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Centre Énergie Matériaux Télécommunications

Neurophysiological Indicators to Assess Quality-of-Experience based on Human Influential Factors in Virtual Reality

By

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A thesis submitted in fulfillment of the requirements for the degree of
Doctorate of Sciences, Ph.D
in Telecommunications

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"People come to the OASIS for all the things they can do, but they stay for all the things they can be"

Parzival

Acknowledgements

My deepest gratitude to my supervisor Dr. Tiago H. Falk for the support, opportunities and challenges provided throughout the PhD program, his role as supervisor surpasses all expectations, as such, his mentorship and attitude have been vital for the completion of this thesis, and for my personal development, it is great pleasure to work with him. I would also like to extend my heartfelt thanks to my co-supervisor, Dr. Alcyr Alves de Oliveira, for his guidance, expertise, and collaboration in this research journey.

I would like also to thank all the members and ex-members of the MuSAE lab for their incredible help, advice, company, and for the fun we have had while discussing ideas, running experiments, rushing for deadlines, debating and so on. In particular, I would like to thank Raymundo Cassani, Abhishek Tiwari, Shruti Rajendra Kshirsagar, Belmir de Jesus Junior, Oliver Rosanne and Marilia Lopez for their support and camaraderie.

Without my family, I would not be the person that I am today, I would like to largely thank my family, my parents Yannick and Thierry, and my brothers Pierre-Henri and Paul-Alexis; who despite the distance are always in my mind, thanks for giving your love, support, advice and care. Finally, I would like to greatly thank to my life partner Fanny, for her love, friendship, support, patience, help, feedback, and humor throughout these years.

There are not words to describe how grateful I am with every single person who helped to make this work possible. This thesis dedicated to all of you.

Abstract

Immersive virtual reality (VR) experiences have gained significant traction across various fields, ranging from entertainment and gaming to professional training, healthcare, and education. These diverse applications offer rich, engaging environments that allow users to interact with digital content in novel ways. A critical factor determining the success of these applications is the user's Quality-of-Experience (QoE), driven by three influential factors: system, context, and the (human) user. While system and context factors have been extensively studied, human influential factors (HIFs), such as the sense of presence, immersion, attention, stress, engagement, and cybersickness, remain underexplored in VR QoE assessment. By examining these factors, we can develop a more comprehensive understanding of how users perceive and respond to VR experiences, thereby informing the design of more effective and engaging applications. Traditional methods for evaluating QoE, such as subjective questionnaires and post-experience evaluations, provide valuable insights but may not adequately capture the complexity of human experiences in VR due to biases, memory limitations, and other factors that can reduce their reliability and validity. Moreover, they typically provide only retrospective assessments, limiting their utility in providing real-time feedback and adaptation. Biosensors offer a promising alternative for QoE assessment; however, their use has primarily been limited to laboratory settings rather than highly ecological environments. In this doctoral thesis, we present an approach for assessing QoE in immersive virtual applications by focusing on human influential factors (HIFs) and utilizing physiological signals in more ecologically valid settings. To achieve this goal, three main tools were developed: (i) an instrumented VR headset to monitor physiological signals in highly-ecological settings with minimal experimenter intervention, (ii) classifiers to map eye movement information from the instrumented headset to QoE-related metrics, and (iii) user experience markers from the recorded physiological data and eye movement-related features to allow for potential real-time QoE assessment.

First, we surveyed the literature to examine existing methods and tools to assess HIFs in immersive experiences, with particular emphasis on psychophysiological methods. Next, we designed and built an instrumented VR headset with several embedded biosensors capable of monitoring electro-physiological signals, such as electroencephalogram (EEG), electrooculogram (EOG), electrocardiogram (ECG), and facial electromyogram (EMG). These signals are explored here as tools for objective measurement of HIF-related features for QoE monitoring in VR environments. Next, we investigated the use of the EOG signals to track eye gaze without the need for an eye tracker or camera, as well as to develop new eye movement features relevant to QoE monitoring. Third, we show an ecological application of the headset for remote monitoring of the gamer experience with minimal experimenter intervention, thus accounting for cognitive, emotional, and perceptual aspects of QoE. Lastly, we show the usefulness of the extracted measures to monitor different correlates of gamer experience HIFs, including a new multimodal measure to track time perception, a marker of presence, immersion, and engagement in VR. Ultimately, it is hoped that the developed tools and markers will allow for a more accurate and comprehensive assessment of QoE in immersive virtual applications, with the potential to enhance the design and development of VR experiences for users across diverse domains.

