4 points a été utilisée. La figure 4.4 illustre les questionnaires développés et les questions associées posées.

En outre, la grille EmojiGrid, adoptée de [1] a été utilisée pour capturer les états émotionnels des participants après chaque condition expérimentale. La grille (voir la Fig. 4.6 à titre d'exemple) a un axe continu de zéro à 100, où l'axe horizontal représente la valence et varie de désagréable (le plus à gauche, zéro), à neutre (50), à agréable (le plus à droite, 100). L'axe vertical représente l'excitation et varie du calme (le plus bas, zéro), au neutre (50), au très excité (le plus haut, 100). Sur les bords extérieures, les expressions faciales sont reflétées par des émojis. Après les deux sessions d'IM, les participants ont évalué le niveau de difficulté de l'exécution de la tâche d'IM à l'aide d'une échelle ACR à 5 points, comprenant les options "très facile", "facile", "neutre", "difficile" et "très difficile".

Après avoir répondu aux évaluations de la dernière session d'IM, les participants ont été invités à enlever les équipements. À la fin de l'expérience complète et lorsque le casque VR a été retiré, les utilisateurs ont été invités à comparer les conditions audiovisuelles et multisensorielles en ce qui concerne la présence, l'immersion, le réalisme, l'interaction, le niveau ressenti de cybermalaise et de l'expérience générale.

0.4.1.5 Analyse des Données de Signaux Biologiques

Analyse des Signaux Pendant les Séances d'entraînement De modalités différentes, notamment les signaux EEG, EMG et EOG, ont été prétraités dans MATLAB (R2021a, The MathWorks, États-Unis). À l'aide de la boîte à outils EEGLAB [135], les signaux EEG et EOG ont été filtrés via un filtre passe-bande entre 0,5 et 45 Hz, puis une normalisation de la moyenne zéro a étéappliquée. L'algorithme de reconstruction du sous-espace des artefacts (ASR) a ensuite été appliqué pour

éliminer les artefacts liés au mouvement [136]. Ensuite, plusieurs mesures ont été dérivées des signaux biologiques prétraités. Le taux de clignement (BR) a été extrait des canaux EOG. La densité spectrale de puissance (DSP) de l'EEG a été extraite à l'aide de la méthode de Welch [137] et les puissances des cinq sous-bandes traditionnelles ont été calculées pour chacun des 11 canaux EEG, à savoir : delta, thêta, alpha, bêta et gamma. À partir de ces derniers, les mesures suivantes ont été calculées. Tout d'abord, l'IE a été calculé en utilisant la moyenne des bandes de puissance bêta, alpha et thêta de tous les canaux, selon l'équation 4.1. Ensuite, un AI et un VI ont été calculés sur la base des puissances des sous-bandes alpha et bêta des électrodes frontales (F3, F4) suivant l'équation [126] et donnés par l'équation 3.1. Enfin, une mesure des tendances de retrait/approche a été calculée en utilisant l'indice FAA, donné par l'équation 4.2.

Le prétraitement du signal EMG comprenait un filtrage du passe-bande de 10 à 500 Hz suivi d'une rectification des ondes. La valeur absolue moyenne (MAV) du signal EMG a été extraite pour chaque bras, comme indiqué dans [138]. Ensuite, les valeurs MAV des bras gauche et droit ont été moyennées pour caractériser l'activité musculaire globale des sujets pendant chaque condition afin de valider l'utilisation du retour de force dans la condition multisensorielle. Enfin, la bibliothèque python HeartPy a été utilisée pour extraire les mesures de la fréquence cardiaque (FC) à partir des signaux PPG enregistrés [139].

Analyse du Signal et Classification des Sessions de MI uniquement sur les modalités des signaux EMG et EEG. Le prétraitement des signaux EEG et EMG suit la procédure décrite dans la section précédente. De même, les MAV sont extraits pour les bras gauche et droit, puis la moyenne est calculée entre les bras pourobtenir une activité musculaire globale finale pour chaque utilisateur. Comme c'est généralement le cas avec les paradigmes de BCI basés sur l'IM, les caractéristiques du modèle spatial commun (CSP) ont été extraites des essais d'IM [140; 141; 142] et introduites dans un classificateur de machine à vecteur de support (SVM) pour distinguer l'imagerie motrice de la main gauche ou de la main droite [143; 144].

Pour les tâches binaires, les caractéristiques CSP calculent des filtres spatiaux qui maximisent la variance d'une classe tout en minimisant simultanément la variance de l'autre classe. Le signal filtré spatialement S d'un essai EEG est donné par:

$$S_{L\times T} = W_{L\times N} \times M_{N\times T}, \tag{1}$$

où W est une matrice $L \times N$ de filtres spatiaux, dont L est le nombre de filtres et N le nombre de canaux EEG. M représente le signal EEG d'un certain essai avec N, lignes et T, points de données. Les premiers lignes J de la matrice W reflètent la variance maximale dans la première classe (et la variance minimum dans la deuxième classe) et les dernières lignes de J reflètent la variance maximale dans la deuxième classe. Dans cette étude, nous utilisé six filtres spatiaux ($J = 6$), trois de chaque côté, comme suggéré par [145].

Pour la confection du classificateur, un outil d'optimisation automatique des hyperparamètres dans MATLAB a été utilisé pour trouver les meilleurs paramètres pour le classificateur SVM afin de minimiser la perte par validation croisée cinq fois. Plusieurs tests sont effectués ici. Tout d'abord, nous explorons la précision obtenue avec les caractéristiques CSP calculées sur l'ensemble de l'essai d'imagerie motrice de 10 secondes (durée du repère). Ensuite,nous explorons l'utilisation de différentes plages, suivies d'une plage fixe d'une durée de 5 secondes (selon les suggestions de [146; 147; 148]) avec des points de départ variables après l'indice de la tâche. Ces essais sont effectués par sujet, puis la moyenne est calculée pour obtenir la précision globale du MI-BCI. Cette opération est effectuée selon deux paramètres : dans le premier, toutes les plaques de gauche et toutes les plaques de droite sont regroupées en deux classes : gauche et droite. Dans le second, la classification de l'imagerie gauche par rapport à l'imagerie droite a été effectuée par niveau (c'est-à-dire la distance entre les plaques, comme le montre la Fig. 4.2a). Dans chacun des scénarios, 70% de l'ensemble de données a été utilisé pour la confection, tandis que le reste a été laissé pour les tests. Cette partition a été effectuée 200 fois afin de réduire les risques de sur- et sous-interprétation.

0.4.1.6 Analyse Statistique

L'analyse statistique a été effectuée pour les évaluations subjectives ainsi que pour les mesures extraites basées sur les signaux biologiques en utilisant IBM SPSS 20. La normalité des variables a été évaluée à l'aide du test de normalité de Shapiro-Wilk (S-W), recommandé pour les ensembles de données de petite taille [149]. Un test t d'échantillon apparié a été utilisé pour analyser les différences statistiquement significatives entre les conditions expérimentales pour les mesures don't la distribution était normale. Un test non paramétrique de Wilcoxon (signed-rank) a également été effectué pour les mesures qui n'étaient pas normalement distribuées. La moyenne (M) et l'écart type (ET), ainsi que les valeurs p, sont indiqués dans le présent document. Enfin, pour révélerl'association entre les variables (à la fois entre les sous-échelles de QdE et les sous-échelles de QdE avec les mesures de signaux biologiques), une approche de corrélation à mesures répétées (rmcorr) a été exploitée [150]. Pour toutes les analyses, un niveau de probabilité de $p < .05$ a été considéré comme statistiquement significatif.

0.4.2 Résultats et Discussion

0.4.2.1 Évaluation de la Qualité d'Expérience

L'expérience actuelle a examiné l'impact d'un environnement RV multisensoriel sur la qualité d'expérience et ses sous-échelles par rapport à une expérience immersive audiovisuelle conventionnelle ; les sous-échelles comprennent l'immersion, la présence, le réalisme, l'interaction et la sensation de cybermalaise. Nous avons quantifié les améliorations obtenues en matière de qualité d'expérience en incluant des stimuli de retour olfactif et de force, et nous avons exploré la mesure de l'expérience

globale à l'aide d'un HMD VR instrumenté par BCI. Dans cette section, nous présentons les résultats et discutons des conclusions que nous avons obtenues.

Évaluations Subjectives et EmojiGrid La Figure 4.5 illustre les diagrammes à barres des évaluations moyennes fournies par les 11 participants pour chacune des sous-échelles de la qualité d'expérience, ainsi que pour la qualité d'expérience globale. Le test S-W a indiqué une distribution anormale de ces évaluations; les statistiques suivantes ont été trouvées par condition:

- Audio-visuel: présence: M=3.73, ET=.467; immersion: M=3.73, ET=1.104; réalisme: M=3.18, ET=.603; interaction: M=3.55, ET=.934; cybermalaise: M=1,09, ET=.302; et expérience globale: M=3,82, ET=.405.
- Multisensoriel: présence: M=4.36, ET=.505; immersion: M=4.36, ET=.505; réalisme: M=3.73, ET=.467; interaction: M=4.45, ET=.52; cybermalaise: M=1,00, ET=.000; et expérience globale: M=4.27, ET=.467.

Une différence statistiquement significative a été observée pour les évaluations de la présence (Z= 2.646, p= .008), de l'interaction (Z= 1.983, p= .047) et de l'expérience globale (Z= 2.121, p= .034). Les résultats ont mis en évidence les avantages de l'inclusion de stimuli olfactifs et de retour de force pour augmenter de manière significative le sentiment de présence, l'interaction et l'expérience globale par rapport à une expérience immersive audiovisuelle traditionnelle (Fig. 4.5). En fait, les niveaux d'immersion et de réalisme ont également montré une augmentation, bien que statistiquement non significative. En raison de la nature stationnaire de l'expérience, tous les participants ont répondu "non" à la question sur les symptômes du cybermalaise dans la session multisensorielle, tandis qu'un seul participant a signalé des symptômes "légers" de vertige dans la session audiovisuelle.

Les évaluations d'EmojiGrid, quant à elles, ont donné lieu à des données normalement distribuées. Les statistiques suivantes ont été observées:

- Audio-visuel: Valence: M=67.90, ET=16.640; Arousal: M=52.09, ET=16.525.
- Multisensoriel: Valence: M=78.09, ET=14.929; Arousal: M=79.72, ET=11.967.

Une différence statistiquement significative de la valence (t(10)= 3.290, p= .008) et de l'excitation (t(10)= 7.066, $p =< .001$) a été observée entre les deux conditions. La Figure 4.6 représente un diagramme de dispersion des évaluations d'EmojiGrid rapportées pour les eux conditions (bleu = audiovisuel ; orange = multisensoriel). L'analyse des évaluations d'EmojiGrid montre que l'expérience multisensorielle a entraîné une augmentation du degré d'agrément (valence). et d'intensité (excitation), alors qu'avec la condition audiovisuelle traditionnelle, les participants ontévalué leurs niveaux de valence comme étant principalement neutres (Fig. 4.6).

Analyse des Données Provenant des Signaux Biomédicaux Le test S-W a révélé une distribution normale des caractéristiques extraites de tous les paramètres des signaux biomédicaux ; à l'exception des paramètres EI et VI. Comme le montre le tableau 4.2 des changements statistiquement significatifs ont été observés dans les conditions audiovisuelles et multisensorielles pour FAA (t(10)= 2.516, p= .031) et MAV (t(10)= 3.334, p= .008), ainsi que pour EI (Z= 2.578, p= .010) et VI (t(10)= 3.944, p= .003). Aucune différence statistiquement significative n'a été trouvée pour l'IA, la fréquence cardiaque et le taux de clignement. Néanmoins, une tendance ascendante a été observée de la condition audiovisuelle à la condition multisensorielle pour la fréquence cardiaque et le taux de clignement. Les changements significatifs observés dans la métrique MAV valident les effets de la modalité de retour de force sur l'expérience multisensorielle.

En fait, ces résultats sont conformes aux résultats d'EmojiGrid (tableau 4.2). Par exemple, l'indice de valence a montré une augmentation significative dans la condition multisensorielle, tandis que la mesure FAA a montré une augmentation significative d'une valeur négative (suggérant une tendance au retrait) à une valeur positive (suggérant une tendance à l'approche). L'indiced'interaction a également montré une corrélation significative avec la qualité d'expérience globale, l'excitation, la présence et le réalisme, corroborant ainsi l'importance de l'interaction dans la tâche sur la perception globale de la qualité, comme le montre le tableau 4.1.

Relation Entre les Évaluations Subjectives et les Mesures des Signaux Biomédicaux Le tableau 4.3 montre que les mesures extraites du BCI-HMD sont en corrélation significative avec plusieurs sous- échelles de qualité d'expérience, ainsi qu'avec la qualité d'expérience globale. Plus précisément, l'IE est en corrélation à l'expérience globale, l'IV et l'IE à l'excitation et à la présence, et l'IE au réalisme.Ces résultats corroborent des rapports récents sur l'effet de la rétroaction multisensorielle sur la présence en augmentant le caractère agréable de la tâche et, par la suite, en optimisant l'interaction dans la tâche [40]. En fait, ces résultats soutiennent les rapports précédents sur la relation directe entre la présence et une meilleure performance de l'utilisateur en introduisant «l'agrément » comme l'un des facteurs médiateurs [151; 152].

0.4.2.2 Performance du MI-BCI

Évaluations Subjectives Le diagramme à barres superposées de la Fig. 5.1 illustre les difficultés perçues par chaque participant suite à l'exécution des tâches MI. Une différence statistiquement significative a été observée entre la première (M= 2.82, ET= 1.079) et la dernière (M= 2.00, ET= .775) session MI (t(10)= 2.764, p= .020), suggérant que la dernière tâche a été perçue comme plus facile par rapport à lapremière. Ceci est attendu, puisque les tâches d'imagerie motrice ont été rapportées comme devenant plus faciles avec l'entraînement, particulièrement dans la RV [153]. Pour la première tâche de MI, quatre participants l'ont évaluée comme "facile", tandis que quatre autres

l'ont évaluée comme "difficile". La deuxième fois, par contre, tous les participants ont évalué la tâche comme étant "très facile", "facile" ou "neutre".

Performance de l'ICB-MI par Sujet Comme décrit précédemment, chaque essai de l'ICB-MI consistait en 10 secondes d'imagerie suivies de 5 secondes de repos. On a demandé aux participants d'effectuer la tâche MI 15 fois pour toutes les oranges de gauche et 15 fois pour toutes les oranges de droite, soit un total de 30 essais par sujet. Pour la classification, 20 essais ont été utilisés pour l'entraînement et 10 essais ont été laissés pour le test, par sujet. La figure 5.2 illustre la précision (moyenne de tous les participants) obtenue pour la première et la dernière tâche MI. Comme on peut le voir, une différence statistiquement significative entre la première (M= 77.76, ET= 2.23) et la dernière (M= 80.32, ET= 2.62) session de MI a été observée (t(9)= 2.567, p= .030). Ce résultat, concorde avec les rapports subjectifs décrits ci-dessus et souligne l'importance de l'entraînement RV avant d'effectuer la tâche d'imagerie motrice.

Dorénavant, nous sommes intéressés par l'étude des avantages de l'entraînement multisensoriel du RV par rapport à l'entraînement conventionnel du RV. À cette fin, la figure 5.3 illustre la précision obtenue dans la première (verte) et la dernière (beige) tâche MI, mais maintenant séparée en fonction des sujets qui ont effectué la formation multisensorielle d'abord, suivie de la formation audiovisuelle (graphique de gauche), par rapport à ceux qui ont effectué la formation audiovisuelle d'abord et la formation multisensorielle en dernier (graphique de droite). Comme nous pouvons le percevoir, alors que dans les deux conditions, la première session de MI a atteint une précision moyenne similaire pour tous les sujets, ceux qui ont effectué la tâche multisensorielle en dernier ont pu atteindre une précision substantiellement plus élevée dans ladernière tâche de MI. Cela suggère que non seulement l'entraînement RV peut être utile pour améliorer l'efficacité de la BCI, mais aussi le type d'entraînement utilisé avec les avantages supplémentaires obtenus avec l'amorçage multisensoriel.

Afin d'étudier davantage l'impact de la formation et de l'ordre de formation, nous traçons l'activité moyenne obtenue à partir des six filtres CSP, où une plus grande activité peut indiquer une meilleure discrimination entre les deux classes. Comme le montre la figure 5.4 dans les deux cas, l'activité de la CSP était plus élevée dans la dernière session de l'IM par rapport à la première, comme prévu étant donné les effets de la formation sur l'efficacité de la BCI [154]. Il est important de noter que lorsque le dernier type de formation comprenait un amorçage multisensoriel, l'activité du CSP était sensiblement plus élevée que lorsque l'amorçage était uniquement audiovisuel.

Effet de l'étendue de la période d'expérimentation et du temps écoulé Depuis le Signal sur la Précision Les résultatsprésentés ci-dessus supposent que les caractéristiques CSP ont été calculées sur la totalité de la durée de 10 secondes. Pour les opérations en temps réel, il peut être préférable de réduire la durée de la période d'expérimentation. À cette fin, nous explorons l'effet que cette étendue a sur la précision globale. Les figures 5.5 (a) et (b) illustrent la précision obtenue en fonction de la taille de la durée d'expérimentation pour la première et la dernière tâche MI,

respectivement. La précision est indiquée par sujet, ainsi que la moyenne des sujets (ligne pointillée). Comme on peut le voir, pour des plages de 1 à 4 secondes, des niveaux de chance ou inférieurs à la chance sont atteints sur l'ensemble de données de test non vues. Lors de la première tâche d'imagerie motrice, les niveaux de précision se sont stabilisés pour des plages de plus de 8 secondes, alors que lors de la dernière session d'imagerie motrice, ce niveau a pu être atteint pour la plupart des sujets autour de 7 secondes et pour certains même à 6 secondes. Comme la tâche d'imagerie motrice était assez longue (saisir une orange, se déplacer au milieu de la table, puis la presser), on peut s'attendre à ce que la précision maximale soit atteinte une fois la tâche complète effectuée. Avec l'entraînement RV, les résultatssuggèrent que cela peut être atteint potentiellement 2 secondes plus vite.

Par la suite, nous avons examiné l'effet du temps écoulé depuis le signal sur la précision globale.Le temps écoulé entre le moment où les sujets ont reçu l'indication d'effectuer la tâche et le moment où le calcul du CSP a été effectué. Pour cette analyse, nous avons gardé l'étendue de la période d'expérimentation constante et avons fait varier le point de départ de l'analyse. Une fenêtre de 5 secondes a été utilisée, car elle a permis d'obtenir une précision d'environ 65-70% pour les deux tâches MI. La figure 5.6 montre la précision obtenue par sujet en fonction du temps écoulé depuis le repère en secondes. Comme on peut voir, les gains les plus importants ont été constatés lorsqu'une seconde ou plus d'une a été considérée après la présentation du signal pour le calcul des caractéristiques du CSP ; ces résultats corroborent ceux rapportés précédemment dans la littérature (par exemple, [145]).

Activité EMG Enfin, pour évaluer les changements de l'activité EMG pendant les tâches d'entraînement, la Fig. 5.7 illustre les changements de l'EMG MAV pendant les deux tâches MI, ainsi que les deux conditions d'entraînement. Comme prévu, une différence statistiquement significative a été observée (t(10)= 3.055, p= .014) dans l'activité musculaire entre les sessions d'entraînement audiovisuelles (M= 8.16, ET= 1.40) et multisensorielles (M= 9.51, ET= 2.30), car les gants de retour de force n'étaient activés que dans la dernière condition. De plus, une baisse significative ($p \leq .001$) de la VMA a été observée entre la première (M= 2.55, ET= .70) session de l'IM. et les conditions d'entraînement (Audio-visuel : t(10)= 13.302, multisensoriel : t(10)= 10.440) et le dernier MI (M= 1.99, ET= .79) et les conditions de formation (Audio-visuel: t(10)= 18.677, multisensorielle: t(10)= 13.217).

0.5 Conclusion

Dans ce travail, nous avons d'abord exploré le rôle de différentes modalités de rétroaction, notamment la rétroaction audiovisuelle, olfactive et haptique. Les résultats montrent que la rétroaction haptique et les odeurs affectent de manière significative le sentiment d'immersion et d'interaction, respectivement.Dans l'ensemble, une expérience immersive multisensorielle composée

de stimuli audiovisuels, olfactifs et haptiques a obtenu les meilleures notes, y comprispour la qualité globale de l'expérience. En outre, plusieurs mesures instrumentales ont confirmé ces améliorations, notamment l'indice d'interaction, l'indice d'éveil, l'asymétrie alpha frontale et le taux de clignement des yeux.

Ensuite, nous avons affiné le matériel utilisé, afin de fournir plus de confort pendant le jeu, et conçu un nouvel environnement virtuel avec une tâche de jeu attrayante. Parallèlement à notre objectif principal d'explorer l'effet de l'entraînement multisensoriel sur l'expérience de la BCI-MI, nous avons également étudié le rôle de la rétroaction combinée olfaction-plus-force sur l'expérience de l'utilisateur. Nous avons proposé l'utilisation d'un affichage monté sur la tête instrumentée par une interface cerveau-ordinateur, appelé BCI-HMD, pour surveiller les mesures de signes biomédicaux qui sont en corrélation avec ces sous-échelles de qualité d'expérience. Nos résultats ont montré l'importance de l'ajout de stimuli olfactifs et de retour de force pour améliorer l'interaction dans la tâche, le sentiment de présence et l'agrément général de l'expérience. Les données physiologiques capturées par le BCI-HMD ont permis de calculer plusieurs sous-échelles de qualité d'expérience en temps réel, ouvrant ainsi la voie à des expériences multisensorielles adaptatives qui maximisent la qualité d'expérience pour chaque utilisateur. Explorer les effets d'un entraînement multisensoriel en RV sur. Les performances de l'IM ont montré que des améliorations significatives pouvaient être obtenues après la formation multisensorielle par rapport à la formation VR audiovisuelle conventionnelle. Une activité accrue dans les six filtres de motifs spatiaux communs utilisés a également été observée après la phase de formation multisensorielle. Elle a pu atteindre aussi des niveaux maximums de précision au courant d'une plage plus courte (6-7 secondes) par rapport aux durées optimales nécessaires avant la formation (8 secondes). Globalement, ces résultats préliminaires suggèrent que l'entraînement immersif multisensoriel pourrait conduire à une amélioration significative des performances d'imagerie motrice, ce qui pourrait offrir un nouveau paradigme pour les futures études MI-BCI.

À l'avenir, il conviendrait d'étudier un plus grand nombre de participants, de mettre au point un jeu plus réaliste avec d'autres senteurs et d'utiliser d'autres modalités physiologiques comme corrélats du HIF. Par exemple, les expressions faciales et les gestes de la main pourraient être utiles pour caractériser davantage le comportement de l'utilisateur. De plus, le poids du gant haptique(environ 350 grammes) est passé à 490 grammes avec le montage du contrôleur Quest2. Cette augmentation était nécessaire pour permettre une cartographie précise de l'emplacement spatial des mains dans le jeu. Les travaux futurs devraient explorer le suivi du bras à l'aide d'une caméra, ce qui permettrait de retirer les contrôleurs et d'alléger ainsi le gant. En dernier lieu, le développement de l'environnement virtuel a été guidé par les fonctionnalités disponibles du gant haptique, ainsi que par les odeurs disponibles dans le kit OVR, qui a été développé sur mesure pour les scènes de nature. En tant que tels, les travaux futurs pourraient explorer le développement d'autres tâches d'amorçage multisensoriel, ainsi que des algorithmes plus récents d'extraction de caractéristiques et de classification (par exemple, des réseaux neuronaux profonds).