Keywords: Virtual reality, physiological signals, quality of experience, remote experience, machine learning

Résumé

Les expériences immersives de réalité virtuelle (RV) ont gagné en importance dans divers domaines, allant du divertissement et des jeux à la formation professionnelle, aux soins de santé et à l'éducation. Ces diverses applications offrent des environnements riches et attrayants qui permettent aux utilisateurs d'interagir avec le contenu numérique de manière inédite. La qualité de l'expérience de l'utilisateur est un facteur essentiel qui détermine le succès de ces applications. Elle est déterminée par trois facteurs influents : le système, le contexte et l'utilisateur (humain). Alors que les facteurs liés au système et au contexte ont été largement étudiés, les facteurs d'influence humaine, tels que le sentiment de présence, l'immersion, l'attention, le stress, l'engagement et le cybermalaise, restent sous-explorés dans l'évaluation de la qualité de l'expérience de RV. En examinant ces facteurs, nous pouvons développer une compréhension plus complète de la manière dont les utilisateurs perçoivent les expériences de RV et y réagissent, ce qui permet de concevoir des applications plus efficaces et plus attrayantes. Les méthodes traditionnelles d'évaluation de la qualité de l'expérience, telles que les questionnaires subjectifs et les évaluations post-expérience, fournissent des informations précieuses mais peuvent ne pas saisir de manière adéquate la complexité des expériences humaines dans la RV en raison de biais, de limitations de la mémoire et d'autres facteurs qui peuvent réduire leur fiabilité et leur validité. En outre, elles ne fournissent généralement que des évaluations rétrospectives, ce qui limite leur utilité en matière de retour d'information et d'adaptation en temps réel. Les biocapteurs offrent une alternative prometteuse pour l'évaluation de la qualité de l'expérience ; cependant, leur utilisation a été principalement limitée à des environnements de laboratoire plutôt qu'à des environnements en situation réelle. Dans cette thèse de doctorat, nous présentons une approche pour évaluer la qualité de l'expérience dans les applications virtuelles immersives en nous concentrant sur les facteurs d'influence humains (FIH) et en utilisant les signaux physiologiques dans des contextes plus écologiques. Pour atteindre cet objectif, trois outils principaux ont été développés : (i) un casque de RV instrumenté pour surveiller les signaux physiologiques dans des environnements hautement écologiques avec une intervention minimale de l'expérimentateur, (ii) des classificateurs pour mettre en correspondance les informations sur les mouvements oculaires provenant du casque instrumenté avec des mesures liées à la qualité de l'expérience, et (iii) des marqueurs de l'expérience utilisateur à partir des données physiologiques enregistrées et des caractéristiques liées aux mouvements oculaires pour permettre une évaluation potentielle de la qualité de l'expérience en temps réel.

Tout d'abord, nous avons étudié la littérature afin d'examiner les méthodes et outils existants pour évaluer les FIH dans les expériences immersives, en mettant particulièrement l'accent sur les méthodes psychophysiologiques. Ensuite, nous avons conçu et construit un casque de RV instrumenté avec plusieurs biocapteurs intégrés capables de surveiller les signaux électro-physiologiques, tels que l'électroencéphalogramme (EEG), l'électrooculogramme (EOG), l'électrocardiogramme (ECG) et l'électromyogramme facial (EMG). Ces signaux sont étudiés ici en tant qu'outils de mesure objective des caractéristiques liées au FIH pour le contrôle de la qualité de l'expérience dans les environnements de RV. Ensuite, nous avons étudié l'utilisation des signaux EOG pour suivre le regard sans avoir besoin d'un eye tracker ou d'une caméra, ainsi que pour développer de nouvelles caractéristiques de mouvement oculaire pertinentes pour la surveillance de la qualité de l'expérience. Troisièmement, nous montrons une application écologique du casque pour le suivi à distance de l'expérience du joueur avec une intervention minimale de l'expérimentateur, prenant ainsi en compte les aspects cognitifs, émotionnels et perceptifs de la qualité de l'expérience. Enfin, nous montrons l'utilité des mesures extraites pour surveiller différents corrélats des FIH de l'expérience du joueur, y compris une nouvelle mesure multimodale pour suivre la perception du temps, un marqueur de la présence, de l'immersion et de l'engagement dans la RV. En fin de compte, nous espérons que les outils et les marqueurs développés permettront une évaluation plus précise et plus complète de la qualité de l'expérience dans les applications virtuelles immersives, avec le potentiel d'améliorer la conception et le développement d'expériences de RV pour les utilisateurs dans divers domaines.

Mots-clés: Réalité virtuelle, signaux physiologiques, qualité de l'expérience, expérience à distance, apprentissage automatique

Contents

List of Figures

List of Tables

List of Abbreviations

AAF	Asymétrie Alpha Frontale
ACI	Analyse en Composantes Indépendante
AED	Activité Électrodermale
AI	Arousal Index
ASR	Artifact Subspace Reconstruction
BMI	Body-Machine Interface
CM	Cross-Media
CSPM	Cohérence Spectrale de Phase et de Magnitude
CSPM-MA	Cohérence Spectrale de Phase et de Magnitude des caractéristiques de Modulation d'Amplitude
DSP	Densité Spectrale de Puissance
EAM	Erreur Absolue Moyenne
ECG	Electrocardiogram
EDA	Electrodermal Activity
EEG	Electroencephalogram
EMG	Electromyogram
EMI	Expérience Médiatique Immersive
EOG	Electrooculogram
EQM	Erreur Quadratique Moyenne
ERP	Event-Related Potential
ERS	Event-Related Synchronization
ES	Engagement Score
FAA	Frontal alpha asymmetry
FC	Fréquence Cardiaque
FIHs	Facteurs d'Influence Humains
FOV	Field Of View
GPR	Gaussian Process Regressor
GSR	Galvanic Skin Response
GUI	Graphical User Interface
HF	High Frequency
HIFs	Human Influential Factors
HMD	Head-Mounted Display

HR	Heart Rate
HRV	Heart Rate Variability
IA	Indice d'Arousal
IBI	Interbeat Intervals
ICA	Independent Component Analysis
IFs	Influential Factors
IMEx	Immersive Media Experiences
IV	Indive de Valence
LF	Low Frequency
LSL	Lab Streaming Layer
MAE	Mean Absolute Error
MMN	Mismatch Negativity
mRMR	minimum Redundancy Maximum Relevance
MSSQ-Short	Motion Sickness Susceptibility Questionnaire-Short
MuLES	MuSAE Lab EEG server
MVS	Machine à Vecteurs de Support
NCC	Niveau de Conductivité Cutanée
NIRS	Near-Infrared Spectroscopy
NS-SCRs	Nonspecific Skin Conductance Responses
PEVES	Potentiels Évoqués Visuels à l'État Stable
PMC	Perceptron Multicouche
PMSC	Phase and Magnitude Spectral Coherence
PMSC-AM	Phase and Magnitude Spectral Coherence of Amplitude Modulation
PQ	Presence Questionnaire
PSD	Power Spectral Density
QdE	Qualité de l'Expérience
QoE	Quality of Experience
QRs	Questions de Recherche
RGP	Réponse Galvanique de la Peau
RMSE	Root Mean Square Error
RQs	Research Questions
RSA	Reconstruction du Sous-espace des Artefact
RSB	Rapport Signal-Bruit
RV	Réalité Virtuelle
SAM	Self-Assessment Manikins
SCL	Skin Conductance Level
SCRs	Skin Conductance Responses
SDNN	Standard Deviation of NN Intervals
SE	Score d'Engagement

SNR	Signal-to-Noise Ratio
SNS	Sympathetic Nervous System
SSQ	Simulator Sickness Questionnaire
SSVEP	Steady State Visually Evoked Potential
SVM	Support Vector Machine
TCP/IP	Transmission Control Protocol/Internet Protocol
ULF	Ultra-Low-Frequency
VE	Shared Virtual Environment
VE	Virtual Environment
VFC	Variabilité de la fFréquence Cardiaque
VI	Valence Index
VLF	Very Low Frequency
VR	Virtual Reality
VRSQ	Virtual Reality Symptom Questionnaire