Chapter 1

Introduction

1.1 Motivation

Recent statistics have shown that one in every four people over the age of 25 will suffer from stroke in their lifespan, with 60% occurring in people under the age of 70 years old [2]. With over 13 million new cases being reported annually worldwide, stroke is known to cause long-term cognitive and physical disabilities, thus affecting the quality-of-life of stroke survivors [3]. Physical impairments can range from mild (hemiparesis) to severe (hemiplegia) and commonly affect the left or right side of the body, while cognitive impairments can range from memory, language, and attention dysfunction to neuropsychiatric consequences such as post-stroke depression [155]. To assist with improvements in performing activities of daily life, physical rehabilitation is recommended right away or within six months after the onset of stroke to maximize the chances of success [4]. Overall, based on principles of motor learning theory, neural plasticity can be modulated greater if the training method is purposefully repeated sufficiently [5]. In fact, the frequency of the rehabilitation sessions and their intensity have been shown to be the key factors in recovery [6].

In many places around the world, however, access to rehabilitation professionals multiple times within the week is not possible due to either high cost, personnel availability, or insurance coverage purposes, to name a few factors. As such, routine rehabilitation sessions are seldom achieved [7]. To overcome this limitation, forms of in-home rehabilitation tools have been explored by exploiting technology-mediated interventions. Virtual reality (VR) has emerged as a low-cost, engaging,

interactive, and effective option shown to enhance functional outcomes and decrease depression levels [8]. In fact, VR experiences promise users an increased sense of presence and immersion, as well as higher engagement levels. Realistic virtual environments can allow for training of e.g., police officers under different scenarios and medical personnel under rare medical conditions, thus improving their training and potential to handle unknowns in the future.

Recently, VR combined with an exoskeleton or with physiological computing tools has been proposed to improve upper/lower limb rehabilitation, balance control, walking, and gait performance [9; 10; 11; 12; 13; 14; 15; 16]. Here, physiological computing refers to the use of (multimodal) physiological data to monitor a user's psycho-physiological state. Inferred states can then be used as feedback to the user or to the machine in an adaptive manner [156]. Dynamic and customized virtual environments can then be easily updated to accommodate user-specific interventions, can be tailored to a patient's specific rehabilitation plan, and allow for automated tracking of the patient's progression and adjusting the task accordingly. Commonly, cost-effective data acquisition devices to monitor electroencephalography (EEG), electromyography (EMG), and electrooculography (EOG) have been explored in novel interventions.

VR-based interventions have relied on the patient interacting with virtual objects through either active hand movements or imagined movements detected via a brain-computer interface (BCI) [17; 18; 19] or via biofeedback [20]. Recent research has shown that modulating neuroplasticity through VR can improve the motor function and muscle strength of stroke survivors [21]. In fact, in [157], VR was shown to be a suitable substitute for conventional rehabilitation to improve walking speed, balance, and mobility in stroke patients. Motor imagery (MI) paradigm, for instance, has shown to engage the same underlying neural circuits associated with imagined and executed actions [22]. Therefore, MI tasks are widely used to explore neural plasticity and control in both healthy individuals and patients [17]. Hence, MI tasks were dominantly applied for different purposes such as improving attention levels [23], reducing chronic post-traumatic stress disorder [24], and stroke rehabilitation [25]

With head-mounted display VR (HMD-VR) systems, the sense of realism and perceived immersion play key roles in rehabilitation [26; 27]. Realistic environments can provide more engaging content and motivate stroke survivors to use the systems more frequently, with reported improvements in their quality-of-life [28]. Moreover, virtual experiences can influence the patient's sense of ownership

and agency over a virtual limb, i.e., embodiment [158]. The majority of these applications, however, exploit only two senses: audio and visual. The richness of the experience, on the contrary, could be improved if additional senses are stimulated [29]. Recent innovations in wearable devices, especially those tailored to VR applications, have allowed for these multisensory experiences to emerge [30]. For example, haptic suits, vests, gloves, and sleeves are emerging in the market, providing users with haptic feedback synchronized with the experience (e.g., feeling a shot to the chest in a shooting game). Moreover, scent diffusion devices attached to VR headsets can provide users with real-time bursts of different aromas (e.g., meditation applications with lavender smells to increase relaxation), making the experiences more realistic and immersive. As highlighted by [31], however, the success of new immersive applications will rely on the experience that they provide to the user and not on the technology they use. As such, measurement of the quality-of-experience (QoE) has become crucial.

1.2 Thesis Objectives and Contributions

The use of HMD-VR coupled with physiological computing for rehabilitation purposes is on the rise [32]. With VR-based interventions, so-called human influential factors (HIFs) play a crucial role in the perceived immersive media experience (IMEx). While two individuals can use the same VR headset, play the same game in the same location, and have the same goals, the two individuals can have very different experiences, with varying perceptions of immersion, presence, realism, engagement, and cybersickness. Therefore the clinical and non-clinical results of VR-based interventions are highly correlated with QoE and HIFs [33]. This can be particularly true in multisensory immersive experiences where, in addition to audio-visual stimuli, olfactory and haptic feedback can be used to enhance the QoE [30]. Therefore, characterizing these experiences, will be crucial for the success of emerging multisensory technologies.

Accordingly, the first step of this thesis was to systematically review the existing literature about technological aspects of HMD systems, biosignal applications, and wearables that have been used for rehabilitation purposes. The goal of the presented review in chapter 2 was to gauge the potential of physiological computing systems coupled with HMD-based VR for rehabilitation applications. The chapter covers the reported effectiveness of existing solutions, their employed hardware, and the effects of multimodal feedback on (non)clinical outcomes. This review highlighted the extensive usage of VR-BCI in designing novel interventions. Enhancing the effectiveness of such a system,

however, is interwoven with both the quality of the VR experience and new user control strategies, as such training paradigms are essential to improve BCI performance.

Next, we explore the impact of the inclusion of smells, haptics, and smell-plus-haptics on the perceived QoE and user behaviour with emphasis on the correlation between neurophysiological measures and subjective ratings. More specifically, we strive to answer the following research question: What impact does the inclusion of smells, haptics, and smell-plus-haptics have on the user's sense of realism, presence, immersion, engagement, and overall experience, and correlation of neurophysiological measures with these factors across multisensory experiences. To this end, we implemented an interactive multisensory VR environment with the inclusion of audio-visual, olfactory, and haptic modalities. To capture underlying modulations in the psychophysiological state of participants, a biosensor-instrumented VR headset (termed as BCI-HMD) was developed where electroencephalography (EEG), electrooculography (EOG), photoplethysmogram (PPG), and electrocardiogram (ECG) sensors were integrated into the headset. After playing the game, users reported their perceived sense of realism, presence, immersion, and engagement with the game, as well as their cybersickness levels through questionnaires. Our first experiment showed a significant impact of smells on the sense of immersion and of haptic feedback on engagement. Overall, audio-visual-olfactory-haptic feedback resulted in the highest overall experience rating. Moreover, several neurophysiological features were extracted and their correlations with the subjective ratings were investigated to further understand user behaviour under multisensory immersive VR experience.

Lastly, after understanding the impact of the multisensory VR experience on HIFs, we explored the impact of such a system as an MI-BCI paradigm for improved motor imagery (MI) detection. To this end, considering the received user feedback of the previous step, we designed a new VR-based environment with the inclusion of audio-visual, olfactory, and force feedback modalities, where users performed two MI-BCI sessions, one before and one after being exposed to the two training conditions (audio-visual and multisensory). In this experiment, however, we first aimed to understand how inclusion of olfactory and force feedback stimuli affect the perceived levels of realism, presence, immersion, engagement, cybersickness, as well as overall QoE. Furthermore, we investigated the potential benefits of multisensory training on MI-BCI performance of users. The results of this experiment revealed the importance of olfactory and force feedback stimuli to enhance user task engagement, perceived sense of presence, and the overall experience. In terms of MI-BCI performance,

improvements were observed in MI detection accuracy. Overall, our findings suggest the potential of multisensory VR experiences to augment quality-of-experience, and eventually, BCI-MI performance.

1.3 Publications

The work in this thesis resulted in the following publications:

1. Amini Gougeh R, Falk TH (2022a) Enhancing Motor Imagery Efficacy Using Multisensory Virtual Reality Training. Frontiers in Neuroergonomics, pages 1–15. **Submitted**, under review.
2. Amini Gougeh R, Falk TH (2022b) Head-Mounted Display-Based Virtual Reality and Physiological Computing for Stroke Rehabilitation: A Systematic Review. Frontiers in Virtual Reality, 16 pages. **Published**.
3. Amini Gougeh R, Falk TH (2022c) Multisensory immersive experiences: A pilot study on subjective and instrumental human influential factors assessment. 2022 14th International Conference on Quality of Multimedia Experience (QoMEX), IEEE, pages 1–6. **Published**.
4. Amini Gougeh R, Falk TH (2023) Towards Instrumental Quality Assessment of Multisensory Immersive Experiences Using a Biosensor-Equipped Head-Mounted Display. Quality and User Experience. **Submitted**.
5. Amini Gougeh R, Jesus B, Lopes MKS, Moinnereau MA, Schubert W, Falk TH (2022d) Quantifying user behaviour in multisensory immersive experiences. 2022 IEEE International Conference on Metrology for eXtended Reality, Artificial Intelligence, and Neural Engineering (MetroXRAINE), IEEE, pages 1–5. **Published**.

1.4 Thesis Organization

This thesis is comprised of the following additional chapters:

- Chapter 2 describes multisensory immersive experiences and provides definitions of QoE and its subfactors that could be measured to quantify the user experience. Moreover, relevant results from a comprehensive systematic literature review on multimodal HMD-VR systems

used for stroke rehabilitation and suggested improvements to the state-of-the-art are presented in this chapter.

- Chapter 3 reports a preliminary study to explore and quantify the impact of audio-visual, olfactory, and haptic feedback on user behaviour through subjective and objective methods.
- Chapter 4 represents the refined version of the first experiment with new feedback modalities, VR environment, and hardware. The results related to the user experience are reported and discussed in this chapter.
- Chapter 5 explores the effect of multisensory training, as described in the previous chapter, on MI-BCI accuracy.
- Chapter 6 presents the thesis conclusions, study limitations and future research directions.

Chapter 2

Background and Literature Review

2.1 Chapter Overview

VR-mediated rehabilitation is emerging as a useful tool for stroke survivors to recover motor function. Recent studies are showing that VR coupled with physiological computing (i.e., real-time measurement and analysis of different behavioural and psychophysiological signals) and feedback can lead to (1) more engaged and motivated patients, (2) reproducible treatments that can be performed at the comfort of the patient's home, and (3) development of new proxies of intervention outcomes and success. With VR, so-called human influential factors play a crucial role in the final perceived immersive media experience. While two individuals can use the same type of VR headset, play the same game in the same location, and have the same goals, the two individuals can have very different experiences, with varying perceptions of immersion, presence, realism, engagement, and cybersickness. This can be particularly true in multisensory immersive experiences where, in addition to audio-visual stimuli, olfactory and haptic feedback can be used. In this chapter, we describe the multisensory immersive media experience (IMEx) and explore methods to evaluate quality-of-experience (QoE) during VR-based multisensory experience.

Moreover, while multimodal/multisensory systems have shown great potential for stroke rehabilitation, an extensive review of the literature is still lacking. Here, we aim to fill this gap. A detailed analysis of the papers was conducted along with a quality assessment/risk of bias evaluation of each study. It was found that the quality of the majority of the studies ranked as either good or

fair. Study outcomes also showed that VR-based rehabilitation protocols coupled with physiological computing can enhance patient adherence, improve motivation, overall experience, and ultimately, rehabilitation effectiveness and faster recovery times. Limitations of the examined studies are discussed, such as small sample sizes and unbalanced male/female participant ratios, which could limit the generalizability of the obtained findings. Finally, some recommendations for future studies are given. This chapter is based on our paper titled as "Head-mounted display-based virtual reality and physiological computing for stroke rehabilitation: a systematic review" and published in Frontiers in virtual reality [159].

2.2 Multisensory Immersive Experiences

The concept of "sensory immersion" refers to being comprehensively surrounded by a multisensory representation of the real world, but in a virtual setting [34]. Multisensory experiences strive to improve QoE by enhancing the user's sense of immersion, presence, and realism, by fostering greater engagement, as well as by potentially reducing cybersickness. Interwoven with immersion, "presence" revolves around the place and plausibility illusions and indicates the sense of being physically present/immersed in the virtual environment [35]. Realism, in turn, refers to the presentation of virtual objects, lighting, and animations that closely match those seen in the real world [36]. Engagement, on the other hand, reflects the degree in which the users are interacting with the virtual environment [37]. Lastly, cybersickness results from the conflict between the sensory inputs to the brain, which are known to result in mild to severe discomfort in terms of headaches, vertigo, and nausea [38].

Existing VR applications have typically relied on 360-degree videos and 3D audio to allow the user to feel immersed in the environment. As humans, we are used to experiencing the world using our five senses, and not just two. To further improve the experience and increase the user's sense of presence and immersion, recent studies have explored the inclusion of different sensory modalities. For example, touch and somatosensory stimuli have been incorporated via vibrations [39; 40], temperature changes [41], and airflow [42], whereas scent diffusers have been used to provide olfactory stimuli [43; 44], and electrical tongue stimulation to provide virtual sense of taste [45]. Stimulating different human senses creates a customized and enhanced user experience [46; 47; 48]. In [29], for example, an enhanced sense of presence was reported when users were exposed to

olfactory, thermal, and airflow stimuli, even in passive scenarios where users did not have to interact with the environment. Moreover, vibrotactile feedback has also shown to influence engagement levels, improving the interaction with the virtual environment [49]. Commonly with VR, interaction with 3D objects is achieved via the use of either hand-held controllers or hand tracking systems. Recent work, however, has shown the benefits of using force-feedback based exoskeletons/gloves to provide additional cues about object stiffness and texture (e.g., [40; 50; 51]), especially concerning improvements with task execution. Notwithstanding, as highlighted in [30], however, less than 2% of published multisensory studies have relied on more than three stimulated senses. As such, little is known about the impact of different multisensory stimuli on HIFs, as well as their overall impact on IMEx QoE. We also aim to fill this gap.

2.3 QoE Measurement

Measuring the QoE of multisensory experiences, however, can be challenging. While immersive media QoE is commonly measured using the so-called technological and contextual influential factors [52], human preferences (also known as HIFs), play a crucial role in multisensory experiences. For example, certain smells that may be pleasant for some may be unpleasant for others. Moreover, for some, haptic feedback may make the scene seem more realistic and improve the sense of presence and immersion, while for others it may disrupt engagement and degrade the overall experience. As such, measuring these individualized factors (referred to here as QoE subscales or subfactors) in real-time while the user is immersed is important, as it can allow for sensory stimuli adaptation to maximize QoE. Measuring HIFs and their influence on IMEx QoE can follow three principles: questionnaires, behavioural, and psychophysiological data analysis [52]. Therefore, QoE measurements rely on subjective ratings and/or objective metrics to gauge the benefits of immersive experiences.

2.3.1 Subjective QoE evaluation

Questionnaires are the most common method for QoE evaluation and several have been reported in the literature to target certain aspects, such as sense of presence, engagement level, and simulator sickness, to name a few [53; 54; 37]. While most questionnaires target one single factor, recently a unified user experience questionnaire was proposed containing 10 subscales to measure presence,

engagement, immersion, flow, usability, skill, emotion, experience consequence, judgement, and technology adoption [55]. The use of paper-pencil surveys, however, might interrupt the virtual user experience, especially those based on head-mounted displays (HMD). In fact, several HMD-based studies have reported experimenters reading out loud the questions to the participants after certain conditions of the experiment are done to avoid breaking the immersion by removing the headset (e.g., [56]). Alternately, some works have participants fill out the questionnaires at the end of the entire session. While this avoids the issue of immersion disconnection, it relies on human memory, which in multi-condition experiments has been shown to be highly susceptible to errors [57]. As such, VR-based questionnaires have been developed to overcome the issue of immersion disconnection and memory errors [58; 59].

Moreover, questionnaires can be confusing, especially those targeting human emotional states, due to e.g., ambiguity of words used or in differences in expressions used across languages and cultures [60; 61]. As such, graphical self-report approaches have been widely utilized [62; 63; 64]. These tools intuitively link iconic graphical elements to experienced emotions. Recently, the EmojiGrid has exploited the capability of using emojis to characterize evoked emotions after exposing users to 360° VR videos, showing some advantages over other conventional questionnaires [65]. Nevertheless, questionnaires do not allow for real-time monitoring of IMEx HIFs, thus innovations in behavioural and psychophysiological analyses have been the focus of more recent research.

2.3.2 Objective QoE evaluation

Despite widespread use of questionnaires, subjective ratings (and objective experience-based metrics, such as execution time) do not allow for real-time assessment of the user-specific experience (including all relevant QoE subscales), thus neurophysiological signal monitoring and analysis (a process termed "physiological computing") has emerged as a promising alternative. With biosignal-based QoE assessment, additional tools/technologies have to be worn by the user, such as smartwatches to measure heart rate [66], or headbands to measure brain signals. Photoplethysmogram (PPG) signals, for example, have been used to track changes in stress levels [67], whereas electro-oculograms (EOG) have been used to reveal details about covert attention using saccadic eye movements [68]. Moreover, heart rate measures acquired from electrocardiograms (ECG) have been linked to stress, which can result in poor experiences [69].

Electroencephalograms (EEG), in turn, have been proposed to unveil the association between the users mental state and engagement levels, and their impact on VR experience [70]. Mental workload has also been shown to effect a user's overall experience [71], thus real-time measures of workload (e.g., frontal theta band power, 4-8 Hz) could be useful for multisensory experiences [72]. Moreover, EEG have been used to monitor user arousal and valence indices [73], whereas certain EEG subband spectral powers (e.g., beta band, 12-30 Hz) have been linked to different emotional processes in the brain [74], to immersive game exploration (theta band) [75], as well as to cybersickness (delta, 0-4 Hz, theta, and alpha bands 8-12 Hz) [160]. Frontal alpha asymmetry (FAA) has been proposed as a correlate of user enjoyment and satisfaction [76], as well as signifying sense of presence and immersion in VR [75; 77]. As mentioned previously, these works have relied on traditional audio-visual immersive settings. While some recent works have explored the use of heart rate and eye gaze to assess the QoE of 2-dimensional media enhanced with olfaction (e.g., [161]) and others have explored the impact of video quality perception and presence on olfaction-enabled 360-degree videos (e.g., [162; 163]). Lastly, head movements could also provide information about the experience, from emotional states [78] to motion sickness [79]. Moreover, analyzing head orientations could provide an approximation of user's field of attention, which has link to overall experience [80].

Typically with neurophysiological QoE assessment, commercial off-the-shelf wearable devices have been used. Such an approach can have several disadvantages, including poor usability, discomfort, interference with the task, as well as interference with the signal collection, thus limiting the full potential of the methodology. For example, smartwatches or finger-based sensors (e.g., galvanic skin response) may interfere with the placement of haptic gloves/exoskeletons, whereas HMD straps may interfere with the placement of certain EEG electrodes in strategic brain regions. Notwithstanding, recent advances in portable bioamplifiers and wearable brain-computer interfaces (BCI) have allowed for sensors to be placed directly on the head-mounted display, allowing such measures to be computed in real-time while the user is immersed in a multisensory experience without affecting the experience itself [81].

2.4 Review of HMD-VR based neurorehabilitiation applications with physiological computing tools

The use of HMD-based VR and physiological computing for stroke rehabilitation is on the rise. Therefore, we conducted a systematic review of the existing literature to collect information about technological aspects of HMD systems, biosignal applications, and wearables (e.g, exoskeleton) that have been used for rehabilitation purposes. In particular, the remainder of this chapter is aimed at addressing the following questions:

1. What physiological computing systems have been used with HMD-based VR and how effective have they been?;
2. What equipment have been used and what advantages do certain psycho-physiological modalities offer over another?; and
3. What clinical and non-clinical outcomes have been observed from these multimodal feedback based virtual reality interventions?

2.4.1 Methods and Materials

This systematic review was conducted according to the preferred reporting items for systematic reviews and meta-analyses (PRISMA) guidelines [164].

2.4.1.1 Search Strategy

A search over English language peer-reviewed journal papers was conducted across five databases, including Scopus, IEEE, Web of Science, PubMed, and Science Direct, between the years January 2015 to December 2021. The following keywords were used: *(electro* OR respiration OR "galvanic skin") AND "stroke rehabilitation" AND "virtual reality"*. The keywords were searched in the title or abstract of the articles. Mendeley reference manager was used to remove duplicate citations across yielded results. The term "physiological computing" was not used as a keyword as it is a very specialized term that few researchers in the VR space utilize at the moment. By including all possible modalities that begin with 'electro' (e.g., electrocardiogram, electroencephalogram,

electromyogram, electrooculogram, electrodermal activity) we are bound to encompass all studies that utilized physiological computing systems without referring to this terminology directly.

2.4.1.2 Inclusion and Exclusion Criteria

Inclusion criteria included articles that (1) used HMD-based VR experiences,(2) included at least one feedback modality to improve the VR experience, (3) included a valid clinical measure or questionnaire to gauge the effectiveness of the intervention, and (4) developed a rehabilitation tool but tested on healthy subjects. Exclusion criteria included: (1) review papers, (2) studies not relying on HMD-based VR, and (3) studies not focusing on stroke rehabilitation applications. Eligibility criteria according to population, intervention, comparison, outcome, and study design (PICOS) has been tabulated in Table A.1, available in the Appendix. We note that studies with healthy people have only been included if the goal of study was aligned with providing interventions to the population of interest (as described in Table A.1).

2.4.1.3 Screening and Data Extraction

After searching the abovementioned databases and merging the duplicated results, titles and abstracts were screened to exclude any unrelated articles. The full-text screening was then performed on the remaining papers and aligned articles were included in this systematic review. To collect detailed information from each study, a data extraction spreadsheet was developed encompassing details across three domains: (1) study design and demographics (targeted stroke group, number of subjects, control group, gender distribution, target problem, session description, trial design), (2) technological aspects (HMD device, VR engine used, physiological modality, type of feedback, equipment, and electrode placement), and (3) outcomes (clinical/non-clinical scales, clinical results, availability of baseline information, pre- and post-intervention comparisons, and follow-up findings).

2.4.1.4 Quality assessment

To assess the risk of bias (ROB) in the included studies, we utilized the National Institutes of Health — National Heart, Lung, and Blood Institute (NIH-NHLBI) quality assessment tool [165], as well as the checklist for quasi-experimental studies based on the Joanna Briggs Institute (JBI)

critical appraisal tool [166]. For the former, articles are evaluated based on the type of the study and overall quality is judged based on 'good', 'fair', or 'poor' categories. Categories are chosen based on replies to a number of questions, where answers can take the form of *yes, no, cannot determine, not reported*, or *not applicable*. Both NIH-NHLBI and JBI tools examine studies across three aspects, including objectives, methodology, and report of outcomes.