Synopsis

0.1 Chapitre 1: Introduction

Le marché mondial de la réalité virtuelle (RV) devrait atteindre 227,34 milliards de dollars d'ici 2029 [3], grâce à l'essor des applications mobiles et à l'apparition des réseaux sans fil de cinquième génération (5G) dans le monde entier. En 2022, le nombre d'utilisateurs de RV a atteint plus de 171 millions [4]. Les systèmes de RV se composent généralement d'un casque de visualisation qui suit les mouvements de la tête de l'utilisateur et affiche des graphiques 3D, offrant ainsi une expérience immersive. Les avancées récentes dans les casques de RV incluent le HTC Vive XR Elite, le Sony PlayStation VR 2, et le Varjo XR-3 qui ont introduit des améliorations dans la résolution d'affichage, les capacités de suivi et la compatibilité de la plateforme [5]. Cependant, l'efficacité de ces applications émergentes dépendra non seulement de leurs capacités techniques, mais aussi de la qualité de l'expérience (QdE) qu'elles offrent à l'utilisateur. La QdE mesure la performance totale d'un système en utilisant des mesures subjectives et objectives de la satisfaction du client [6]. Dans le domaine des médias immersifs, l'expérience médiatique immersive (EMI) [7] repose sur le concept de QdE en incluant également des facteurs tels que le sentiment de présence et d'immersion, ainsi que le mal des transports virtuels (cybermalaise).

La QdE et l'EMI sont influencées par trois facteurs : le système, le contexte et l'utilisateur (humain). Les facteurs d'influence du système concernent les dispositifs utilisés dans les expériences immersives. La capacité à suivre avec précision les comportements de l'utilisateur influe sur la qualité de l'interaction et le sentiment de présence et d'immersion [8, 7]. Les facteurs d'influence contextuels décrivent l'environnement de l'utilisateur, qui comprend des caractéristiques physiques, temporelles, sociales, économiques, de tâche et techniques [7]. Les facteurs d'influence humains (FIHs) comprennent "toute propriété ou caractéristique variable ou invariable d'un utilisateur humain", tels que l'état émotionnel, les attentes et l'attention [6]. Afin d'améliorer continuellement la technologie de RV, une évaluation constante est nécessaire pour mesurer l'EMI, en prenant en compte les trois facteurs mentionnés ci-dessus. Cette approche globale permet aux chercheurs et aux développeurs d'identifier les domaines à améliorer et de fournir des expériences immersives plus engageantes et satisfaisantes. Alors que le système et le contexte ont été largement explorés, l'impact des facteurs d'influence humains sur l'EMI est un sujet moins étudié, qui sera donc le centre de cette thèse.

Deux méthodes d'évaluation sont généralement utilisées : les méthodes subjectives et instrumentales, cette dernière pouvant être subdivisée en comportementales et psychophysiologiques [9, 10, 11, 12, 13]. Les méthodes subjectives traditionnelles, bien qu'utiles, présentent certaines limites, notamment le fait qu'elles fournissent uniquement un aperçu global de l'expérience perçue, sans apporter d'informations en temps réel pour améliorer l'EMI. De plus, ces méthodes peuvent être influencées par des biais et peuvent ne pas représenter précisément l'expérience réelle de l'utilisateur. D'autre part, l'évaluation comportementale (instrumentale) des FIHs repose sur le suivi des comportements de l'utilisateur, tels que les expressions faciales, les gestes corporels et l'interaction sociale. Les avancées en vision par ordinateur et en apprentissag automatique ont permis une analyse automatisée de ces comportements, offrant des informations en temps réel sur l'expérience utilisateur. Parallèlement, les développements dans les biosenseurs [14] ont permis de surveiller de nombreux FIHs en temps réel dans des environnements immersifs [15]. Les méthodes psychophysiologiques (instrumentales) sont apparues et visent à trouver des corrélats entre les caractéristiques perceptuelles de la QdE/EMI et les métriques physiologiques [16]. Plusieurs signaux physiologiques, tels que l'électroencéphalogramme (EEG), l'électrocardiogramme (ECG) et l'électrooculogramme (EOG), ont montré un grand potentiel pour évaluer l'expérience des utilisateurs dans des environnements immersifs [17, 18, 19]. Cependant, le développement des méthodes psychophysiologiques est encore à ses débuts et beaucoup de travail reste à faire pour prétraiter les signaux obtenus. L'intégration de biosenseurs dans les systèmes de RV et le perfectionnement des méthodes psychophysiologiques ont le potentiel de révolutionner la façon dont nous évaluons et améliorons les expériences virtuelles. Ces avancées ouvrent la voie à des systèmes de RV plus personnalisés et adaptatifs, conduisant à des expériences plus engageantes et agréables pour les utilisateurs. Ainsi, la faisabilité de ces systèmes doit être explorée et leur impact potentiel sur l'avenir des EMI doit être pleinement réalisé.

En conclusion, à mesure que la RV continue de se développer et de s'intégrer dans divers secteurs, la compréhension et l'évaluation de l'expérience utilisateur immersive deviennent de plus en plus cruciales. Cette thèse vise à explorer plus en profondeur l'influence des facteurs humains sur l'expérience utilisateur immersive, en particulier en utilisant des méthodes d'évaluation psychophysiologiques, afin de contribuer à l'amélioration continue de la technologie de réalité virtuelle et à l'enrichissement des expériences des utilisateurs.

0.1.1 Contributions de la thèse

L'objectif principal de cette thèse de doctorat est de développer divers outils permettant d'évaluer la QdE dans les applications virtuelles immersives en se concentrant sur les FIHs et en utilisant des signaux physiologiques dans des environnements en conditions plus réalistes. Pour atteindre cet objectif, plusieurs innovations ont dû être développées, constituant ainsi les principales contributions de cette thèse. Plus précisément, trois innovations principales ont été conceptualisées, développées et évaluées.

1. **Développement d'un casque de RV instrumenté :** Pour surveiller les signaux physiologiques liés à la QdE, un casque de RV instrumenté avec plusieurs biosenseurs a été conçu et construit. Les capteurs comprenaient l'EEG, l'EOG et l'ECG. Cela a permis la collecte et l'analyse des données physiologiques dans des environnements plus écologiquement valides et le développement de mesures objectives de la QdE dans les environnements de RV.
2. **Développement d'un système de suivi du regard à partir de signaux physiologiques :** Les casques commerciaux dotés d'une fonction de suivi du regard n'autorisent généralement l'accès aux données qu'à travers certaines applications spécifiques. Ici, nous avons démontré le potentiel du casque instrumenté pour suivre le regard en utilisant les signaux physiologiques enregistrés. Les données de regard pourraient alors être utilisées pour extraire des caractéristiques liées à l'EMI.
3. **Développement de marqueurs d'expérience utilisateur à partir de signaux multimodaux :** En exploitant les données physiologiques collectées, différents corrélats neurophysiologiques ont été trouvés pour différents FIHs. En particulier, un corrélat multimodal de la perception du temps a été développé pour fournir des indicateurs sur le sentiment de présence, l'immersion et l'engagement en RV.

Ces innovations ont été décrites dans plusieurs manuscrits; une liste détaillée de ces manuscrits se trouve à la Section 1.3.

0.1.2 Organisation de la thèse

Alors que ce chapitre introductif a présenté les défis de l'évaluation de la qualité de l'expérience dans les applications virtuelles immersives et jeté les bases des contributions décrites dans cette thèse, le reste de cette dissertation est structuré de la manière suivante. Le chapitre 2 donne un aperçu des méthodes de pointe en matière d'évaluation de la qualité de l'expérience et des FIHs dans les environnements virtuels immersifs. Le chapitre 3 présente le développement d'un casque de RV instrumenté capable de surveiller les signaux physiologiques, tels que l'EEG, l'EOG et l'ECG, ainsi que les caractéristiques potentielles extraites de ces signaux. Ensuite, le chapitre 4 explore le suivi de nouvelles mesures du regard oculaire à partir du casque instrumenté, y compris l'utilisation d'un classificateur pour détecter le suivi du regard. Ensuite, le chapitre 5 décrit l'étude, dans des conditions réalistes, du casque de RV instrumenté, y compris la collecte de données et les caractéristiques extraites. Le chapitre 6 explore la quantification de la perception du temps en rapport avec le sentiment de présence et l'immersion dans la RV, y compris les dernières recherches dans ce domaine et les orientations futures potentielles de la recherche. Enfin, le chapitre 7 présente les conclusions générales de cette thèse, ainsi que les futurs domaines de recherche.

0.2 Chapitre 2: Évaluation de l'expérience utilisateur en réalité virtuelle : état de l'art

Le travail effectué dans ce chapitre consiste en un examen approfondi de la littérature sur l'évaluation de l'EMI, en mettant l'accent sur l'évaluation des FIHs. Les méthodes subjectives, comportementales et psychophysiologiques existantes ont été explorées, ainsi que les tendances récentes en matière de biosenseurs et d'outils d'évaluation. Les méthodes psychophysiologiques, qui offrent une évaluation en temps réel et une mesure non intrusive, sont présentées comme particulièrement avantageuses.