2.4.2 Results and Discussion

2.4.2.1 Included Studies

From the 218 identified articles, 46 were from PubMed, 16 from ScienceDirect, 59 from IEEEXplore, 38 from Web of Science, and 59 from Scopus. Figure 2.1 depicts a flow chart of the study selection process. After eliminating duplicates, 182 studies were left to be screened based on title and abstract. From this first pass, 130 papers were eliminated as they did not meet the inclusion criteria, resulting in 52 articles included for full-length analysis. In the end, 12 articles focusing on HMD-VR, multimodal physiological computing, and stroke motor rehabilitation were included in this review.

2.4.2.2 Study Design

Detailed information about the configuration, modalities used, study type, experiment duration, and demographics of the participants are available in Table 2.1. Detailed description of hardware used to acquire the physiological signals are described in Table 2.2.

All of the included papers followed a "pre/post study design," which refers to measuring specific metrics prior to the experiment and comparing them with recorded measures after the intervention [168]. As can be seen, among the included articles, four studies recruited only healthy subjects [90; 167; 91; 92], three relied on patients who were in chronic stage of stroke [99; 89; 86], three studies used a mixture of healthy and stroke patients [87; 82; 84], one study used a stroke patient in sub-acute stage [85], and one study used a mixture of stroke patients in the chronic stage and patients with developmental disabilities [83]. The reported numbers in Table 2.1 are for

Table 2.1: HMD-VR rehabilitation systems and utilized technologies, devices and study design.

Study	Hardware	Modalities	Feedback	Study population				Experiment	
				Participants	Stroke onset[a]	Age range	F/M	Duration	Tasks
[99]	Oculus Rift CV1	EEG, EMG	Visual, Hand tracking	Stroke patients (chronic stage, n= 4)	37 ± 48.6	13.54 ± 11.08	1 /3	10 sessions	Left and right: (A) Static hold task, (B) Wrist extensor training
[87]	Oculus Rift, MotionStim 8	EEG, EOG	Visual, FES, EOG	Stroke patients (post-stroke central neuromotor syndrome, n= 7), and controls (n= 3)	N/M	52 to 79	N/M	3 sessions	(A) Virtual therapist in front of user (B) Therapist/user looking at mirror
[85]	Oculus Rift DK2, Tyromotion Amadeo	Finger Tracking	Visual, Audio, finger position and force	Stroke patients (subacute stage, n= 8)	2.18 ± 1.13	69 ± 11.48	5 /3	18 sessions	(A) Passive, (B) Adaptive, (C) 2D game, (D) 3D game
[89]	Oculus Rift, Magstim BiStim, 3T Prisma MRI scanner	EEG, EMG	Visual, Audio, Haptic, EEG	Stroke patients (chronic stage, n= 4)	108.5 ± 48.6	60 ± 5.8	1 /3	10 sessions	Left/right wrist/elbow extension
[86]	Oculus Rift DK1, 3T GE Signa fMRI HDxt, Arduino	EEG, EMG	Visual, Audio, Haptic, EEG	Stroke patients (chronic stage, n= 1)	112	60	0 /1	10 sessions	Left and right hand: (A) MI with arrows-and-bars, (B) MI in VR
[90]	Oculus CV1, LSM9DS09 IMU	EEG, EMG	Visual, Audio, EEG, IMU	Healthy participants (n= 12)	N/A	24.4 ± 2.7	7 /5	90 trials	Hand movement imagination: (A) Screen, (B) HMD-VR, (C) Exercise while using IMU
[82]	HTC Vive Cosmos Elite, Myo Armband, Mi fit 3	EMG	Visual, Audio, Haptic	Stroke patient (n=1), diabetic neuropathy (n= 1), controls (n= 6)	N/M	52.62 ± 24.48	N/M	Four phases	Upper and lower limb exercises
[167]	Oculus Rift, Kinect	Motion Tracking	Visual, Audio	healthy participants (n= 10)	N/A	61 to 75	8/2	1 session	Abduction movements and shoulder adduction, elbow and wrist extension with (A) Screen and (B) HMD-VR
[91]	Oculus Rift DK1, Leap Motion	EEG	Visual, Audio	healthy participants (n= 9)	N/A	27 ± 2	1 /8	3 sessions	(A) Motor execution, (B) online MI, (C) MI with arrows-and-bars
[83]	HTC Vive	Hand Tracking	Visual, Audio, Haptic	Stroke patients (n=9), patients with developmental disabilities (n= 6)	36 to 108	stroke patients: 36 to 87, developmental disabilities: 26.5 ± 3.27	6 /9	1 session	Collecting scores in HMD-VR game
[92]	Oculus Rift, UnlimitedHand	EEG	Visual, Electrotactile	Healthy participants (n= 20)	N/A	26.20 ± 5.37	5 /15	3 sessions	Flexion and extension MI tasks
[84]	HTC Vive, Michelangelo prosthetic hand	EMG	Visual	Healthy participants (n=15), congenital right hand amputation (n=1)	N/A	Healthy: 31.0 ± 7.6, Patient: 33	3 /13	multiple sessions	Box and Block test with HMD-VR

HMD: head-mounted display, MRI: magnetic resonance imaging, fMRI: functional MRI, FES: functional electrical stimulation, IMU: inertial measuring units, MI: motor imagery, DK: development kit, CV: consumer version, F/M: female/male, N/M: not mentioned
[a] Time after stroke onset reported in months.

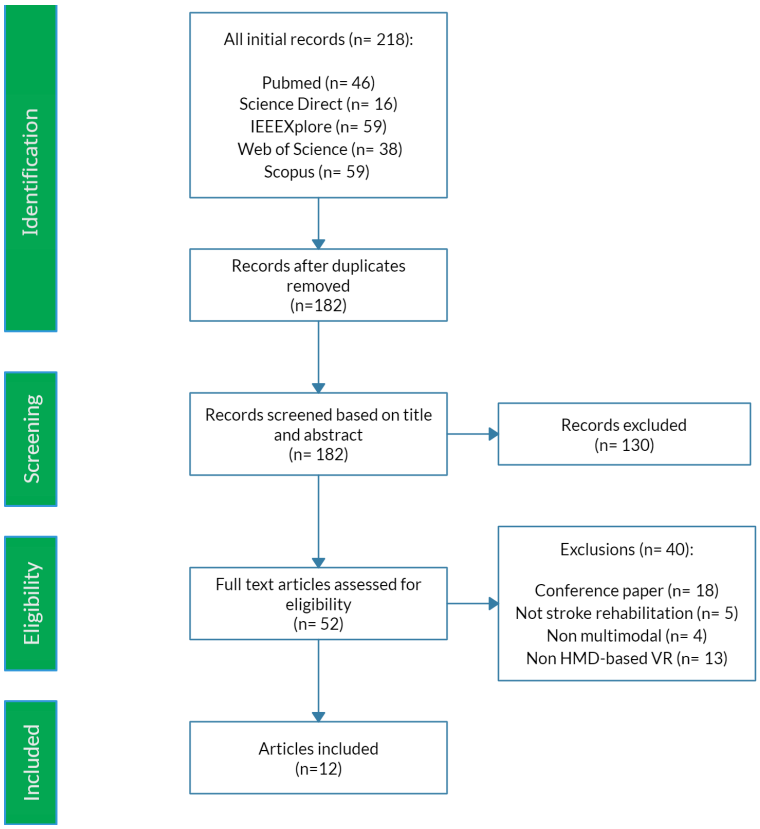


Figure 2.1: Flow chart of paper selection steps.

participants who have completed all the sessions and satisfied all experimental protocols. Overall, 64.1% of participants were healthy subjects, and only 40% of all participants were females.

The reviewed studies relied on virtual environments to deliver rehabilitation exercises by means of gamified interventions. Ten articles focused on upper limb rehabilitation, while the remaining two studies focused on both upper and lower limbs [90; 82]. Table 2.3 details the characteristics of the study (i.e., the aim of the study, target limb, and virtual environment description). As can be seen, among the included articles, only three studies used more than two different virtual environments [85; 82; 84].

2.4.2.3 Quality Assessment

As one of the reviewed papers was a case report, the NIH-NHLBI quality assessment tool for case series studies and the JBI checklist for case reports was used. For the remainder of the studies, the NIH-NHLBI quality assessment tool for before-after (pre-post) studies with no control group

Table 2.2: Detailed information about devices used for physiological computing

Study	EEG device	EEG sample rate	Number of channels	EEG electrode placement	EMG device	EMG sample rate	EMG electrode placement
[99]	Starstim 8	500 Hz	8	FC3, FC4. C3, C4, C5, C6, CP3, CP4	Delsys Trigno Wireless System	2000 Hz	FCR, FCU, ECR, ECU
[87]	g.USBamp	256 Hz	12	FC1, FC2, FC5, FC6, C3, C4, C5, C6, CP1, CP2, CP5, CP6	N/A	N/A	N/A
[89]	Starstim 8	500 Hz	8	FC3, FC4, C3, C4, C5, C6, CP3, CP4	Delsys Trigno Wireless System	2000 Hz	EDC, FCU, BB, TB
[86]	Enobio 8	500 Hz	8	FC5, FC6, C1, C2, C3, C4, CP5, CP6	N/A	N/A	N/A
[90]	OpenBCI	125 Hz	12	F3, F4, C1, C2, C3, C4, CP1, CP2, CP5, CP6, P3, P4	OpenBCI	125 Hz	FCR, FCU, ECR, ECU
[82]	N/A	N/A	N/A	N/A	Myo Armand	100 Hz	Forearm
[91]	g.MOBIlab+	256 Hz	8	FC3, FC4, C3, C4, C5, C6, CP3, CP4	N/A	N/A	N/A
[92]	g.USBamp	256 Hz	16	AF3, AF4, FC3, FCz, FC4, C3, Cz, C4, T7, T8, CP3, CPz, CP4, Pz, O1, O2	N/A	N/A	N/A
[84]	N/A	N/A	N/A	N/A	Myo Armand	100 Hz	Forearm

FCR: flexor carpi radialis, FCU: flexor carpi ulnaris, ECR: extensor carpi radialis longus, ECU: extensor carpi ulnaris, EDC: extensor digitorum comunis, BB: biceps brachii, TB: triceps brachii

and the JBI checklist for quasi-experimental studies was utilized. The detailed responses obtained by both of the assessment tools are presented in Tables A.2 and A.3, respectively, both available in the appendix section. Table 2.4, in turn, presents the results of the quality evaluation using the NIH-NHLBI tool.

As can be seen, from the NIH-NHLBI analysis, the majority of the pre-post studies (n= 11) were rated as fair, while four studies were rated as good, and two as poor. The fair-rated studies showed clear objectives, eligibility criteria, selection of participants, targeting populations of interest, description of intervention, description of outcome measures, and multiple outcome measures, they reflected issues in terms of sample size, blinding of outcome assessors, and follow-up rate. Poor-rated studies, in turn, had issues concerning multiple outcome measures, statistical analysis,

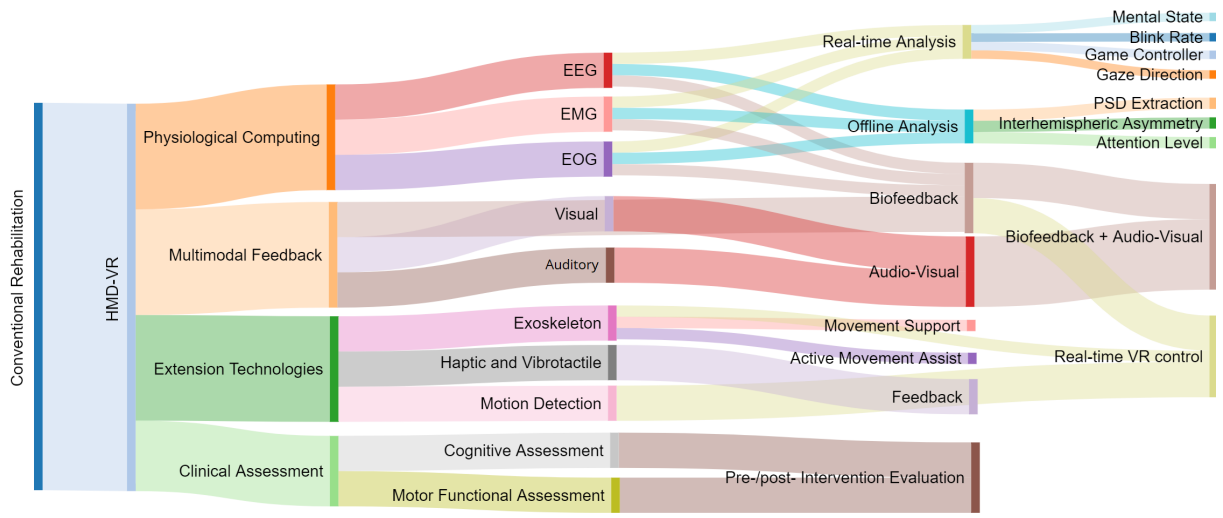


Figure 2.2: Alluvial diagram illustrating mediated approaches and their combinations to shape significant usage within the framework of HMD-VR for rehabilitation.

and group-level interventions. The case study, on the other hand, was rated good quality due to clarity of objectives, detailed description of population and intervention, valid and reliable outcome measurement, and well-described statistical method and results. In terms of JBI criteria, the issues flagged concerned lack of control group, receiving a similar treatment (except exposure to HMD-VR), and lack of follow-up plan. None of the articles showed issues with clarity of cause and effects of their study, similarity of participants, multiple measurement points of the outcome, or similar outcome measurements. Three articles, however, had issues with reliability of outcome measurements due to not using appropriate statistical analysis methods. For the case study, the JBI tool reflected "yes" responses to all of the checklist questions, thus corroborating its quality.

2.4.2.4 Technological Aspects

Overall, the included articles employed different types of technologies. Figure 2.2 demonstrates an alluvial diagram of the methods, their combinations, and target aim. As evidenced, different physiological modalities and technologies have been utilized in VR-based stroke rehabilitation interventions. The following subsections highlight these methods in detail.

Virtual Environment The Unity3D game engine was reported as being the most common for virtual environments design, feedback control, and integration of external devices (e.g., biosignal

Table 2.3: Characteristic of reviewed studies, including target limbs, study aim, and virtual environment description

Study	Target limb	Study aim	Environment description
[99]	Wrist and elbow	Reinforce activation of the wrist extensor muscles without flexor activation	Two arms are resting on a table, and users requested to push the ball off the table with the back of their hand.
[89]	Wrist and elbow	Investigate the effectiveness of BCI-VR in patients with motor disabilities	Two arms resting on a table and the task is to extend a hand toward a target where virtual hands will move via neurofeedback.
[87]	Hand	Hand and fingers flexion and extension via a virtual therapist while leveraging mirror therapy	Virtual therapist gives hand rehabilitation exercises in a face-to-face situation and with the therapist on the left side of the user and a mirror in front.
[85]	Hand	Strengthen force, range of motion, finger coordination, and movement planning.	Five environments including (A) Flying bird-2D, (B) Spaceship-2D, (C) VR-simulated supermarket, (D) VR-simulated kitchen, and (E) space war VR game.
[86]	Hand	Examine the efficacy of the MI-BCI paradigm with VR for post-stroke upper limb rehabilitation	NeuRow, a first-person self-paced BCI game (a boat rowing task through MI) with the goal of collecting scores in a pre-determined amount of time.
[91]	Hand	Increase engagement of sensory-motor networks during rehabilitation	Virtual garage where user's movement is mapped to VR to open the door via rotating a lever.
[92]	Hand	Investigate the effectiveness of visual-electrotactile feedback versus visual-only feedback	Room with chairs and a desk with the user's virtual arm and a ball to present target movements.
[90]	Arm and hand	Compare embodiment and motor imagery BCI performance in HMD-VR versus screen-based VR	Hit a ball with a virtual arm using MI-BCI paradigm and active movement.
[83]	Arm and hand	Leverage modified constraint-induced therapy (mCIT) to influence the use of the weaker arm	Galaxy background with stars appearing. The patient's strong arm is mapped in red and weak arm in green. Patients touch stars that are falling with a goal to increase their score. More points are given if the weak arm is used.
[84]	Arm and hand	Implement a VR-based version of the Box and Block test	Virtual box divided in two parts by a partition. Patients are asked to move small blocks from the right to the left partition. A virtual Jenga game, a squeezable toy, and an interactive kitchen environments were also tested.
[82]	Shoulder, elbow, fist, hip, knee, ankle	Patient should imitate movements shown by a therapist	Patients observe classical rehabilitation movements performed by the virtual therapist and perform them on their own. Six VR games are tested: (A) hitting targets, (B) ball directing, (C) hitting mole, (D) boxing, (E) football, and (F) dancing.
[167]	Shoulder, elbow, fist, hip, knee, ankle	Compare HMD-VR versus TV screen while providing motor and balance rehabilitation exercises	User movements mapped to the VR environment.

Table 2.4: NIH quality assessment results for included studies

Study	Type	Good	Fair	Poor
[99]	Pre-post		✓	
[87]	Pre-post			✓
[85]	Pre-post		✓	
[89]	Pre-post	✓		
[86]	Case-study	✓		
[90]	Pre-post		✓	
[82]	Pre-post		✓	
[167]	Pre-post			✓
[91]	Pre-post	✓		
[83]	Pre-post		✓	
[92]	Pre-post	✓		
[84]	Pre-post		✓	

acquisition systems) into the game flow. Wearable HMDs, which provide stereoscopic close-to-reality experience and increased perception of depth and immersion, were widely used. In particular, three studies used the HTC Vive HMD (Valve Washington, Washington, USA), [82; 83; 84], while the remaining utilized an Oculus HMD (Oculus VR, Irvine, California, United States), likely due to its accessibility to SDKs and lower price. In the studies, varying display refresh rates from 60Hz to 90Hz were reported.

To deliver targeted rehabilitation-oriented content, custom environments were typically developed, though two studies relied on pre-developed games [85; 86]. For example, two studies implemented a virtual therapist to present exercises in a virtual environment [87; 82]. Nevertheless, only one study provided detailed information about the virtual environment design process, including the properties of different objects and the adjustment of feedback intensity [83]. The other reviewed articles failed to provide comprehensive information about concepts of human-centered design, including signifiers, affordances, mapping, and conceptual models [88].

Lastly, a first-person point of view (POV) was shown to be very popular in the reviewed articles, where nine studies had a first-person perspective (patient performs from character's POV), two studies exploited third-person playing mode (patient controls a virtual avatar) [85; 167], and one study had both settings [87]. It is known that the first-person perspective increases the sense of

embodiment (limb ownership and self-location) while the third-person perspective provides space awareness [169].

Physiological Computing Physiological computing has emerged as a powerful tool in human-computer interaction, allowing real-time physiological signal analysis and behavioural information to enhance the interaction by conveying user cognitive/mental/affective state information to the machine, as well as real-time information about patient movement, thus improving the sense of embodiment. Moreover, physiological/behavioural data can provide insights into both conscious and unconscious processes and thus may also convey information about the user's motivational and intentional states. More recently, as wearable devices burgeon, physiological computing has started to gain traction for at-home uses. This, coupled with HMD advances and a drop in costs, has resulted in the development of new in-home VR-based rehabilitation systems. Table 2.2 presents technical information about the EEG and EMG wearable devices used in the reviewed papers, including a description of the devices themselves, their sample rates, and electrode placement details. Inertial measurement units (IMUs) have also been utilized for motion/behavioural tracking and EOG signals to assess if the tests were performed correctly [87]. More details about these modalities are provided below.

EEG As seen in Table 2.2, seven articles have relied on EEG-based physiological computing methods in their VR rehabilitation studies. Since the main aim of the studies concerns motor improvement, most studies acquired EEG signals from electrodes over the motor cortex, corresponding to positions FC3, FC4, C3, C4, C5, C6, CP3, and CP4 electrodes in the 10-20 international positioning system. In terms of BCI paradigms, six studies relied on motor imagery (MI) [87; 89; 86; 90; 91; 92]. The underlying hypothesis with MI is that illusions of movement and a strong feeling of embodiment could improve the neural plasticity needed for rehabilitation, with physiological computing and real-time feedback contributing to an improved embodiment. Sub-acute stroke patients, for example, who used MI-based paradigms could then improve functional outcomes [93]. Stronger desynchronization in the alpha (7-13 Hz) and beta (13-30 Hz) EEG bands of the ipsilesional hemisphere, for example, has been shown [94]. Additionally, increased hemispheric asymmetry has been shown in MI sessions with feedback, suggesting enhancement in fine motor task performance and modifying motor learning [95; 96]. In fact, differences in interhemispheric asymmetry in stroke patients have been reported relative to a control group [97], thus suggesting that physiological computing could be used

not only to customize the environment, but to also track intervention progress and success [98]. The impact of HMD-based rehabilitation has also been quantified by means of post-hoc comparisons based on event-related synchronization/desynchronization (ERS/ERD) [89], corticomuscular coherence (i.e., synchronization between EEG and EMG signals) [99], resting-state alpha rhythm [86], and EEG rhythm power spectral analyses [90; 91; 92].

Despite these reported benefits of using MI-based BCIs, studies have reported that detecting motor imagery tasks using off-the-shelf neuroimaging tools can be challenging for 15% to 20% of the population [170; 171]. Earlier studies referred to this as "BCI illiteracy," which insinuates the issue is on the user. More recently, the terminology "BCI inefficiency" [100] has been incorporated as it combines user-related factors with limitations in hardware (e.g., signal acquisition systems and signal quality) and software (e.g., accuracy of the classification algorithms) [101]. To overcome this issue, recent research has focused on developing new filtering methods, feature extraction techniques, and newer and more complex machine learning algorithms (e.g., [102; 103; 104; 105]) to tackle the software aspect. Moreover, improvements in bioamplifiers and electrodes (dry versus gel-based; active versus passive) have been explored to address the hardware issues [106].

EMG EMG provides information about the electrical activity of the muscles. The location of electrodes is typically determined based on the aim of the study, i.e., to improve the function of the upper or lower limb. Upper limb studies can include muscles of the hand, wrist, elbow, and rear-/fore-arm, whereas lower limbs can include the foot, ankle, knee, thigh, and hip. As shown in Table 2.2, only five of the twelve relied on EMG signals, two of which used a Delsys Trigno Wireless System (Delsys Incorporated, Natick, USA) [99; 89], two used Myo armbands (Thalmic Labs) [84], and one used an OpenBCI bioamplifier [90]. These systems operated at sample rates of 2000, 100, and 125 Hz, respectively. In addition to post-hoc EMG analyses to monitor the physical improvement due to rehabilitation (e.g., EMG amplitude, rest/active state detection), three studies relied on EMG signals to map the patient's arm/hand into the VR environment to improve the sense of embodiment [99; 82; 84].

Motion Tracking While EMG can provide information about limb motion, it lacks details about e.g., arm/hand orientation. To this end, inertial measuring units (IMUs) have been used as a real-time tool to map arm/hand direction onto the virtual environment. For example, [90] relied

on IMUs to match the virtual arm/hand movements with the user's actual arm/hand movements. Similarly, the controllers used by VR systems can be used as a motion-tracking tool, in addition to delivering haptic feedback [83; 84]. Lastly, optical tracking tools, such as a Leap Motion (Leap Motion, Inc., San Francisco, California, United States) tracking device [91] have been used to map hand orientation and finger movements into the virtual environment.

Feedback Modality Feedback is known to improve the sense of embodiment and to also foster plasticity [172; 173], thus is widely used in neuro-rehabilitation. Visual and audio-based feedback modalities are the most classic form of feedback, but more recent studies have been exploring the use of haptic (e.g., by the controllers, as mentioned above) feedback to improve the sense of immersion and presence. Feedback needs to be easily distinguishable, especially by the patient population [83; 167], thus the volume of audio cues, the shape and color of visual cues, and the intensity of haptic cues are of indispensable importance. In certain conditions, voluntary movement is still not possible by the patient, thus an exoskeleton is used to provide the intended feedback. Additionally, more recent methods have relied on the use of functional electrical stimulation (FES) [87] as a form of feedback, where subtle electrical charges are applied to certain muscles in order to contract them upon detection of motor activation signals from EEG, for example.

Exoskeleton-based Feedback Exoskeleton-based rehabilitation relies on robotic or non-robotic assistive devices which help the patients perform exercises correctly, safely, and in a sustained manner with or without predefined force intensities [12]. The exoskeleton can be set in active, passive, or assistive modes [174]. In the reviewed articles, only one paper relied on exoskeletons. In particular, [85] used a 5-degree-of-freedom Amadeo (Tyromotion GmbH, Graz, Austria) along with audio-visual feedback. The device provided patients with control over finger movements, force, and velocity.

Haptics-based Feedback Haptic feedback adds the sense of touch to the virtual experience and increases the sense of immersion [107]. Gloves, controllers, armbands, or even exoskeletons can be used to provide haptic feedback [108]. As seen from Table 2.1, five studies relied on haptic feedback, where three used the VR system controllers to provide vibration feedback [89; 83; 82], one proposed a custom device based on vibrating motors [86], one used the UnlimitedHand (H2L Inc., Tokyo, Japan) device to supply electrotactile stimulation feedback [92]. Haptic feedback was used primarily

in these studies to inform the subject when a task was finalized and/or in response to an interaction with a specific object in the virtual environment.

2.4.2.5 Clinical/non-clinical Reported Outcomes

The reviewed papers relied on multiple approaches to measure the efficacy of their proposed methods. For example, several different questionnaires, physiological signal analyses, and clinical measures were explored. Table 2.5, presents a description and evaluation domains of the most-utilized clinical/non-clinical scales reported in the papers. As interventions may have outcomes across numerous domains, it is common for studies to use more than one assessment method. As seen from the Table, seven clinical scales have been used most often, including the Fugl–Meyer assessment (FMA), action research arm test (ARAT), Montreal cognitive assessment (MoCA), motor assessment scale, modified Ashworth scale, range of motion (ROM), and stroke impact scale (SIS). Studies typically compared these metrics pre- and post-intervention to gauge the benefits of the VR therapy. Further, to assess detailed alterations in the brain and plasticity improvements, two studies relied on magnetic resonance imaging (MRI) and functional MRI (fMRI) [89; 86]. Table 2.6 includes the significant final outcomes observed by the studies, as well as the time points in which clinical/non-clinical measures were taken for comparisons.

In terms of clinical measures, various metrics are observational, meaning that a clinician (or a physiotherapist) determines a score after the patient performs a specific task. Five studies relied on a certified occupational therapist or rehabilitation specialist to carry out these observational clinical measures [99; 85; 89; 86; 82]. FMA and SIS can be seen to be the most widely used measures. However, FMA has been shown to be subject to ceiling effects [185], whereas SIS potentially has ceiling effects in hand function, memory and thinking, communication, mobility and activities of daily living (ADL), and instrumental ADL domains [186].

In terms of non-clinical measures, post-hoc physiological computing tools have been leveraged to extract changes in the measured biosignals. For example, [91] reported differences in EEG activity of motor imagery in virtual environments relative to regular imagery. In fact, the ANOVA test with a Greenhouse-Geisser correction and pairwise Wilcoxon signed-rank test showed a statistically significant result in the alpha band ($F_{(2.524,\ 20.191)} = 4.800$, $p < 0.05$), between "motor execution and VR (VRMP)" versus the control condition. In the theta band (4-7 Hz), the difference was reflected

Table 2.5: Frequently used clinical measurements and questionnaires

Name	Type	Evaluation domains	Description	Studies
Fugl–Meyer assessment (FMA)	Physical impairment	Extremities motor function, Sensory functioning, Balance, Joint range of motion, Joint pain	Reliable and validated method to evaluate upper and lower limb motor impairment [175]	[99; 85; 89; 86]
Action research arm test (ARAT)	Limb function	Grasp, Grip, Pinch, Gross movement	Quick and short test (only 19 items) covering important aspects of arm functional performance [176]	[99]
Montreal cognitive assessment (MoCA)	Cognition impairment	Visuospatial ability, Executive functioning, Attention, Language, Orientation	Quick and short test (10 minutes) with ability to differentiate mild to severe range of cognitive impairments [177]	[99; 86]
Motor Assessment Scale	Motor function	Supine to side lying, Supine to sitting over the edge of a bed, Balanced sitting, Sitting to standing, Walking, Upper-arm function, Hand movements, Advanced hand activities	Task-oriented evaluation of daily-life motor function [178]	[85]
Modified Ashworth Scale	Limb spasticity	Perceived resistance while extending limb passively from maximal flexion to maximal extension (full range of motion)	Acceptable scale to measure spasticity in muscles of both the upper or lower limbs [179]	[89; 86]
Range of motion (ROM)	Limb extent of movement	Flexion/extension of wrist/ finger/ hand, Wrist deviations	Evaluate wrist, finger, or hand range of motion in three states: passive, active, assisted [180]	[99; 82; 85]
Stroke impact scale	Quality of life	Strength, Hand function, Activities of daily living, Instrumental activities of daily living, Mobility, Communication, Emotion, Memory and thinking, Role function	Self-report assessment consists of 59 items evaluating multidimensional stroke outcomes [181]	[99; 89; 86]
Saltin–Grimby physical activity level scale (SGPALS)	Physical activity	Four level physical activity questionnaire during leisure time	Evaluates leisure and work time physical activity levels [182]	[82]
Simulator sickness questionnaire (SSQ)	Simulator sickness	Nausea-related questions, Oculomotor, Disorientation	16 questions in three categories to evaluate severity of simulator sickness [54]	[99; 89; 90]
Vividness of movement imagery questionnaire (VMIQ2)	Movement imagery	Walking, Running, Kicking a stone, Bending down,Running up stairs, Jumping sideways, Throwing a stone into water, Kicking a ball in the air, Running downhill, Riding a bike, Swinging on a rope, Jumping off a high wall	Evaluates capability to perform 12 imagined movements from external perspective, internal visual imagined movements and kinesthetic imagery [183]	[86; 91]
Presence questionnaire (PQ)	Presence	Realism, Possibility to act, Possibility to examine, Quality of interface, Self-evaluation of performance	Evaluate sense of presence in the virtual environment [184]	[91; 90]

between motor-execution and VRMP ($F_{(1.874,\ 14.990)} = 7.615$, $p < 0.05$). Interhemispheric interaction was also observed in several studies to be affected by visual, audio, or haptic feedback [91; 86; 89; 92]. [86] calculated ipsilateral ERD/ERS of the beta band using C3 and C4 electrodes. Subsequently, by running a t-test, a statistically significant difference was observed between the first and last

Table 2.6: Measurement time points and clinical/non-clinical outcomes of each study

Study	Measures and time points	Outcomes
[99]	FMA-UE, ARAT, MoCA, SIS-16, Wrist ROM, Grip strength, and EEG in sessions 1 and 10. SSQ evaluated in sessions 2 and 9. EMG recorded during all sessions. Enjoyment questionnaire evaluated in session 10.	Improvement in SIS-16, FMA, and Wrist ROM was observed. No significant changes were seen in ARAT. Minor levels of discomfort after HMD-VR via SSQ were reported. EMG-EEG: Improved motor control, significant beta-band cortico-muscular coherence during wrist extension was observed.
[87]	Control error rate and satisfaction questionnaire after each session.	VR-BCI-FES combination resulted in faster rehabilitation periods, increased user optimism and a desire to exercise more in order to recover lost skills.
[85]	FMA, MAS, active ROM, force intensity before/after training.	Improvement in motor skills, including 37.5% and 38.8% increase in FMA and MAS, respectively.
[89]	fMRI, T2-weighted and diffusion-weighted MRI, single- and paired-pulse TMS, FMA-UA, MAS, and SIS in sessions 1 and 2. EMG and EEG during all sessions. SSQ and enjoyment questionnaire before and after training.	Patients with severe motor impairments are shown to benefit the most from EEG-based neurofeedback. No significant differences were seen between pre- and post-intervention for all tested clinical scales. A significant negative correlation was observed between the VR task score and the FMA score. Cortical physiology changes were observed in one subject using TMS.
[86]	fMRI, MoCA, Modified Ashworth scale, FMA, SIS, and VMIQ2 before and after training, as well as one month after intervention.	Improvement were seen in FMA-UE (pre: 31, post: 40, follow-up: 44). An increase in brain activation plastic changes was observed in the fMRI modality.
[90]	SSQ, PQ, EQ, EEG, and EMG before training, after condition 1 and after condition 2.	A relationship between neurofeedback performance and sensorimotor desynchronization was observed. Higher levels of embodiment were reported in HMD-VR. Similar performance was achieved between HMD-VR and flat-screen conditions.
[82]	SGPAS, VR experience Questionnaire, and ROM before and after training.	Gamified exercises are reported to be useful, interesting, and entertaining. An increase in motivation was observed in gamified intervention.
[167]	Brum e Rieder questionnaire after training.	Visual and aural feedback was confirmed to be more intuitive. 20% of participants showed difficulty with spatial orientation.
[91]	PQ, VMIQ2, NASA TLX, and EEG recording in each session.	A significant difference in classification accuracy of motor execution before MI compared to standard motor imagery was observed. An increase in the mean power of all EEG rhythms in VR-based tasks has been shown.
[83]	Interview, scores achieved during game after each session.	The reward system increased the performance of executed movements. Feedback should be strong enough to be distinguishable by all participants.
[92]	System perception questionnaire after each session.	Improved mean classification accuracy for the grasping and flexion/extension MI tasks with visual-electrotactile feedback was reported. Higher attention levels with such a hybrid feedback modality were seen.
[84]	Number of moved blocks during trial.	Participants using prostheses outperformed other users in the VR setting.

FMA-UE: Fugl–Meyer assessment-upper extremity, ARAT: action research arm test, MoCA: Montreal cognitive assessment, SIS: stroke impact scale, ROM: range of motion, SSQ: simulator sickness questionnaire, MAS: motor assessment scale, VMIQ2: vividness of movement imagery questionnaire, PQ: presence questionnaire, EQ: embodiment questionnaire, TLX: task load index.

session ($t(199)= -16.921$, $p < 0.001$). Moreover, it is known that treatments with greater engagement levels keep patients motivated and yield better outcomes [109]. As there is a direct relationship between engagement and attention [110] and attention deficits could result from strokes [111], leveraging VR tools to increase patient focus could be highly beneficial. Certain rhythms (e.g., alpha and beta bands over the parietal region for visual stimulus), for example, have been related to attention [112; 113; 114; 115] and associated with motor function [116].

To this end, [91] found a relationship between the ability to perform kinesthetic imagery and alpha-beta band modulation ($\rho= 0.50$, $p < .05$) and, thus potentially pointing towards improved attention levels. Furthermore, [92] noted higher attention levels in visual-electrotactile stimulation compared to visual-only condition, and higher attention levels were also shown to be correlated with haptic feedback and exoskeleton usage [117]. In fact, a significant inverse Spearman correlation was found between attention level and difficulty level (ρ= -0.45, p= .04). However, a Spearman correlation between attention level and beta band of channels regarding somatosensory and prefrontal regions was observed in both grasping (e.g., AF3 channel: $\rho= 0.58$, $p= .04$) and flexion/extension (e.g., AF3 channel: ρ= -0.5, p= .02) MI tasks. Indeed, by adding haptic feedback, [86] reported 9 points improvement in the FMA score at the end of the intervention (pre: 31, post: 40) in a case report on a patient with left hemiparesis. These insights suggest that haptic-based feedback could be utilized to boost attention levels in VR-based interventions and lead to improved outcomes [92; 82; 86]. Notwithstanding, [89] noted that patients with more severe impairments showed the most significant improvement using motor imagery-based paradigms in a VR setting, while EMG-based feedback was shown more promising for patients with mild impairments.

VR-based solutions typically rely on their improved sense of realism [118], immersion and presence [119], and sense of embodiment [120] to boost rehabilitation performance [121]. To achieve these goals, [89], for example, customized hand models in the virtual environment to match the patient's skin tone and gender and [82] provided close-to-reality animations of outdoor exercises. [90], in turn, leveraged linear regression to examine the relationship between neurofeedback performance and overall embodiment and reported a significant relationship in the HMD-VR experimental condition ($F_{(1,\ 10)}= 8.293$, $p= .016$, R^2=.399).

The gamification potential of VR-based solutions can also allow for reward mechanisms to be put in place to improve outcomes. For example, the reward has been shown to improve motor

learning [187; 188] and rehabilitation outcomes [189; 190]. Reinforcement feedback also induces motivation [191]. This is important, as lack of motivation has been said to be one of the major barriers in conventional rehabilitation [192]. As such, reward-based VR interventions improve outcomes [193], result in higher rates of satisfaction, and have increased adherence [83; 85; 82; 167]. For example, [83] encouraged patients to use their affected weaker limb by giving them higher scores when an action was carried out with such affected limb. Overall, only four of the reviewed articles relied on reward feedback as part of their intervention [167; 83; 84; 82].

Notwithstanding, VR-based solutions relying on HMDs are also known to elicit in certain individuals discomfort and nausea (known as cybersickness). [167], for example, reported a subtle improvement in the sense of comfort when screen-based tasks were given to the participants, relative to those given via an HMD. Other studies, in turn, utilized the simulator sickness questionnaire, and only very minor degrees of discomfort were reported when using HMD-VR [99; 89]. More recently, cybersickness has been associated with activity in delta (1-4 Hz), theta, and alpha EEG frequency bands [194]. Future studies could also explore the use of collected EEG signals to measure cybersickness levels; this was not performed in any of the evaluated papers. Moreover, it is known that stroke can result in a range of cognitive impairments, thus it is necessary to investigate the perception and interaction skills of patients [195] in virtual environments. To this end, [84] implemented a clinical assessment method called *Box and Block test* in a virtual environment to measure gross manual dexterity and compared the performance of the patients in both conventional and VR-based settings. The results showed better control of a virtual prosthesis by a patient compared to the healthy control group.

Lastly, one additional advantage of a VR-based intervention with physiological computing is that it enables automated, repeatable, and reliable interventions. Such factors are crucial for treatment fidelity, which has been directly linked with intervention quality [196]. For example, [197] proposed a treatment fidelity plan based on design, training, delivery, receipt, and enactment for stroke exercise interventions. In non-VR-based interventions, there is a great chance of inconsistency in delivering the treatment by a physiotherapist. VR-based treatments, in turn, are programmed, thus system functionality could be used as a proxy for treatment fidelity [198]. While the study by [82] utilized a specific order for all of the participants to assure consistency in the treatment, none of the reviewed articles used a fidelity checklist explicitly.

2.4.3 Recommendations from the Literature Review

The included articles show the potential of VR-based interventions, coupled with physiological computing, for improved rehabilitation outcomes for stroke survivors. Moreover, several studies investigated the efficacy of an HMD-based intervention received *in parallel with conventional therapy*, thus making it difficult to truly gauge the benefits of the VR intervention per se. Overall, nonetheless, the results suggest that an additional VR-based intervention (in addition to the conventional treatment) is better than having two conventional treatments. Moreover, patient involvement is crucial for successful rehabilitation outcomes [199]. Incorporating some principles from iterative designing [200] and gamer user experience into the virtual environment could be beneficial [201; 202]. Integrating many of the physiological computing tools directly into the VR headset could also alleviate some of these issues; such instrumented HMDs are already emerging [81; 203; 204].

Regarding the effects of feedback type, studies herein showed that as more senses were stimulated, improved outcomes and attention could be observed. Recently, olfactory feedback has emerged as an additional feedback modality, as tools such as the OVR ION (OVR Tech, Burlington, USA) have appeared in the market. Integrating olfactory feedback may further boost attention, sense of embodiment, and presence, which could show improvements in outcomes, as was the case in other allied domains [205; 206]. Additionally, none of the studies used glove-based haptic feedback systems. Such systems could provide finger tracking capabilities and individual finger and full hand vibrations, thus potentially also benefiting interventions of the upper limbs [207; 208]. Lastly, the reviewed studies did not report experiments with patients suffering from post-stroke visual impairment/disturbances. Such patients may be incapable of benefiting completely from audio-visual VR-based interventions, thus multisensory experiences should be explored. The work of [209] and [210], for example, leveraged the use of auditory and haptic stimuli to make VR experiences more accessible to those with visual impairments. In fact, VR interventions could potentially be used soon after the stroke to identify the risk of visual after-effects [211].

2.5 Proposed Improvements

Considering the presented background and literature review, the purpose of this thesis is to gain further insights into new MI-BCI control strategies that could be leveraged by exploiting multisensory

VR training sessions. To this end, however, we need to first assess the effects of multisensory experiences on the user's perceived QoE (e.g., it will not increase the odds of cybersickness). As such, an exploratory analysis is first conducted to identify neurophysiological features and their correlation with subjective ratings, as well as user behavior under multisensory immersive environments. Finally, we propose a new multisensory training paradigm to improve MI-BCI performance.

Chapter 3

Exploring the Influence of Multisensory Immersive Experiences on User Behaviour

3.1 Chapter Overview

As mentioned previously, multimodal/multisensory HMD-based interventions, such as immersive MI-BCI training, could potentially enhance neurorehabilitation outcomes. Optimizing the patient interaction with a multisensory VR environment, however, is a crucial aspect of the intervention. As such, understanding the impact that multisensory immersive experiences have on user behaviour is crucial. In this chapter, such an evaluation is carried out.

In particular, a VR game was developed to combine audio-visual, olfactory, and haptic feedback. After game play, participants were asked about their IMEx using five scales: realism, immersion, presence, engagement, and overall quality of experience (QoE). Moreover, using an instrumented VR headset we measure electroencephalography (EEG), electrocardiography (ECG), and electrooculography (EOG) signals and compute several instrumental measures of human influential factors, including an engagement index, arousal and valence indices, frontal alpha asymmetry, heart rate, several EEG subband powers, and eye blink rate. Using the subjective ratings, we measure the

contribution that each IMEx subscale has on overall QoE, as a function of the type of sensory stimuli used. The contents of this chapter have appeared in two published manuscripts [212; 213].

3.2 Materials and Methods

3.2.1 Participants

Data were collected from 11 healthy participants (two female, mean age 25.4 ± 2.3 years old). The procedure of the experiment was reviewed and approved by the INRS-EMT Ethics Committee. Safety steps were taken to minimize COVID-19 risks, including maintaining social distancing and sanitizing the equipment using an UV-C chamber and alcohol pads.

3.2.2 Hardware

Different hardware were required for this experiment, in particular: (1) a VR headset, (2) a bioamplifier to collect the psychophysiological signals, (3) a scent-diffuser unit (scentware), and (4) haptic sleeves. Affordable devices have been selected to increase reproducibility and accessibility. In particular, an Oculus Quest was used to present virtual content in an OLED display with a 1440 x 1600 resolution, 72Hz frame rate, and 90° field of view. OpenBCI Cyton and Daisy bioamplifiers were used to record 16 channels of EEG, EOG, and ECG at a 125 Hz sample rate. We followed published guidelines on how to instrument VR HMDs available in [122]. Taking advantage of the strap locations of the VR headset, EEG signals were collected from three regions using 11 silver/silver chloride (Ag/AgCl) dry electrodes, namely: frontal (Fp1, Fpz, and Fp2), central (F3, F4, FCz, C3, and C4), and occipital (O1, Oz, and O2). Two horizontal and two vertical electrodes placed on the faceplate of the VR headset were used to record EOG signals. Two electrodes were placed on mastoids as a reference, and a disposable electrode on the left collarbone was used to record ECG. The OpenBCI bioamplifiers were encased into a 3d-printed box and mounted on the top strap of the headset.

An ION2 scentware device was mounted on the headset and used to diffuse scents close to the nose while user is interacting with virtual environment. The device is capable of diffusing nine different scents. Figure 3.1 depicts a visual of the headset, the mounted ExG electrodes, and the

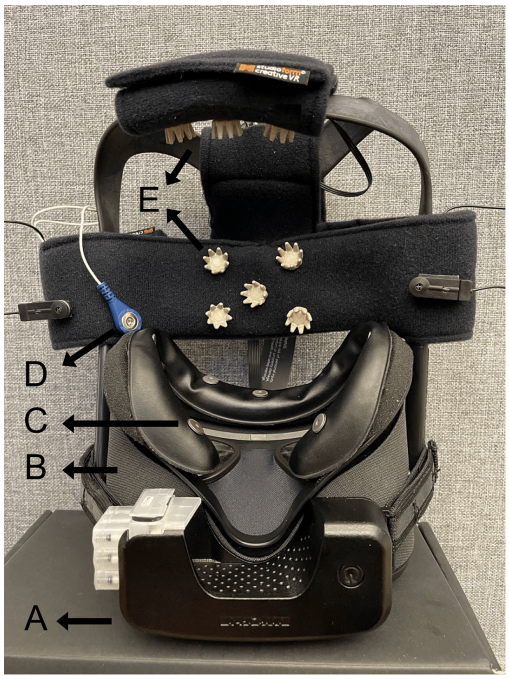


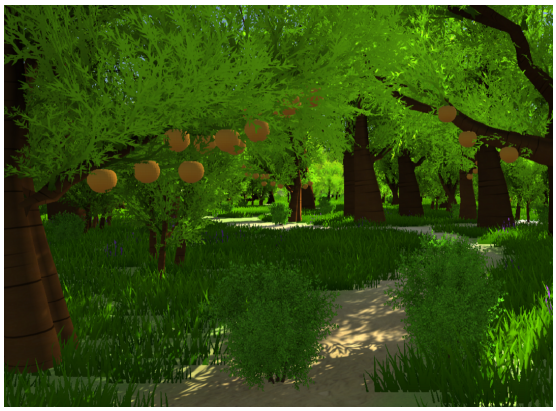
Figure 3.1: Instrumented VR headset equipped with (A) ION2 Scentware, (B) an Oculus Quest, (C) 4 EOG and 3 frontal EEG, (D) one ECG, and (E) 8 EEG channels.

attached scentware device. Lastly, a haptic sleeve from bHaptics was used to provide haptic feedback. The device has six eccentric rotating mass motors arranged in three columns and two rows. A visual of the sleeves, along with the other hardware used, can be seen in Fig. 3.2c.

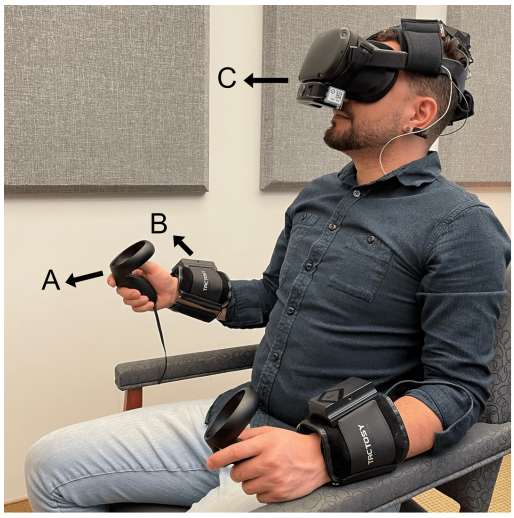
3.2.3 Gaming Environment

The virtual environment for the game was implemented in Unity3D 2021.3.25f1 and consists of an orange grove in which gamers are expected to collect as many oranges as possible (see Fig. 3.2b). In the condition involving smells, background scents, such as grass, flowers, and forest were always present to simulate the scent of the grove. Mentioned ambient scents were dispersed every five seconds with maximum intensity that can be defined in the provided software development kit (SDK) by the company. When oranges were grabbed, a cloud of mist would appear, an auditory "poof" would present in the condition involving audio, and the orange would disappear for 3.5 seconds and then reappear. In the conditions involving smells, a burst of citrus would also be produced in synchrony with the audio-visual content. In the conditions involving haptics, vibrations in the haptic sleeve would occur once the oranges were successfully grabbed. All six motors of the haptic sleeve function simultaneously and deliver vibration in the form of a square waveform and amplitude of 70%

(a)



(b)



(c)

Figure 3.2: (a) In-game five-level absolute category rating scale, (b) visual of the game environment, and (c) an engaged user with A- Oculus controller, B-bHaptics sleeve, and C-instrumented headset + ION2.

of the maximum intensity that can be defined in the bHaptics control panel. Synchronization of all modalities with game events was achieved via Unity SDKs offered by each respective manufacturer. A demo of the game is available at (https://imreza.ir/oranges). Users were asked to explore the environment, get close to the trees, and collect as many oranges as possible for two minutes using the Oculus controllers. At the end of the game, while still in VR, users were asked to rate their perceived level of presence, immersion, realism, engagement, and overall experience using the 5-point absolute category rating (ACR) [123]. The toolkit described in [124] was used to create the environment and Fig. 3.2a shows a screenshot of the questionnaire.

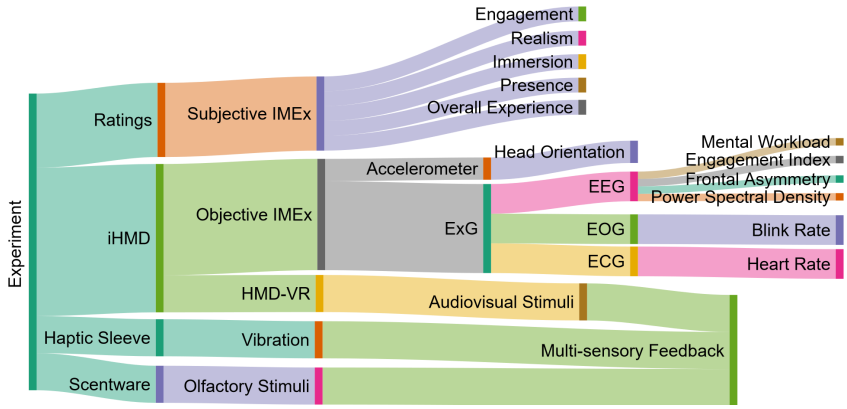


Figure 3.3: The Alluvial diagram describing different flows and aspects of conducted study including qualitative ratings, instrumented measures, feedback types, and features per ExG modalities.

3.2.4 Experiment Design

To explore the impact of introducing haptic and olfactory inputs on overall multisensory IMEx QoE, five conditions were tested, namely: visual-only (VO), audio-visual (AV), audio-visual-smell (AVS), audio-visual-haptic (AVH), and audio-visual-smell-haptic (AVSH). To avoid biases, the ordering of the conditions was counterbalanced across participants. Prior to starting the experiment, participants donned the instrumented headset and signal quality was tested using the OpenBCI software. Any necessary adjustments were made to ensure high signal quality. Participants were then exposed to the ION2 and haptic sleeves to familiarize themselves with the technology. The experiment then proceeded with the randomized ordering of the five conditions. As the names suggest, VO only presented the user with the visuals, including the mist upon successfully shooting an orange. AV included the additional "poofs" time-aligned with the mist cloud visuals. In the AVS condition, the background scents and the orange bursts were presented, whereas in the AVH condition, the sleeves vibrated upon orange shooting. Lastly, the AVSH condition included all of the above time-aligned sensory stimuli. At the end, participants were asked for feedback on the different conditions with the goal of obtaining insights for improved future iterations of the experiment.

3.2.5 Data Analysis

Figure 3.3 depicts an alluvial diagram of how the different hardware, types of feedback, subjective, and psychophysiological (objective) measures have been used to quantify user behaviour in the multisensory VR game. Data analysis methods are discussed in detail below.

3.2.5.1 Feature Extraction

To process the EEG signals, the widely-used EEGLAB toolbox for MATLAB was used. For pre-processing, a band-pass filter between 0.5 and 45 Hz was applied followed by zero-mean normalization. The artifact subspace reconstruction algorithm was then applied to remove movement-related artifacts. EEG subband spectral powers were computed for the five conventional bands, namely: delta (0-4HZ), theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz), and gamma (30-80Hz) for each EEG channel. These values were then used to compute an engagement index (EI), an arousal index (AI), a valence index (VI), and FAA. EI is calculated based on the beta / (alpha + theta) power bands ratio, averaged over all electrodes [125]. AI and VI, in turn, are computed based on subband powers from specific electrodes, as per [126]; namely:

$$AI = \frac{beta_{(\mathrm{F3})} + beta_{(\mathrm{F4})}}{alpha_{(\mathrm{F3})} + alpha_{(\mathrm{F4})}}, \tag{3.1}$$

$$VI = \frac{alpha_{(\mathrm{F4})}}{beta_{(\mathrm{F4})}} - \frac{alpha_{(\mathrm{F3})}}{beta_{(\mathrm{F3})}}. \tag{3.2}$$

From the EEG, FAA is computed by subtracting the log-power of the alpha band in the F4 electrode from the log-power of the alpha band in F3 electrode. Moreover, mental workload was quantified by computing average EEG theta power band activity across Fp1, Fpz, Fp2, F3, F4, and FCz electrodes [72]. Additionally, the OpenBCI triple-axes accelerometer was used to identify changes in head orientation, including horizontal and vertical movements throughout experiment.

From the EOG signals, in turn, the Blinker toolbox was used to extract the EBR feature [127]. From the ECG signal, the BioSPPy python package was used to extract HR [128]. Lastly, the number of successful interactions with the oranges were recorded and kept as the user's "score" in the game for each condition.

3.2.5.2 Statistical and Regression Analyses

To analyze the impact of the different sensory stimuli on the subjective ratings, repeated measure ANOVA with Greenhouse-Geisser correction was performed using IBM SPSS 20 with significance testing at the 95% confidence interval. In addition, five separate multiple linear regression models were defined to predict overall experience as a function of the realism, presence, engagement, and

immersion ratings. To identify the contribution of each variable in the model, feature importance was calculated based on the residual sum of squares by removing one predictor at a time from the final model (with all of the predictors). Such analysis provides insight on the contribution of each IMEx HIF on overall QoE as a function of sensory stimuli. Lastly, Pearson correlation between the psychophysiological features and the subjective ratings is performed to assess which instrumental measures could be most suitable for real-time QoE monitoring. We report correlations that show significance at the 95% level.

3.3 Results and Discussion

3.3.1 Subjective Analysis

Figure 3.4 depicts bar plots of the average ratings provided by the 11 participants for each HIF subcategory and overall quality for each of the five experimental conditions. In the plot, significant differences at the 95% level are depicted by one asterisk, at the 99% by two and 99.9% with three asterisks. As can be seen, all three multisensory conditions (AVS, AVH, AVSH) increased realism, presence, immersion, engagement and overall experience relative to the VO and AV conditions. Inclusion of both haptic and olfactory stimuli showed to significantly improve sense of presence relative to using the additional sensory inputs individually, as well as engagement relative to the AVS condition. Interestingly, incorporating either haptic or smells resulted in similar realism and immersion ratings and the combined AVSH condition showed only a slight increase in immersion relative to AVS and AVH, saturation may have occurred. The AVH condition, however, resulted in increased sense of presence, engagement, and overall experience, relative to AVS, thus suggesting greater impact of haptic feedback on these HIFs. Across all five conditions, statistical analysis revealed a significant difference for overall experience ($F_{(2.201,\ 22.013)}= 12.564$, $p \leq .001$), realism ($F_{(1.718,\ 17.180)}= 4.915$, $p= .024$), presence ($F_{(1.792,\ 17.918)} = 7.953$, $p= .004$), immersion ($F_{(2.293,\ 22.930)}= 3.351$, $p= .047$), and engagement ($F_{(2.875,\ 28.746)}= 9.349$, $p \leq .001$).

Figure 3.5, in turn, depicts the relative importance of each individual HIF rating on overall experience for each of the five experimental conditions. It is important to emphasize that since the modeling procedure was within-condition, one should be cautious when comparing reported results across conditions. As can be seen, in the VO and AV conditions, realism contributed the most

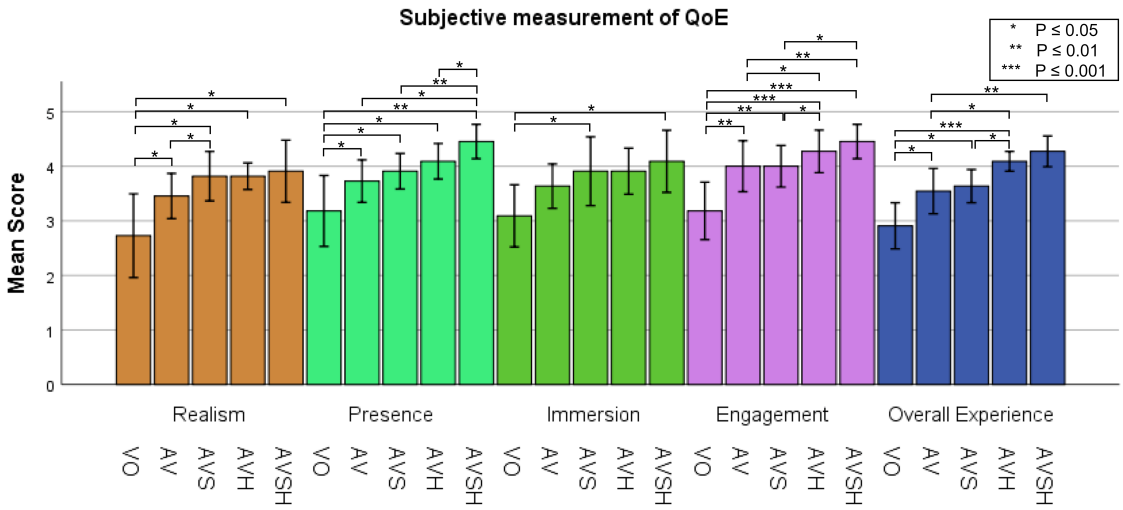


Figure 3.4: Average ratings across 11 participants for four HIFs and QoE across five experimental conditions

to overall QoE. In these conditions, realism is highly intertwined with details implemented in the environment (e.g., shape of leaves, trees, wind animation). Interestingly, realism contributed the most in the AV condition, thus corroborating previous findings that showed the effect of auditory stimuli on visual fidelity [214]. Introducing other sensory modalities boosted the impact that immersion and presence have on QoE, with smells causing the greatest impact on the importance of immersion, raising it from 18% to 50% contribution of the overall QoE. The AVSH condition showed a balanced contribution between realism, presence and immersion on overall QoE. Interestingly, for most of the conditions, engagement showed to contribute the least towards QoE, with the exception of the AVH condition where its role was shown to be more important than realism. Indeed, haptic feedback has shown to be important in improving engagement across different VR tasks (e.g., [215]).

In terms of scores (number of oranges shot) achieved in each condition, a significant increase ($p \leq .001$) was observed in the AVSH (M= 97.18, SD= 7.38) condition compared to AV (M= 77.54, SD= 8.79).The scores achieved in the AVSH condition, in turn, showed a significant correlation with the immersion rating (r= .723, p= .012), thus corroborating previous findings on the impact of immersion on gamer experience [216].

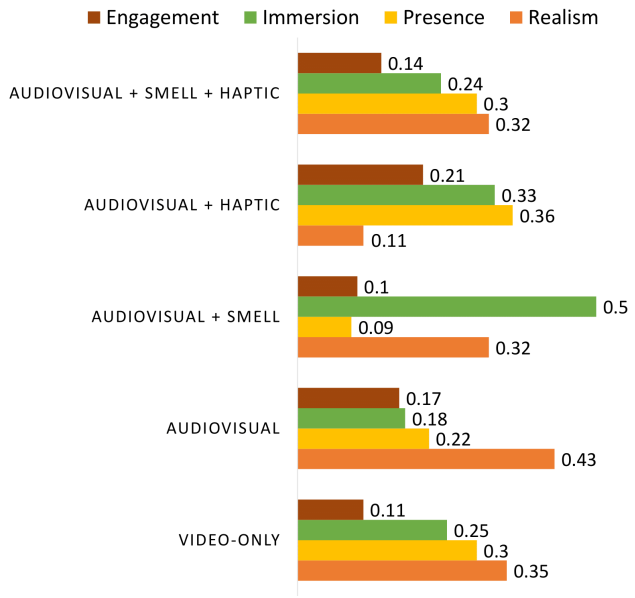


Figure 3.5: Contribution of individual HIFs on overall QoE

3.3.2 Instrumental Measures Analysis

Table 3.1 shows the impact that the different experimental conditions have on the six psychophysiological features extracted. Statistical analysis suggests that only AI showed a significant difference ($F(4, 40)= 3.000$, $p= .030$) between AVS and VO ($p= .021$), AVSH and VO ($p= .013$), and AVS and AVH ($p= .049$). Overall, AVS showed the highest AI, suggesting this condition was most exciting for the participants. Regarding FAA, positive values indicate greater approach-tendency (higher left hemisphere oscillation) whereas negative values are associated with withdrawal-tendency (high right hemisphere oscillation) [129]. FAA results showed an increasing trend, as more modalities were added, thus suggesting a greater desire to continue playing and increased motivations, such as enjoyment. Candid feedback from the participants post-experiment corroborate this hypothesis. Lastly, EBR showed increased values when additional sensory input was provided, thus corroborating findings in [130] that showed a link between EBR and presence. Moreover, an increase in the average theta power band, as a measure of mental workload, was seen from AV (M= 4.16, SD= 1.74) to AVSH (M= 4.91, SD= 2.43), suggesting higher order processing for the multisensory task [131]. In fact, increases in theta power and mental workload could be linked to the combined increases in engagement and attention, as reported in [71] and shown in [132] with olfactory stimuli.

Next, we analyze the Pearson correlation coefficients between the subjective ratings and the six instrumental psychophysiological ratings, as well as the EEG subband powers. We found a positive

significant correlation between engagement and AI (r= .647, p= .043) in VO. In the AV condition, significant correlations between realism and delta (r= .734, p= .016) and gamma subband spectral powers (r= 810, p= .004) were observed. Additionally, a significant correlation between engagement and theta band power (r= .706, p= .023) was observed in the AV condition, thus corroborating previous studies [217]. In the AVS condition, presence and theta power (r= .724, p= .018) showed a significant correlation, as did EI with realism (r= .715, p= .02). This is an important finding, as realism played the second strongest role in QoE for the AVS condition, thus suggesting the potential of the EI parameter for instrumental multisensory IMEX QoE measurement.

Lastly, we compiled the candid feedback provided by the participants in the post-experiment interview concerning the different experimental conditions they experienced. Overall, users described the AVSH condition as being enjoyable and that really boosted their sense of presence. Some participants mentioned that the orange bursts were masked by the background smells. As we have a small sample size of only 11 participants, this could explain the different patterns observed in Fig. 3.5 for the AVS condition. Lastly, some participants mentioned that a vibrating sleeve was not very realistic and suggested vibrating controllers or haptic gloves instead. This insight could explain the reduced contribution of realism in the AVH condition in Fig. 3.5. Notwithstanding, many participants mentioned that the haptic condition was very engaging, more so than smells alone, and drove their final QoE decisions. These insights corroborate the findings in Fig. 3.4, as well as the increased contribution of the engagement HIF in Fig. 3.5 for the AVH condition relative to AVS.

Table 3.1: Changes in instrumental measures per experimental conditions. Values in parentheses correspond to standard deviation across participants.

Feature	VO	AV	AVS	AVH	AVSH
EI	73.5 (2.9)	73.4 (1.6)	74.3 (3.8)	73.3 (2.6)	73.9 (1.9)
AI	27.3 (3.9)	31.9 (5.6)	34.5 (6.1)	28.9 (5.6)	31.8 (1.21)
VI	54.8 (11.2)	52.7 (9.1)	49.7 (14.3)	45.1 (9.1)	51.6 (12.6)
FAA	-0.19 (0.3)	-0.16 (0.6)	0.07 (0.2)	0.10 (0.2)	0.13 (0.8)
HR	81.1 (6.4)	80.6 (6.1)	80.4 (5.1)	81.8 (5.7)	80.8 (6.82)
EBR	13.9 (2.13)	14.5 (1.7)	15.6 (1.3)	15.7 (1.9)	15.2 (1.6)

3.3.3 User Behaviour Analysis

Evaluating accelerometer data showed significant differences in the number of changes in head tilt across conditions. A statistically significant difference ($p \leq .001$) was observed in horizontal head

movements between AV (M= 34.54, SD= 9.22) and AVSH (M= 57.18, SD= 7.74). Additionally, a statistically significant difference ($p \leq .001$) was seen in vertical head tilt between AV (M= 23.54, SD= 8.32) and AVSH (M= 40.72, SD= 7.05). These changes in head movement, combined with the increased scores (i.e., oranges shot) obtained in the AVSH condition suggest users becoming more engaged and immersed in the environment, thus increasing environment exploration in order to find more oranges to burst them and receive the multisensory feedback. This hypothesis was in fact confirmed during informal post-experiment interviews. The majority of the participants referred to the multisensory experience as enjoyable, more realistic, and mentioned that in the AVSH condition they had greater motivation to shoot the oranges to receive the desired multisensory feedback. This corroborates the shift to positive FAA values reported above.

3.3.4 Study Limitations

This study was conducted during the sixth wave of the COVID-19 pandemic, thus many constraints were in place to ensure participant safety, including a quarantine period between participants and thorough cleaning of all hardware. This resulted in a limited (and gender/age unbalanced) participant pool. As a result, statistical power decreased and limited the scope of study to identify significant differences across conditions or to explore any gender- or age-specific effects, which could be present in multisensory experiments (e.g., [218]). Notwithstanding, despite these limitations, changes seen herein across several features were consistent with those previously reported in the literature. Moreover, the game environment developed may seem contrived as it was driven by scents available with the OVR kit, which has been tuned for multisensory VR-based relaxation.

3.4 Conclusions

This chapter has described an experiment in which olfactory and haptic stimuli are added to conventional audio-visual VR immersive experiences to explore their impact, not only on overall QoE, but also on four different HIFs, namely: sense of realism, presence, immersion, and engagement. Moreover, via a biosensor-instrumented VR headset, six instrumental psychophysiological measures are computed and tested as correlates of the four HIFs. Experimental results on 11 participants show a significant impact of smells on the sense of immersion and of haptic feedback on engagement. A

complete multisensory immersive experience combining audio-visual-olfactory-haptic stimuli achieved the highest values across all ratings, including the overall experience. These enhancements were also shown to be reflected in certain instrumental measures, including EI, AI, FAA, and EBR. In the future, the real-time benefits of biosignals measurement, combined with the integration of ExG sensors directly on the VR headset, can enable user-aware game adaptation to maximize QoE.

Chapter 4

Augmenting the VR-based MI-BCI Training with Multisensory Feedback: A View on User Behaviour

4.1 Chapter Overview

Brain-computer interfaces (BCIs) have been developed to allow users to communicate with the external world by translating brain activity into control signals. Motor imagery (MI) has been a popular paradigm in BCI control where the user imagines movements of e.g., their left and right limbs and classifiers are then trained to detect such intent directly from EEG signals. For some users, however, it is difficult to elicit patterns in the EEG signal that can be detected with existing features and classifiers. As such, new user control strategies and training paradigms are highly sought-after to help improve motor imagery performance. VR training has emerged as one potential tool where improvements in user engagement and level of immersion have been shown to improve BCI accuracy. In this study, we take the first steps to explore if multisensory VR training, where not only audio-visual feedback is provided, but also haptic and olfactory, can further improve levels of engagement and sense of presence, and ultimately, improve MI-BCI accuracy.

In particular, we describe an interactive multisensory VR game that was developed with the inclusion of audio-visual, olfactory, and force feedback modalities to compare multisensory VR

training to conventional audio-visual VR training. To this end, a refined version of the experiment described in the previous chapter was developed, taking into account the candid user feedback received (e.g., replacing a haptic sleeve with a haptic glove). Users underwent two MI-BCI sessions, one before and one after being exposed to the two training conditions, i.e., audio-visual only and multisensory, and MI-BCI accuracy was compared between the two conditions. In this Chapter, the focus on the user experience of the enhanced immersive experience is quantified. Material from this chapter was compiled from [219]. The MI-BCI accuracy itself will be addressed in the subsequent chapter.

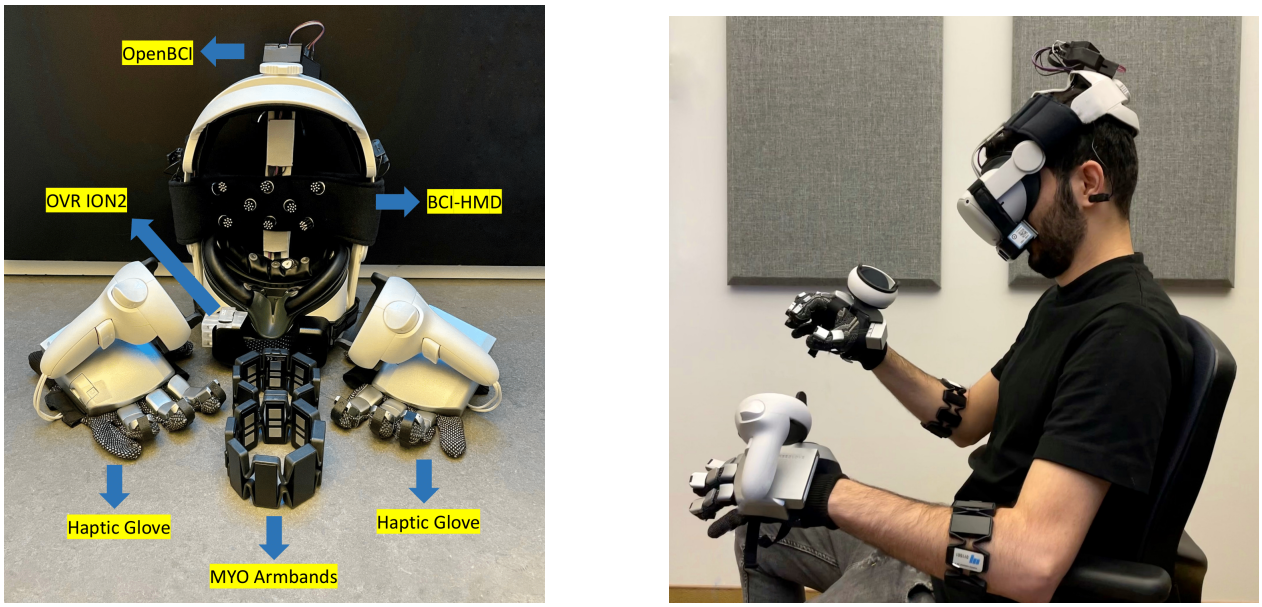
4.2 Materials and Methods

4.2.1 Participants

Eleven healthy participants (three female, 25.81 ± 3.88 years old), different from the previous chapter's participation pool, were recruited to participate in this experiment. Eligibility criteria included healthy individuals. Participants with a history of severe cybersickness and sensitivity to scents were excluded. The experiment protocol was reviewed and approved by the Ethics Committee of the Institut national de la recherche scientifique (INRS), University of Quebec (number: CER-22-663). During data collection, COVID-19 safety measures were considered and put in place, including maintaining social distance, wearing a face mask, and disinfecting all devices with alcohol wipes and a UV-C chamber. All participants are considered novice BCI users, and this was their first time performing a motor imagery task. It is important to emphasize that the data from one subject was considered too noisy for analysis, thus is discarded here from the analysis.

4.2.2 Equipment and Data Integration

In this study, a VR-HMD was coupled with force feedback haptic gloves, an electromyogram (EMG) armband, a scent diffusion device, and a wireless BCI system (henceforth referred as "BCI-HMD") embedded directly into the headset following guidelines described by [122]. An illustration of the different components of the system is shown in Fig. 4.1a, along with a visual of a user wearing



(a) (b)

Figure 4.1: (a) Instrumented BCI-HMD headset composed of a HMD-VR and bioamplifier to monitor electroencephalography (EEG), electrooculography (EOG), facial electromyography (EMG), and photoplethysmography (PPG). Other devices include the OVR ION2 scentware, Myo armbands and a Senseglove Nova haptic gloves. (b) A participant wearing the BCI-HMD system.

them in Fig. 4.1b. In addition, a VR game was created and synchronized with hardware. More details about the instrumented HMD is given next.

4.2.2.1 Instrumented Headset: BCI-HMD

A Meta Quest2 HMD (LCD display with a resolution of 1920×1832, 72Hz refresh rate, and 89° field of view) was used. Three physiological signal modalities, including electroencephalography (EEG), electrooculography (EOG), and photoplethysmography (PPG) were integrated into the facial foam and head straps of the VR headset and directly connected to an OpenBCI bioamplifier encased in a 3D-printed box and placed on top of the HMD straps (see Fig. 4.1b). According to the international 10-20 system [133], OpenBCI Cyton and Daisy bioamplifiers (OpenBCI, USA) were used to capture 11 EEG channels from frontal (Fp1, Fpz, Fp2, F3, F4, Fz, Fc1, Fc2) and central (C3, C4, Cz) regions at a 125 Hz sample rate. In order to ensure participant comfort, softPulse^{TM} soft dry EEG electrodes (Datwyler, Switzerland) were employed. A PPG sensor was used to monitor heart rate and was integrated into the faceplate of the HMD, as well as two pairs of vertical and horizontal EOG electrodes. A green LED light was used in the PPG sensor to ensure more accurate measurements [220]. Moreover, a pair of Myo 8-channel armbands (Thalmic labs, Canada) were

placed on the participant forearms in order to capture electromyography (EMG) signals at a rate of 200 Hz using dry electrodes. Different modalities and signal inputs were synchronized and recorded using lab streaming layer (LSL).

4.2.2.2 Multisensory Feedback

A pair of Nova^{TM} haptic gloves (SenseGlove, Netherlands) were employed to deliver accurate force feedback to each finger. The gloves can also track wrist, hand, and finger gestures using inertial measurement unit (IMU) sensors. Taking advantage of linear resonant actuators on the thumb and index fingers, participants can perceive the texture and stiffness of a 3D object in a virtual environment. Mounting the Meta Quest2 controllers on the gloves enabled 3D mapping of the hand locations onto the virtual space, as shown in Fig. 4.1b. Furthermore, an OVR ION2 scentware device (OVR Technologies, USA) was connected to the BCI-HMD to provide olfactory feedback via dispersing aromas close to the user nose with maximum intensity that can be defined in the provided software development kit (SDK) by the company. The employed scent kit contains nature-oriented scents including beach, flowers, earth dirt, pine forest, ocean breeze, wood, citrus, ozone, and grass smells. In this study, the citrus scent was chosen for olfactory feedback.

4.2.2.3 Developed Virtual Environment

A custom virtual environment was designed in Unity3D 2021. As illustrated in Fig. 4.2a, five oranges are placed on each of six plates positioned on top of a table. The participant is seated at the center and three plates to the left and three to the right side of the participant were strategically positioned at three different distances (three levels). The nearest plates (level 1) positioned at a relative distance of 20 cm from subject in the real-world, while the farthest plates (level 3) are located at 60 cm; the middle plates were placed at 40cm (level 2). The environment and the distance are devised in a way that even the oranges placed on the farthest plate are accessible by full arm extension, without the need for any additional body movement.

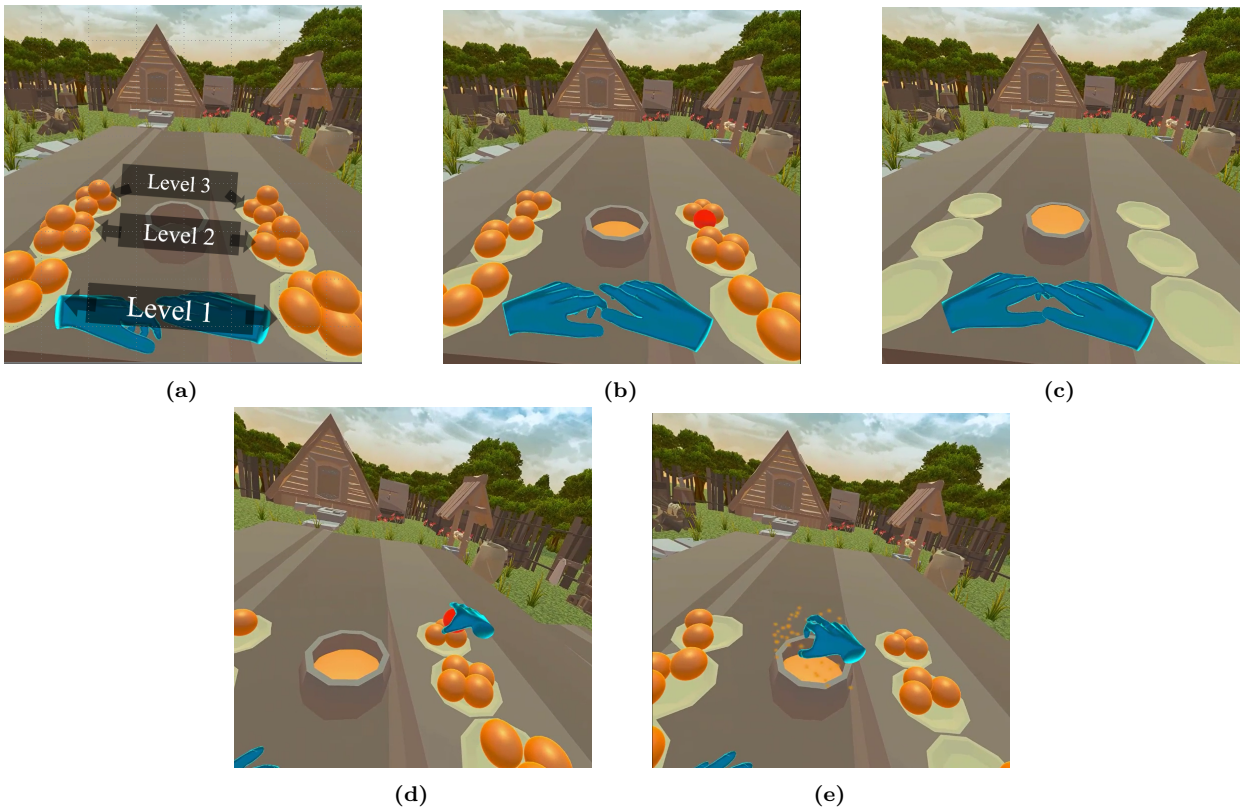


Figure 4.2: (a) Developed game environment, five oranges placed in each of the 6 plates (overall 30 oranges). (b) A randomly cued orange in the MI session. The tas in the MI session is to imagine grabbing a cued orange, moving it on top of the bowl placed in center, and squeezing it. (c) After finishing the task, the bowl fills up with orange juice. (d) A randomly cued orange that participants required to grab, move to the top of the center bowl and squeeze. In the multisensory condition, participants feel the volume and texture of the 3D object, while in audio-visual, oranges can be grabbed and squeezed with less force. (e) After successful squeezing the orange, the cued orange disappears simultaneously with playing an animation. In the multisensory condition, this event is synced with olfactory feedback, whereas in audio-visual condition, it is followed by auditory effects.

4.2.3 Experimental Design

A repeated measures experimental design (so-called within-subject experimental protocol) was followed in which all the participants underwent the same experimental conditions (with counterbalanced ordering). Figure 4.3 illustrates the step-by-step protocol timelines and experimental blocks. In the pre-experiment phase, participants were first assessed for any known motion sickness or sensitivity to smells, as well as their comfort with the BCI-HMD and haptic gloves. Each participant was then given comprehensive instructions orally, before wearing the Myo armbands and BCI-HMD. Afterwards, all the systems were calibrated, signal quality checked, and any adjustments were

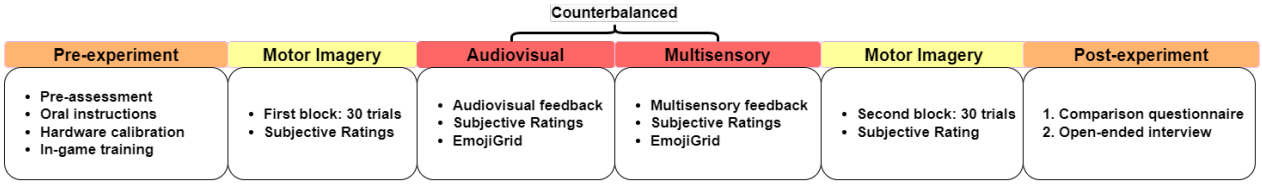


Figure 4.3: An overview of the experiment timeline. Screening for motion sickness and smell sensitivity is part of the pre-assessment process. Afterwards, instructions were given, followed by system calibration and in-game training. The experiments begin with a motor imagery session, followed by two conditions with varying types of sensory feedback. Another motor imagery session was conducted as a final session.

made to increase signal quality. Finally, participants received in-game training with and without multisensory feedback.

At the second step, participants were asked to perform a common BCI MI task where they imagine grabbing an orange using either their left or right hand [134]. In this MI session, the user is cued to imagine grabbing the orange that has turned red for a duration of 10 seconds. Oranges are randomly turned red between the left and right sides, as shown in Fig. 4.2b. During the 10 seconds, the participants were instructed to imagine grabbing the cued orange, moving it to the middle of the table, and squeezing it onto the center bowl. Afterwards, the orange disappears for a 5-second rest period, after which another orange is cued and the procedure is repeated until all 30 oranges (5 oranges × 6 plates) have been squeezed, all plates become empty, and the center bowl will be filled with orange juice, as depicted by Fig. 4.2c).

Following this first motor imagery task, participants were instructed to then play the motor priming game twice, once with only audio-visual feedback and once with the multisensory stimuli. A counterbalanced ordering of conditions was applied across subjects to eliminate any biases. In these experimental conditions, similar to the MI sessions, a randomly assigned orange was cued in red color and users were instructed to grab them (Fig. 4.2d), move them over the center bowl, and squeeze the orange until all juice was extracted, causing the orange to burst and vanish and the juice level in the bowl to rise (Fig. 4.2e). Participants had their real-world hand movement mapped onto the virtual hand models (shown as blue hands in the figures) with a 100 Hz refresh rate. In the experimental condition with only audio-visual feedback, squeezing an orange is followed by a "squish" sound effect synced with an animation without applying any physical force feedback. In the multisensory condition, on the other hand, users were able to feel the 3D shape and texture of the oranges in the virtual environment and had to apply force in order to successfully squeeze and extract the orange juice. In this condition, the audio-visual feedback was also time-aligned with a

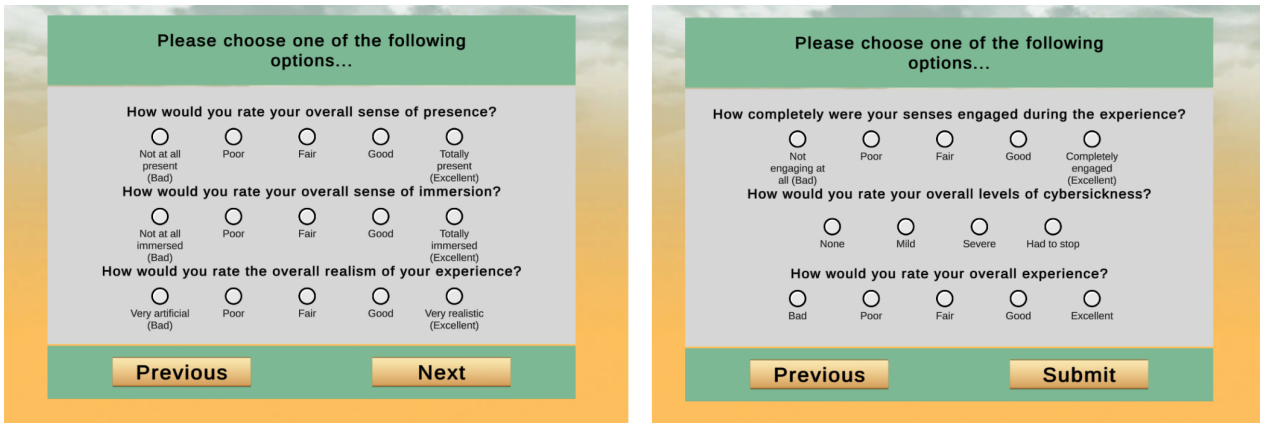


Figure 4.4: The in-game tailored questionnaire to gauge different QoE subscales including, presence, immersion, realism, engagement, cybersickness, and overall experience

burst of citrus scent that was presented for a duration of 3 seconds. Participants were allowed to interact with the virtual environment at their own pace while they were seated on a swivel chair. The experiment concluded when all oranges had been squeezed and all juice extracted.

After the two counterbalanced conditions were performed, users underwent a second motor imagery task following the same instructions and procedure as the first session described above. Upon completion of the experimental conditions, participants responded to several questionnaires that appeared directly into the game environment (more details in the next section) as well as the EmojiGrid, a graphical tool to gauge user emotions. At the end, a post-experiment comparison questionnaire was answered and an open-ended interview was conducted.

4.2.4 Subjective Ratings

Along with real-time monitoring of the psychophysiological state of the users, a battery of QoE-related questionnaires were exploited after each experimental condition, including questions related to perceived level of presence, immersion, realism, engagement, and overall experience using the 5-point absolute category rating (ACR) scale [123], tailored inside the game using a toolkit developed by [124]. For cybersickness, a 4-point scale was used. Figure 4.4 illustrates the developed questionnaires and associated questions asked.

Moreover, the EmojiGrid, adopted from [1], was used to capture the participants' emotional states after each experimental condition. The grid (see Fig. 4.6 as an example) has a continuous axis from zero to 100, where the horizontal axis represents valence and varies from unpleasant (left

most, zero), to neutral (50), to pleasant (rightmost, 100). The vertical axis represents arousal, varying from calm (bottom-most, zero), to neutral (50), to very excited (topmost, 100). On the outer edges, facial expressions are reflected via emojis. Participants were shown the EmojiGrid during the pre-experiment session to familiarize themselves with the axes, the meaning of each quadrant, and how to use the grid in the in-VR setting.

Lastly, after the end of the complete experiment and when the VR headset was removed, users were asked to compare the audio-visual and multisensory conditions in terms of presence, immersion, realism, engagement, cybersickness, and overall experience. Analysis of the questionnaires and ratings related to MI session is will be reported in the next chapter.

4.2.5 Biosignals Processing

Different modalities including EEG, EMG, and EOG signals were pre-processed in MATLAB (R2021a, The MathWorks, USA). Using the EEGLAB toolbox [135], EEG and EOG signals were filtered via a band-pass filter between 0.5 and 45 Hz, then zero-mean normalization was applied. The artifact subspace reconstruction (ASR) algorithm was subsequently applied to remove movement-related artifacts [136]. Next, several metrics were derived from the pre-processed biosignals. From the EOG channels, blink rate (BR) was extracted. From EEG, the power spectral density (PSD) was extracted using Welch's method [137] and powers across the five traditional subbands were computed for each of the 11 EEG channels, namely: delta (0-4HZ), theta (4-8Hz), alpha (8-12Hz), beta (12-30Hz), and gamma (30-80Hz). From these subband powers, the following metrics were computed. First, the task engagement index (EI) was computed using the average beta, alpha, and theta power bands across all channels. As highlighted in [125], EI reflects the cognitive engagement of a user with a particular task and is given by:

$$EI = \frac{beta}{alpha + theta}. \tag{4.1}$$

Next, an arousal (AI) and a valence index (VI) were computed based on alpha and beta subband powers of frontal electrodes (F3, F4) following [126] and given by equation 3.1. Lastly, a measure of withdrawal/approach tendencies was computed using the frontal alpha asymmetry (FAA) index. In particular, positive FAA values indicate higher left hemisphere activity, i.e., higher approach-tendency,

and consequently, higher positive emotions throughout the experience. In contrast, negative values are concerned with withdrawal tendencies (high right hemisphere activity) [129]. FAA is given by:

$$FAA = \ln(alpha_{(\mathrm{F3})}) - \ln(alpha_{(\mathrm{F4})}), \tag{4.2}$$

where $\ln(alpha)$ indicates log of the alpha power band at a specific electrode location. EMG signal pre-processing, in turn, included band-pass filtering from 10 to 500 Hz followed by full-wave rectification. The mean absolute value (MAV) of the EMG signal was extracted for each arm, as per [138]. Afterwards, the MAV values of left and right arms were averaged to characterize the subjects' overall muscle activity during each experimental condition to validate the use of force feedback in the multisensory condition. Lastly, the HeartPy python library was used to extract heart rate (HR) measures from the recorded PPG signals [139].

4.2.6 Statistical Analysis

Statistical analysis was performed for both the subjective ratings as well as the extracted biosignal-based metrics using IBM SPSS 20. Normality of the variables was assessed using the Shapiro-Wilk (S-W) normality test, recommended for small sample size datasets [149]. A paired sample t-test was employed to analyze statistically significant differences across experimental conditions for measures found to be normally distributed. In turn, a non-parametric Wilcoxon signed-rank test was performed for measures found to not be normally distributed. Mean (M) and standard deviation (SD), as well as p-values are reported herein. Next, to determine the contribution of each QoE subscale to overall QoE, we performed a simple linear regression on presence, immersion, realism, engagement, and cybersickness ratings to predict the overall experience rating.

Finally, to reveal the association between variables (both between QoE subscales and QoE subscales with biosignal metrics), a repeated measures correlation (rmcorr) approach was exploited [150]. This approach examines the within-individual association in paired measures between two variables and has been extensively used in human-computer interaction studies (e.g., [221; 222; 223]). Relative to Pearson's correlation, the null hypothesis of rmcorr states that there is no association between two variables, whereas the alternative hypothesis states that there is. The rmcorr coefficient (r_{rm}) is bounded between -1 to 1 and reflects the strength and direction of the linear association between

two variables [224]. For all analyses, a probability level of $p < .05$ was considered to be statistically significant.

4.3 Results

4.3.1 Subjective Ratings

Figure 4.5 illustrates bar plots of the average ratings provided by the 11 subjects for each of the QoE subscales, as well as overall QoE. The S-W test indicated a non-normal distribution of these ratings; the following statistics were found per condition:

- Audio-visual: Presence: M=3.73, SD=.467; Immersion: M=3.73, SD=1.104; Realism: M=3.18, SD=.603; Engagement: M=3.55, SD=.934; Cybersickness: M=1.09, SD=.302; and Overall experience: M=3.82, SD=.405.
- Multisensory: Presence: M=4.36, SD=.505; Immersion: M=4.36, SD=.505; Realism: M=3.73, SD=.467; Engagement: M=4.45, SD=.52; Cybersickness: M=1.00, SD=.000; and Overall experience: M=4.27, SD=.467.

A statistically significance difference was observed for the presence (Z= 2.646, p= .008), engagement (Z= 1.983, p= .047) and overall experience (Z= 2.121, p= .034) ratings.

4.3.2 EmojiGrid

EmojiGrid ratings, in turn, resulted in normally distributed data. The following statistics were observed:

- Audio-visual: Valence: M=67.90, SD=16.640; Arousal: M=52.09, SD=16.525.
- Multisensory: Valence: M=78.09, SD=14.929; Arousal: M=79.72, SD=11.967.

A statistically significance difference in valence (t(10)= 3.290, p= .008) and arousal (t(10)= 7.066, p =< .001) was seen between the two conditions. Figure 4.6 depicts a scatter plot of the reported EmojiGrid ratings for the two conditions (blue = audio-visual; orange = multisensory).

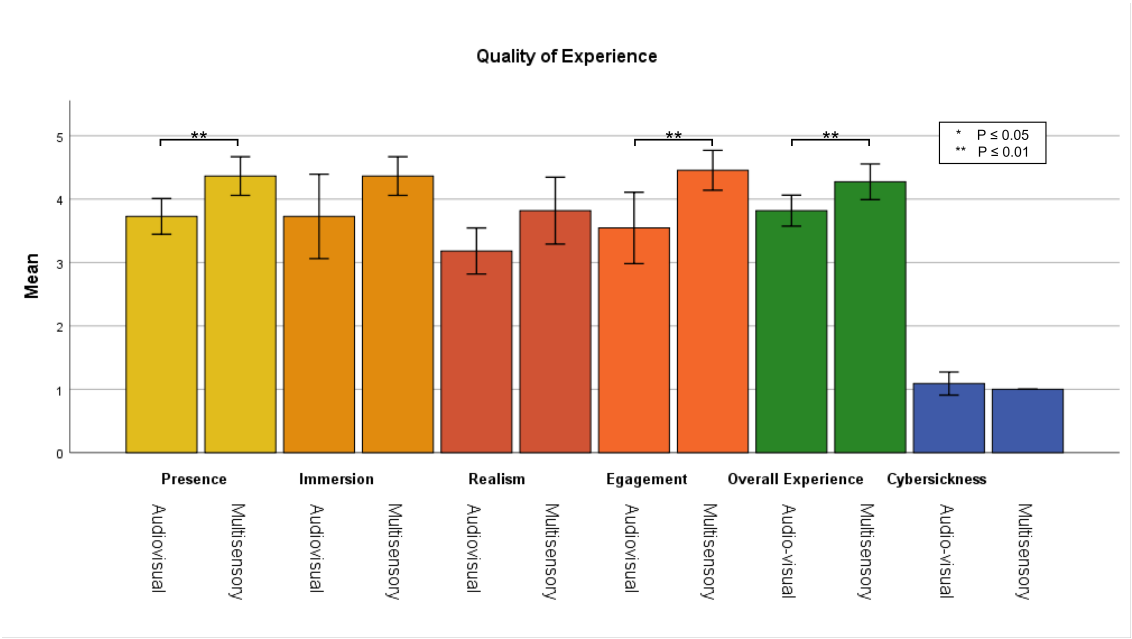


Figure 4.5: Average ratings across participants for subjective ratings for the two experimental conditions.

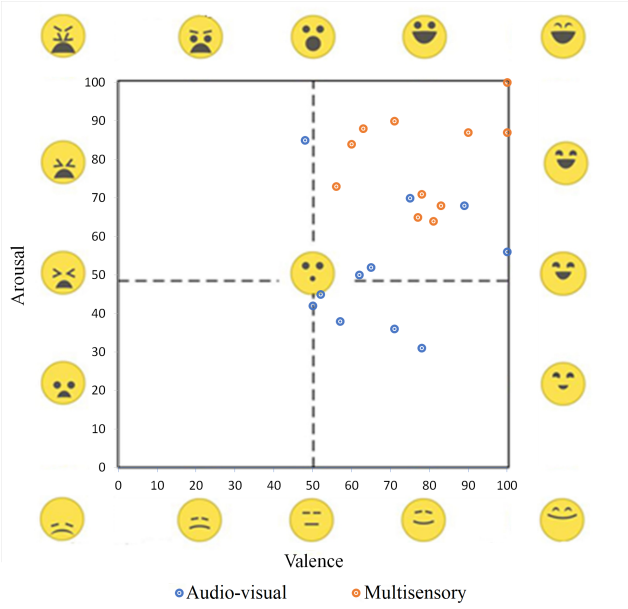


Figure 4.6: Distribution of arousal-valence ratings after audio-visual and multisensory conditions on EmojiGrid adopted from [1]. The horizontal axis represents valence and varies from unpleasant (left most, zero) to neutral (50) to pleasant (right most, 100). The vertical axis represents arousal, varying from calm (bottom-most, zero) to neutral (50) to very excited (top most, 100).

4.3.3 QoE Subscale Regression Analysis

Next, we examined the contribution of each QoE subscale (presence, immersion, realism, engagement, and cybersickness) on overall experience through linear regression analysis. Regression

Table 4.1: Linear regression weights indicating the contribution of each QoE subscale on overall experience.

QoE subscale	Audio-visual	Multisensory
Presence	.50	.18
Immersion	.18	.21
Realism	.23	.27
Engagement	.08	.33
Cybersickness	.01	.01

weights are conditioned to sum to unity, thus indicating overall importance of a subscale on overall QoE. As shown in Table 4.1, presence and realism showed higher contributions in shaping the overall experience of the audio-visual condition, in line with the results of chapter 3. In the multisensory condition, in turn, engagement and realism played the most significant roles, but closely followed by sense of immersion and presence. In both conditions, cybersickness played a minor role on overall QoE.

4.3.4 Biosignal Data Analysis

The S-W test revealed a normal distribution of features extracted from all biosignal metrics with the exception of the EI and VI metrics. As shown in Table 4.2, statistically significant changes were observed across audio-visual and multisensory conditions for FAA ($t(10)= 2.516$, $p= .031$) and MAV ($t(10)= 3.334$, $p= .008$), as well as for EI ($Z= 2.578$, $p= .010$) and VI ($t(10)= 3.944$, $p= .003$). No statistically significant difference was found for AI, heart rate, and blink rate. Notwithstanding, an ascending trend was observed from the audio-visual to the multisensory condition was observed for heart rate and blink rate. The significant changes seen in the MAV metric validate the effects of the force feedback modality on the multisensory experience.

Table 4.2: Changes in frontal alpha asymmetry, EMG MAV, heart rate, blink rate, VI, AI, and EI per experimental conditions. Values in parentheses correspond to standard deviation across participants. An asterisk indicates a statistically significant difference across two conditions.

Feature	Audio-visual	Multisensory
Frontal alpha asymmetry*	-.565 (0.517)	0.272 (0.418)
EMG MAV*	8.16 (1.32)	9.49 (2.18)
Heart rate	66.23 (5.38)	70.32 (11.89)
Blink rate	49.91 (15.11)	58.24 (13.01)
VI*	49.57 (9.06)	57.95 (7.82)
AI	30.47 (7.01)	30.64 (14.17)
EI*	44.47 (4.59)	60.68 (6.87)

4.3.5 Repeated Measures Correlation

Several correlations between subjective and objective measures were analyzed with the rmcorr metric and reported in Table 4.3. As can be seen, the overall experience rating showed a statistically significant relationship with the engagement, presence, and realism subjective ratings, with the EmojiGrid valence ratings, as well as with the EI metric. In turn, the engagement and presence ratings showed a statistically significant correlation with the EmojiGrid arousal rating. Regarding the biosignal metrics, VI and EI showed significant relationships with EmojiGrid arousal and presence, whereas EI also showed correlations with realism.

4.3.6 Post-experiment Comparisons

The stacked bar chart in Fig. 4.7 illustrates the preferences of the participants across experimental conditions for each of the QoE subscales, as well as the overall experience. The plot shows the number of participants who showed a preference for the audio-visual or multisensory conditions, or reported no difference (equal). As can be seen, the multisensory sessions were preferred over the audio-visual condition for the majority of the participants for presence, immersion, realism,

Table 4.3: Statistically significant rmcorr coefficients across different subjective and objective measures.

Variables	Correlation coefficient (r_{rm})	95% confidence interval	p
Overall Experience and Engagement	.763	[.256, .941]	.004
Overall Experience and Presence	.668	[.067, .913]	.018
Overall Experience and Realism	.600	[-.047, .893]	.039
Overall Experience and Valence (EmojiGrid)	.767	[.266, .942]	.004
Overall Experience and EI	.604	[-.042, .894]	.038
Engagement and Arousal (EmojiGrid)	.637	[.012, .904]	.026
Presence and Arousal (EmojiGrid)	.809	[.366, .953]	.001
Arousal (EmojiGrid) and VI	.800	[.344, .951]	.002
Arousal (EmojiGrid) and EI	.732	[.191, .932]	.007
Presence and VI	.589	[-.064, .889]	.044
Presence and EI	.782	[.301, .946]	.003
Realism and EI	.604	[-.041, .894]	.037

engagement, and overall experience. For cybersickness, in turn, subjects assigned no difference between the two conditions.

4.4 Discussion

The current experiment examined the impact that a multisensory VR environment has on QoE and its subscales relative to a conventional audio-visual immersive experience; subscales include immersion, presence, realism, engagement, and cybersickness. We quantified the improvements

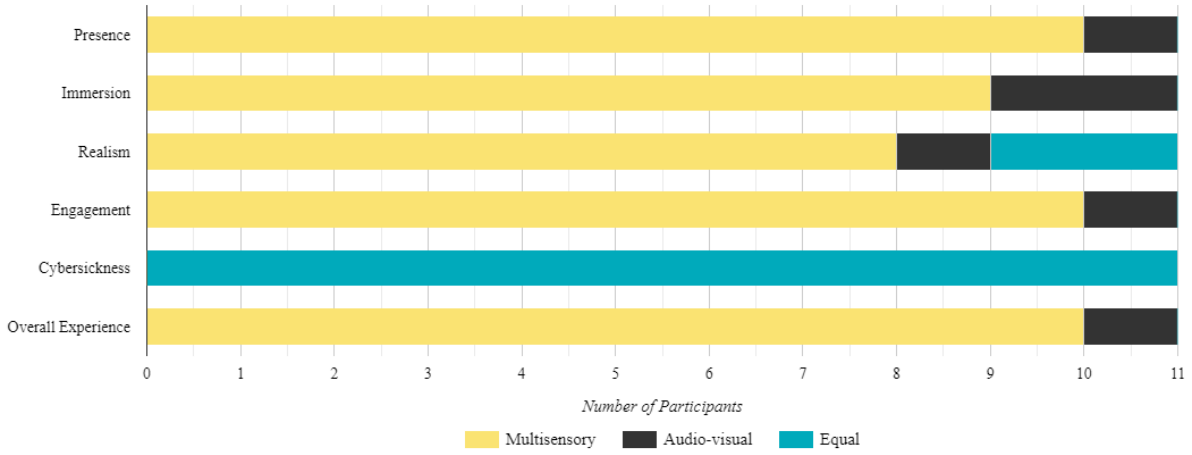


Figure 4.7: Stacked bar chart of comparison between multisensory and audio-visual experimental conditions

obtained in QoE by including olfactory and force feedback stimuli, as well as explored the measurement of the overall experience using a BCI-instrumented VR HMD. In this section, we discuss our obtained findings.

4.4.1 Subjective Ratings and QoE

This study has highlighted the benefits of including olfactory and force feedback stimuli to significantly increase the sense of presence, engagement, and overall experience relative to a traditional audio-visual immersive experience (Fig. 4.5). In fact, immersion and realism levels also showed an increase, albeit not statistically significant. Due to the stationary nature of the experiment, all of participants rated "no" to the cybersickness symptoms question in the multisensory session, while only one participant reported "mild" symptoms of dizziness in the audio-visual session. Moreover, regression analysis (Table 4.1) revealed the importance of the sense of engagement in overall multisensory QoE, followed closely by realism, immersion and presence. For the audio-visual condition, on the other hand, presence contributed the most towards overall QoE, followed by realism and immersion. These findings suggest that the additional sensory modalities improved user engagement, which in turn helped improve the user experience. This could be related to plausibility illusion that force feedback brings, by simulating real-world interactions, into virtual experience [225]. With only the audio-visual stimuli present, the realism of the environment and sense of presence were more crucial. This finding corroborates previous work (e.g., [162]) that showed that 360-degree

video quality can be reduced once additional senses are stimulated, without any significant drops in QoE.

4.4.2 User Emotional States and Task Engagement

Analysis of the EmojiGrid ratings showed the multisensory experience resulting in high pleasantness (valence) and intensity (arousal), whereas with the traditional audio-visual condition, participants rated their valence levels as mostly neutral (Fig. 4.6). In fact, these findings were also corroborated by the biosignal metrics (Table 4.2). For example, the valence index showed significant increases in the multisensory condition, whereas the FAA measure showed a significant increase from a negative value (suggesting withdrawal-tendency) to a positive value (suggesting approach-tendency). The engagement index also showed to significantly correlate with overall QoE, arousal, presence and realism, thus corroborating the importance of task engagement on overall quality perception, as highlighted by Table 4.1.

4.4.3 Relationship Between Subjective Ratings and Biosignal Metrics

Table 4.3 showed that metrics extracted from the BCI-HMD correlated significantly with several QoE subscales, as well as overall QoE. More specifically, EI was show to correlate with overall experience, VI and EI with arousal and presence, and EI with realism. These findings corroborate recent reports on the effect of multisensory feedback on presence in increasing pleasantness of the task, and subsequently, optimizing task engagement [40]. In fact, these findings support previous reports on the direct relationship between presence and better user performance by introducing "pleasantness" as one of the mediator factors [151; 152].

4.4.4 Post-Experiment Interview

Based on the post-experiment interview, all of the participants were able to perceive and identify the olfactory stimuli. However, the perceived intensity and degree of the pleasantness of the citrus scent were unique to each subject. This effect could be due to age- or gender-specific factors, as outlined in previous studies [226]. Nevertheless, 100% of the participants could feel the force feedback and the resistance during pressing the objects, corroborating the increases in the MAV feature

reported in Table 4.2. None of the participants reported delays in receiving feedback. Several participants mentioned that the inclusion of scents helped them increase their sense of immersion, while the force feedback gloves helped improve their sense of presence, allowing them to feel like they were really interacting with a 3D object. Moreover, three participants reported arm fatigue after the experiment, likely due to the fact that Quest2 controllers needed to be attached to the gloves in order to enable hand tracking. Notwithstanding, only one participant mentioned the weight of BCI-HMD coupled with the OVR scentware.

4.5 Conclusion

In this chapter, we have described an experiment to investigate the influence of olfactory and force feedback stimuli on overall quality of experience assessment, as well as on several QoE subscales, including sense of presence, immersion, realism, engagement, emotions, and cybersickness. In addition to measuring these factors subjectively via questionnaires and graphical tools (i.e., EmojiGrid), we have proposed the use of a brain-computer interface instrumented head-mounted display, termed BCI-HMD, to monitor biosignal metrics that correlate with these QoE subscales. Our results showed the importance of adding olfactory and force feedback stimuli to enhance task engagement, sense of presence, and the overall pleasantness of the experience. The physiological data captured from the BCI-HMD allowed for several QoE subscales to be computed in real-time, thus potentially opening the door to adaptive multisensory experiences which maximize QoE for each individual user.

Chapter 5

Augmenting the VR-based MI-BCI Training with Multisensory Feedback: A View on BCI Accuracy

5.1 Chapter Overview

MI-based BCIs are very popular [227] as they have shown to engage the same underlying neural circuits associated with executed motor actions [22]. As such, they have been used to control, for example, wheelchairs, drones, and exoskeletons [228] or to improve attention levels [23] in both healthy and patient populations [17]. Traditionally, audio-visual modalities have been the most common for feedback during MI-BCI based training [172; 229]. More recently, however, improved MI-BCI accuracy has been reported when HMD-VR have been used, as was highlighted in Chapter 2, and we hypothesize that multisensory training can provide additional benefits.

Building from the experiment described in the previous Chapter 4, the present Chapter explores the benefits the multisensory training brought to MI-BCI accuracy. The contents of this chapter have been taken from [230].

5.2 Materials and Methods

The population demographics, hardware, and experimental design of the study presented here follows those presented in Chapter 4. Next, we highlight the subjective ratings relevant to the MI task, as well as the features extracted for the MI-BCI itself.

5.2.1 Subjective Ratings for MI BCIs

After both MI sessions, participants were asked to rate their perceived difficulty in performing each motor imagery task using a 5-point scale with options "very easy", "easy", "neutral", "difficult", and "very difficult". At the end of the overall experiment, users were asked to rate their preference for the audio-visual or multisensory priming conditions in terms of presence, immersion, realism, engagement, and overall experience. Lastly, an open-ended interview was conducted to gather candid feedback from the participants.

5.2.2 Signal Processing and Classification

Physiological data including EEG, EOG, EMG, and PPG signals were synchronized with game events using lab stream layer (LSL). In this section, we focus only on the EMG and EEG signals collected during the two motor imagery sessions. Using MATLAB (R2021a, The MathWorks, USA), the EMG signal is band-pass filtered between 10 and 500 Hz and full-wave rectified. The mean absolute value (MAV) of the EMG signal is then extracted for both left and right arms, as suggested by [231], and finally averaged across arms to obtain a final overall muscle activity for each user.

Using the EEGLAB toolbox [135], in turn, the EEG signals were band-pass filtered between 4 and 70 Hz, then zero-mean normalized, and spectral power from alpha (7-13 Hz) and beta (13-30 Hz) bands were computed, as suggested by [232]. Artifact subspace reconstruction (ASR) was also employed to eliminate movement-related artifacts [136]. As is commonly done with MI-based BCI paradigms, common spatial pattern (CSP) features were extracted from the MI trials [140; 141; 142] and input to a support vector machine (SVM) classifier to discriminate between left or right hand motor imagery [143; 144].

For binary tasks, CSP features calculate spatial filters that maximize the variance of one class while simultaneously minimizing the variance for the other class. The spatially filtered signal S of an EEG trial is given by:

$$S_{L\times T} = W_{L\times N} \times M_{N\times T}, \tag{5.1}$$

where W is a $L \times N$ matrix of spatial filters, whereas L is the number of filters and N number of EEG channels. M represents the EEG signal of a certain trial with N rows and T data points. The first J rows of the W matrix reflect the maximum variance in the first class (and minimum variance in the second class) and the last J rows reflect maximum variance in second class. In this study, we used six spatial filters ($J = 6$), three from each side, as suggested by [145].

For classifier training, an automatic hyperparameter optimization tool in MATLAB was used to find the best parameters for the SVM classifier to minimize five-fold cross-validation loss. Here, several tests are performed. First, we explore the accuracy achieved with CSP features computed over the entire 10-second (cue duration) motor imagery trial. Next, we explore the use of different window sizes, followed by a fixed window of 5-second duration (as per suggestions by [146; 147; 148]) with varying starting points post task cue. This is performed per subject and then averaged to obtain an overall MI-BCI accuracy. This is done under two settings: in the first, all plates on the left and all plates on the right are aggregated into two classes: left and right. In the second, classification of left versus right imagery was done per level (i.e., plate distance, as shown in Fig. 4.2a). In each of the scenarios, 70% of the dataset was used for training while the remainder was left for testing. This partition was done 200 times to reduce odds of over/underfitting.

Statistical analysis is then performed using IBM SPSS 20 using a paired sample t-test. We report the obtained mean (M) and standard deviation (SD) across the 200 runs, as well as the p-value of the t-test. For all analyses, a probability level of $p < .05$ was considered to be statistically significant.

5.3 Results and Discussion

5.3.1 Subjective ratings

The stacked bar chart in Fig. 5.1 depicts the perceived difficulty ratings as reported by each subject after execution of the MI tasks. A statistically significant difference was observed across the

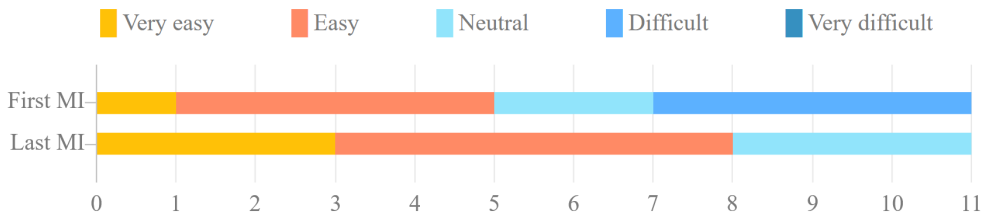


Figure 5.1: Stacked bar chart of comparison of difficulty of performing MI task during the first and last MI sessions.

first (M= 2.82, SD= 1.079) and the last (M= 2.00, SD= .775) MI session (t(10)= 2.764, p= .020), suggesting the latter task was perceived as being easier relative to the first. This is expected, as motor imagery tasks have been reported to become easier with training, especially in VR [153]. For the first MI task, four participants rated it as "easy," whereas four others rated it "difficult". The second time, on the other hand, had all participants rating the task as either "very easy", "easy", or "neutral."

5.3.2 MI-BCI Performance per Subject

As previously described, each MI trial consisted of 10 seconds of imagery followed by 5 seconds of rest. Participants were asked to perform the MI task 15 times for all of the left oranges and 15 times for all of the right oranges, totalling 30 trials per subject. For classification, 20 trials were used for training and 10 trials were left for testing, per subject. Figure 5.2 depicts the accuracy (averaged across participants) achieved for the first and last MI tasks. As can be seen, a statistically significant difference between the initial (M= 77.76, SD= 2.23) and the final (M= 80.32, SD= 2.62) MI sessions were observed (t(9)= 2.567, p= .030). This finding, aligned with the subjective reports described above, highlight the importance of VR training prior to performing the motor imagery task.

More importantly, we are interested in investigating the benefits of multisensory VR training relative to conventional VR training. To this end, Fig. 5.3 illustrates the accuracy achieved in the first (green) and last (beige) MI task, but now separated based on the subjects that performed the multisensory training first, followed by audio-visual training (left graph), versus those that performed the audio-visual training first and the multisensory last (right graph). As can be seen, while in both conditions the first MI session achieved a similar average accuracy across subjects, those that performed the multisensory task last were able to achieve a substantially higher accuracy in the last

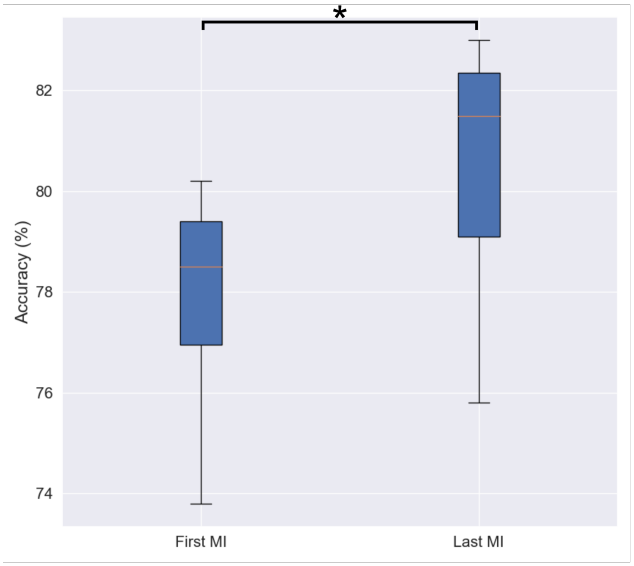


Figure 5.2: Box-plot of binary classification accuracy for first and last motor imagery sessions. Asterisk show statistically significant difference among two conditions.

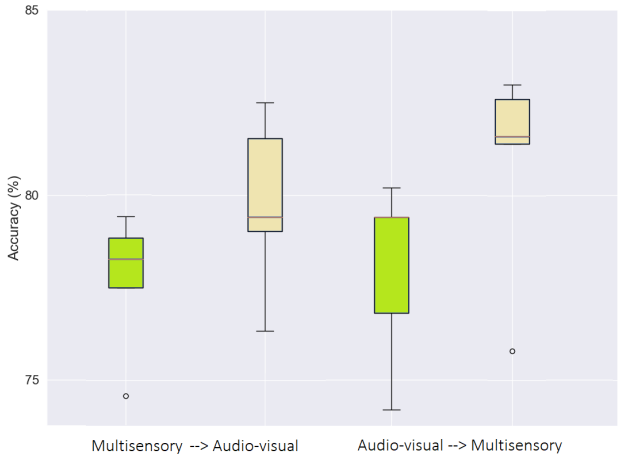


Figure 5.3: Box-plot of binary classification accuracy for the first (green) and last (beige) motor imagery sessions grouped by training order.

MI task. This suggests that not only VR training can be useful to improve BCI efficiency, but also the type of training used with additional benefits obtained with multisensory priming.

To further investigate the impact of training and training order, we plot the average activity obtained from the six CSP filters, where greater activity can be indicative of higher discriminability between the two classes. As shown in Fig. 5.4, in both cases the CSP activity was higher in the last MI session relative to the first, as expected given the training effects on BCI efficiency [154]. Notwithstanding, when the last training type was comprised of multisensory priming, the CSP activity was substantially higher than when the audio-visual only priming was performed.

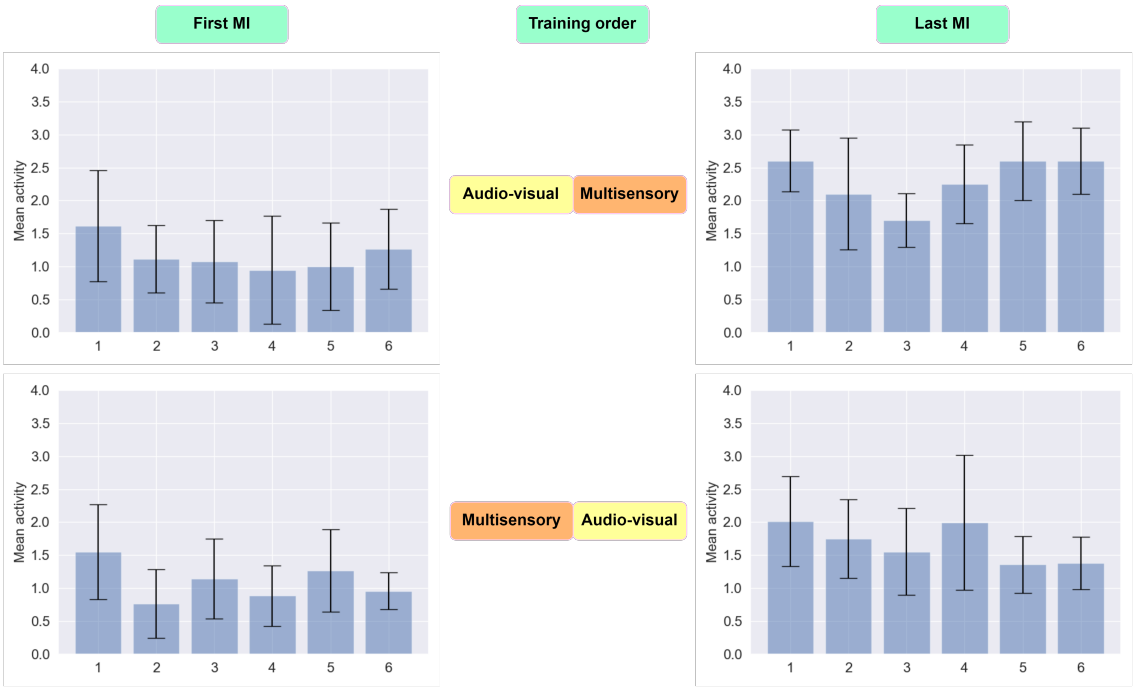
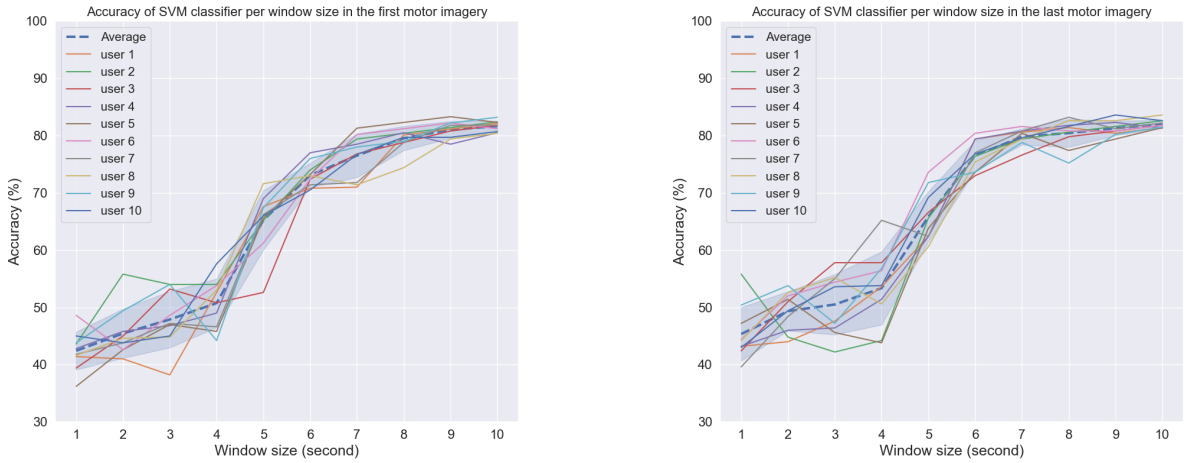


Figure 5.4: Distribution of extracted data using six CSP filters. The first row reflects the average activity of newly spatially filtered data during the first and last MI session for participants who received multisensory training prior to audio-visual experience. In the second row, however, the average activity of newly spatially filtered data are reflected for subjects who exposed to audio-visual training session as their first training condition.

5.3.3 Effect of Window Size and Time-from-Cue on Accuracy

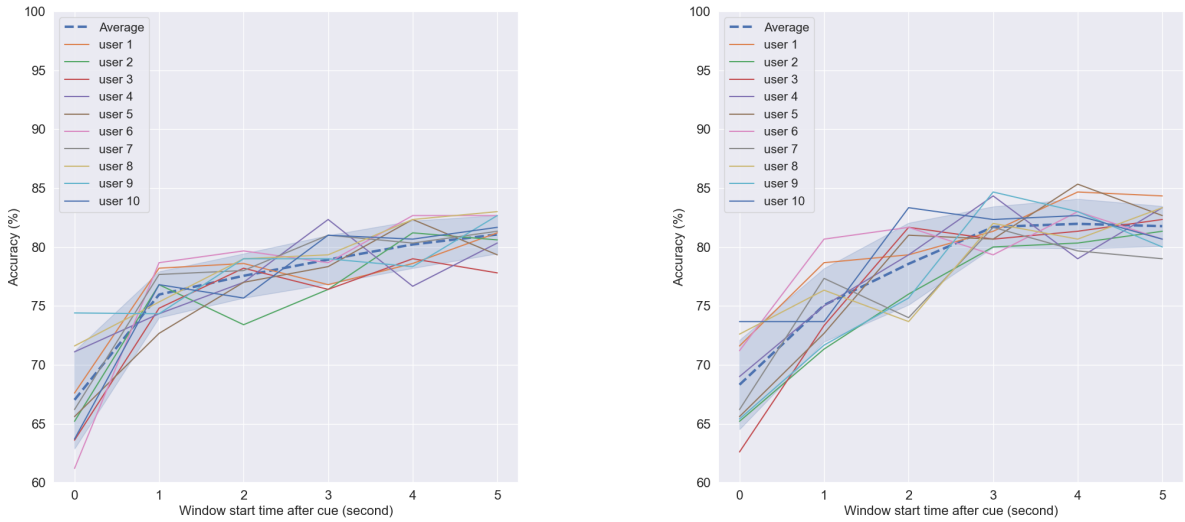
The results reported above assume that CSP features were computed over the entire 10-second window. For real-time applications, lower window duration may be preferred. To this end, we explore the effect that this window size has on overall accuracy. Figures 5.5 (a) and (b) depict the achieved accuracy as a function of window size for the first and last MI tasks, respectively. Accuracy is reported per subject, as well as averaged across subjects (dashed line). As can be seen, for window sizes between 1-4 seconds, chance or below-chance levels are achieved on the unseen test dataset. In the first MI task, accuracy levels stabilized for window sizes greater than 8 seconds, whereas in the last MI session, this could be achieved for most subjects around 7 seconds and for some even at 6 seconds. As the motor imagery task was fairly long (grab an orange, move to the middle of the table, and then squeeze), it is expected that peak accuracy is achieved once the full task is performed. With VR training, results suggest that this can be achieved potentially 2 seconds faster.

Next, we examined the effect of time-from-cue on overall accuracy. Time from cue indicates the amount of time waited once the subjects were cued to perform the task until CSP computation is



(a) (b)

Figure 5.5: Accuracy as a function of window size per subject in the (a) first motor imagery session and (b) last motor imagery session. Dashed line indicates average accuracy across users per window length while shaded interval shows the standard deviation.



(a) (b)

Figure 5.6: Accuracy of SVM classifier using 5-seconds fixed-length window size with different start points after cue in (a) First motor imagery session, (b) Last motor imagery session. Dashed line indicates average accuracy across users per window length while shaded interval show standard deviation.

performed. For this analysis, we kept the window size constant and varied the starting point for analysis. A 5-second window length was used as it showed to result in roughly 65-70% accuracy for both MI tasks. Figure 5.6 shows the achieved accuracy per subject as a function of time-from-cue in seconds. As can be seen, the greatest gains were seen when one second or more were considered post cue presentation for CSP feature computation; such findings corroborate those reported previously in the literature (e.g., [145]).

Table 5.1: Global performance accuracy achieved once all left or right oranges were grouped together (binary), versus when the classification was done per distance level. The values reported indicate the average 5-fold accuracy, whereas values in parenthesis reflect test set accuracy.

Classification Mode	First MI Accuracy %	Last MI Accuracy %
Binary	81.2 (79.1)	82.7 (81.3)
Level 1	79.9 (74.3)	76.3 (73.7)
Level 2	78.6 (75.9)	80.4 (77.1)
Level 3	76.4 (73.4)	78.1 (75.3)

5.3.4 Global MI-BCI Accuracy

Results reported up to now have been based on classifiers trained and tested on the same subject. Here, we train a global classifier where data from all subjects are pooled together. In this case, a total of 300 trials are available (150 left-side oranges and 150 right-side), of which 210 trials are used used for training and 90 are left for testing. Five-fold cross-validation is used on the training set for model optimization. The first row of Table 5.1 depicts the average accuracy achieved on the training set (average over the five folds), as well as the unseen test set (reported between parentheses) for the first and last MI sessions.

Next, we are interested in observing if the distance of the imagined movement has an effect on overall MI-BCI accuracy. In this case, the left versus right classification task is performed three times, once for plates closest to the participant (level 1), at middle distance (level 2), and furthest away (level 3), each comprised of 100 trials. As can be seen, for level 1 classification, the last MI session actually achieved slightly lower accuracy compared to the first MI session. For the other two levels, higher validation and test set accuracy were achieved during the last MI task. This finding may be explained by the underlying effects of *distance* postulated by Fitt's law in previous studies (e.g., [233; 234; 235; 236]). For instance, the work by [237] showed a linear relationship between time elapsed to imagine a movement with width and distance to the cues. This influence could be a result of spatial presence in virtual environments [238]. Therefore, alongside duration and type of feedback, the distance to the cued object from the participants or the depth of the 3D objects in the virtual environment could potentially play an important role in MI performance. Further studies would be needed to validate this hypothesis.

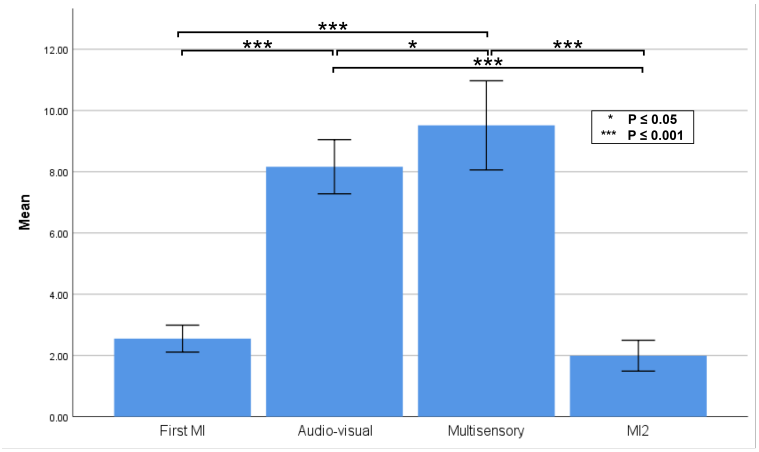


Figure 5.7: EMG MAV during each experimental condition. Asterisks indicate statistically significant difference.

5.3.5 EMG Activity

Lastly, to gauge the changes in EMG activity during the training tasks, Fig. 5.7 illustrates the changes in EMG MAV during the two MI tasks, as well as the two training conditions. As expected, a statistically significant difference was observed (t(10)= 3.055, p= .014) in muscle activity between the audio-visual (M= 8.16, SD= 1.40) and multisensory (M= 9.51, SD= 2.30) training sessions, as the force feedback gloves were on only in the latter condition. Moreover, a significant drop ($p \leq .001$) in MAV was observed between the first (M= 2.55, SD= .70) MI session and training conditions (audio-visual: t(10)= 13.302, Multisensory: t(10)= 10.440) and the last MI session (M= 1.99, SD= .79) and training conditions (audio-visual: t(10)= 18.677, Multisensory: t(10)= 13.217).

5.3.6 Interviews and User Feedback

As mentioned previously, at the very end of the experiment an open-ended interview was conducted with each participant. All of the participants reported being able to perceive and recognize the olfactory and force feedback in the multisensory condition. All confirmed they could feel the texture of the objects in the virtual environment and that this helped improve their sense of presence and the realism of the interaction. Regarding the citrus scent, some participants reported it as pleasant, while others suggested it was too intense. Such variability could be associated with age and/or gender related factors, as reported previously by [226]. The majority reported that the olfactory stimuli helped them enhance their sense of immersion, thus corroborating previous

studies [239; 40]. Overall, it is believed the improved sense of presence, immersion, quality of experience and engagement available with the multisensory priming has helped improve motor imagery performance.

5.3.7 Study Limitations

The presented study was conducted during the sixth wave of the COVID-19 pandemic, therefore, several limitations were applied to ensure participant safety. Consequently, this limited our sample size as well as the generalizability of the achieved results, thus future work should aim to increase the participant pool size. Nevertheless, the observed significant changes observe corroborate those found in previous studies with higher number of participants. One additional limitation of the proposed multisensory priming task is that it requires the user to have some functional motor control, thus could have limitations for users with e.g., locked-in syndrome or with severe motor disabilities post-stroke.

5.4 Conclusion

In this chapter, we report an experiment that was conducted on 10 participants to evaluate the impact of multisensory VR training, where olfactory and haptic feedback were included in addition to audio-visual feedback, on improving motor imagery performance. To this end, a brain-computer interface instrumented head-mounted display was developed and coupled with an off-the-shelf scent diffuser and haptic glove. Experimental results showed the benefits of multisensory priming in VR-based training, relative to conventional audio-visual priming, with significant improvements in motor imagery detection accuracy post multisensory training. Optimal window size and time-from-cue insights were also obtained and reported. Overall, these preliminary results provide fresh insights into the influence of multisensory priming on motor imagery performance and offer new perspectives on how to potentially improve BCI performance.

Chapter 6

Conclusions and Future Research Directions

HMD-VR systems are emerging as a useful tool in rehabilitation for stroke survivors to recover motor function. Recent studies are showing promising results with VR-based interventions coupled with multimodal feedback and physiological computing. Such interventions improve patient engagement and motivation, allow for personalized treatments, and, ultimately, improve outcomes. In this thesis, we explored the benefits of using multisensory immersive feedback on user behaviour, overall experience, and on motor imagery performance.

6.1 Summary of Research

Here, we started by surveying the literature to explore the latest innovations in VR-based interventions for stroke rehabilitation coupled with physiological computing principles. From the survey, limitations were found and the work proposed herein aimed at filling those gaps.

First, we explored the role of different feedback modalities, including audio-visual, olfactory, and haptic on user behaviour and found that haptic feedback and smells significantly improved the user's sense of immersion and engagement, respectively. Overall, a multisensory immersive experience was proposed comprised of audio-visual-olfactory-haptic feedback and shown to achieve the highest subjective ratings, including overall perceived quality of experience. Moreover, an instrumented VR

headset was implemented and used to monitor physioloigvcal signals in real-time. From these signals, several measures were extracted to monitor engagement, arousal, valence, frontal alpha asymmetry, and eye blinks. Several such measures show to correlate with the subjective ratings, suggesting their potential use in customizing experiences on a per-user basis.

From the feedback received from the participants, an improved hardware and software combo was developed, alongside a more engaging and dynamical immersive environment. Experiments again corroborated the previous findings that as more senses were stimulated, greater sense of immersion, engagement, presence and overall experience was achieved. Lastly, this immersive environment was used as a priming tool to enhance motor imagery BCI accuracy. In particular, we showed that multisensory VR training was able to not only improve MI-BCI accuracy relative to conventional audio-visual VR training, but also resulted in increased activity in the six common spatial pattern filters used, as well as achieved peak accuracy with shorter window durations (6-7 seconds) relative to the optimal durations needed prior to training (8 seconds).

Overall, the findings reported herein suggest that multisensory immersive training could lead to significantly better motor imagery performance, thus may offer a new paradigm for future MI-BCI studies that are widely used for stroke rehabilitation. While tests with a patient population were not possible due to contraints imposed by the global COVID-19 pandemic, the results achieved with healthy subjects are promising.

6.2 Future Research Directions

In the future, a larger number of participants should be explored to allow for factors such as age and/or gender to be factored in. Moreover, the environments developed were limited by the scents available with the OVR ION device, i.e., the nature package. In the future, a more realistic game could be developed with alternate scents and optimized per user. Here, EEG, EOG and PPGs were used but recent research is showing the benefits of functional near-infrared spectroscopy for HIFs assessment. As such, future work could explore the addition of these alternate modalities into the VR headset. Moreover, facial EMG could be useful to characterize facial expressions, whereas cameras or bracelets could be used to track hand gestures, both if which could be useful to further characterize user behaviour.

Moreover, the weight of the haptic glove used in Chapters 4 and 5 (approx. 350 grams) was increased to 490 grams by mounting the Quest2 controller. This was needed to allow for accurate mapping of the spatial location of the hands into the game. Future work should explore camera-based arm tracking, which could allow for removal of the controllers, thus making the glove lighter. Some participants during their interview complained of the weight of the gloves, which could have led to a lower experience rating. Also, the metrics explored herein, such as engagement index, arousal and valence are traditional ones reported in the literature. More recent work is showing benefits of other metrics, such as ultra-short-term heart rate variability, mental workload, stress, flow, and attention, to name a few [240; 241; 242]. Future work could explore such new measures to build customized QoE measures per user. Lastly, as mentioned above, the tools developed herein have been tested only on healthy participants. Future work should explore the short and long-term benefits achieved for stroke patients.

Besides, this thesis relied on "passive" physiological computing tools, in the sense that signals were measured and used to gauge QoE metrics. More "active" tools, such as non-invasive brain stimulation (e.g., transcranial magnetic stimulation and transcranial direct current stimulation, tDCS), have recently emerged and shown to provide some success in rehabilitation when coupled with VR [243]. Future studies could couple passive and active physiological computing (e.g., via an EEG-tDCS headset) and explore the benefits that such hybrid architectures could bring. As observed in literature review, the majority of the studies utilized EEG sensors to measure neural responses and plasticity. Functional near-infrared spectroscopy (fNIRS) is also emerging as a useful tool for plasticity monitoring [244] and hybrid fNIRS-EEG headsets are already available in the market. As such, future studies could explore the advantages of integrating the improved spatial resolution advantages of fNIRS with the improved temporal resolution of EEG for stroke rehabilitation. Alternate feature representations, beyond simple ERD/ERS and EEG frequency subband powers, could also be explored as proxies of brain plasticity and intervention outcomes [245].

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Appendix A

Table A.1: Population, intervention, comparison, outcome, and study design (PICOS) table for inclusion and exclusion criteria

	Inclusion criteria	Exclusion criteria
Population	People with post-stroke symptoms; stable consciousness state; adult age group (over 18 years old); sufficient cognitive functions to allow learning; sufficient physical exercise tolerance; in subacute or chronic phase of recovery; any gender; population not restricted to a specific country; OR healthy people in rehabilitation-aligned studies	Stroke patients who are not in subacute or chronic phase of recovery; non-stroke caused functional deficits; severe cognitive dysfunction; visual, hearing impairment, suggested; previous history of epilepsy.
Interventions	Multimodal HMD-VR for rehabilitation therapy; physiological computing, multimodal feedback, exoskeleton, haptic, and motion detection coupled with HMD-VR for rehabilitation purposes; Multimodal VR-based version of clinical assessments for rehabilitation.	Traditional and other forms of rehabilitation procedures; non-HMD-VR interventions (such as games on flat screen); unimodal HMD-VR settings; HMD-VR without rehabilitation purposes; 360° videos; augmented reality.
Comparison	HMD-VR vs non-VR intervention; comparison of pre- and post-intervention with/out follow-up; studies with/out MRI, fMRI, TMS, and fNIRS.	VR without physical exercise or movements; biological signal including EEG, ECG, EMG, EOG.
Outcomes	Patient relevant outcomes; clinical/non-clinical measurements; improved or not improved outcome; subjective ratings; objective assessment.	None
Study Design	Studies followed (non)randomized procedure, before-after, and case study designs; qualitative/quantitative studies.	Studies without a full text report (e.g., conference abstract); reviews, meta-analyses, abstracts, book chapters.

HMD: head-mounted display; VR: virtual reality; MRI: magnetic resonance imaging; fMRI: functional MRI; TMS: transcranial magnetic stimulation; fNIRS: functional near-infrared spectroscopy; EEG: electroencephalography; EMG: electromyography (EMG); EOG: electrooculography; ECG: electrocardiography.

Table A.2: The corresponding score per study using National Institutes of Health — National Heart, Lung, and Blood Institute (NIH-NHLBI) quality assessment tool for before-after (pre-post) studies with no control group

Study	D1	D2	D3	D4	D5	D6	D7	D8	D9	D10	D11	D12
[99]	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	NA
[87]	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	Yes	NA
[85]	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	No	Yes	NA
[89]	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	Yes	NA
[90]	Yes	Yes	NA	Yes	Yes	Yes	Yes	No	No	Yes	Yes	NA
[82]	Yes	Yes	No	Yes	No	Yes	Yes	No	No	No	Yes	NA
[167]	Yes	Yes	NA	Yes	Yes	Yes	No	No	No	No	No	NA
[91]	Yes	Yes	NA	Yes	No	Yes	Yes	No	No	Yes	Yes	NA
[83]	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	No	No	No	NA
[92]	Yes	Yes	NA	Yes	Yes	Yes	No	No	No	Yes	Yes	NA
[84]	Yes	Yes	No	Yes	Yes	Yes	No	No	No	Yes	Yes	NA

Note: D1: Study objective; D2: Eligibility criteria and study population; D3: Study participants representative of clinical populations of interest; D4: All eligible participants enrolled; D5: Sample size; D6: Intervention clearly described; D7: Outcome measures clearly described, valid, and reliable; D8: Blinding of outcome assessors; D9: Followup rate; D10: Statistical analysis; D11: Multiple outcome measures; D12: Group-level interventions and individual-level outcome efforts.

Table A.3: The corresponding score per study using the Joanna Briggs Institute (JBI) checklist for quasi-experimental studies

Study	D1	D2	D3	D4	D5	D6	D7	D8	D9
[99]	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes
[87]	Yes	Yes	Unclear	No	No	No	Yes	No	No
[85]	Yes	Yes	No	No	Yes	No	Yes	No	No
[89]	Yes	Yes	No	No	Yes	No	Yes	Yes	Yes
[90]	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes
[82]	Yes	Yes	No	No	Yes	No	Yes	No	No
[167]	Yes	Yes	Yes	No	No	No	Yes	No	No
[91]	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes
[83]	Yes	Yes	Unclear	No	Yes	No	Yes	No	No
[92]	Yes	Yes	Yes	No	Yes	No	Yes	Yes	Yes
[84]	Yes	Yes	No	No	No	No	Yes	Yes	Yes

Note: D1: Clarity of cause and effect; D2: Similar participants; D3: Similar treatment (except VR exposure); D4: Existence of a control group; D5: Multiple measurement points of the outcome; D6: Completion of follow-Up; D7: Similar outcome measurements; D8: Reliability of outcome measurements; D9: Appropriate statistical methods.