0.2.1 Évaluation subjective de l'EMI

L'évaluation subjective est la méthode la plus courante pour évaluer les EMI/FIHs, généralement appliquée peu après une expérience via des questionnaires ou des échelles de notation [20, 21, 22, 23]. De nombreux questionnaires ont été développés compte tenu du manque d'une définition commune de la présence et de l'immersion [24, 25, 26, 27, 28, 29, 30, 31, 10, 26, 32, 33, 34]. Nous avons examiné quatre aspects de l'EMI mesurés à partir d'évaluations subjectives: le sentiment de présence et la perception de l'immersion, la qualité de l'expérience utilisateur, le cybermalaise, et l'état mental/affectif.

Questionnaires pour l'évaluation de la présence

La présence en réalité virtuelle est le sentiment d'être dans le monde virtuel [24, 25, 26]. De nombreux types de présence ont été listés, y compris la présence personnelle (la sensation d'être là), la présence sociale (être là avec d'autres), et la présence environnementale (se sentir immergé physiquement dans l'environnement virtuel) [27, 32]. Le sentiment de présence est influencé par divers éléments, y compris les facteurs d'équipement, les facteurs subjectifs de l'utilisateur, les facteurs sociaux, et les facteurs affectifs [33, 34]. Le tableau 2.1 liste les questionnaires couramment utilisés pour mesurer le sentiment de présence en RV, notamment le *Presence Questionnaire* (PQ) [26], le *GlobalED Questionnaire* [35], et le *Igroup Presence Questionnaire* [28].

Questionnaires pour l'évaluation de l'expérience utilisateur

L'expérience utilisateur en RV est évaluée par divers critères tels que l'engagement, le “flow”, l'immersion, ainsi que les préférences et comportements de l'utilisateur lors de l'utilisation [36]. L'immersion, en particulier, joue un rôle crucial dans l'expérience globale. Le tableau 2.2 répertorie les questionnaires les plus couramment utilisés pour évaluer cette expérience utilisateur en RV [37].

Questionnaires pour l'évaluation du cybermalaise

Le cymbermalaise, c'est-à-dire le malaise lié à l'utilisation de la RV, est une autre préoccupation majeure. Elle peut toucher entre 30% et 80% des utilisateurs, avec des symptômes pouvant durer plusieurs heures [38]. Les symptômes du cybermalaise varient mais incluent généralement la nausée, le mal de tête, la désorientation et la fatigue oculaire [39]. Plusieurs questionnaires ont été développés pour évaluer le cybermalaise, comme le montre le tableau 2.3. Bien que le *Simulator Sickness Questionnaire* (SSQ) soit largement utilisé, il a été critiqué pour sa qualité psychométrique et son applicabilité en RV [40]. Des questionnaires plus récents, tels que le *Virtual Reality Symptom Questionnaire* (VRSQ), ont été spécifiquement développés pour les dispositifs de visiocasques et ont montré de meilleurs indicateurs de validité [41, 42]. Pour une revue détaillée de l'évaluation du cybermalaise en RV, le lecteur peut se référer à [43, 44, 40].

Questionnaires pour le suivi de l'état affectif/mental

L'expression "expérience utilisateur" implique que l'utilisateur a une implication émotionnelle lorsqu'il explore un contenu média immersif. Les expériences émotionnelles peuvent être caractérisées par trois composantes fondamentales : la valence (le degré d'agrément associé à un stimulus), l'arousal (l'intensité de l'émotion provoquée par un stimulus) et la dominance (l'étendue du contrôle exercé par un stimulus). Le modèle arousal-valence est le cadre le plus reconnu pour décrire les états émotionnels [45].

Des outils graphiques, tels que le *Self-Assessment Manikin* (SAM), permettent aux utilisateurs de rapporter efficacement et intuitivement leurs sentiments en indiquant ou en évaluant la partie de la figure qui représente le mieux leur état affectif actuel. Néanmoins, les utilisateurs peuvent avoir du mal à interpréter ces pictogrammes [46]. Plus récemment, une variante basée sur les emojis a été proposée. Les emojis, qui sont des pictogrammes ou des idéogrammes représentant des émotions, des concepts et des idées, deviennent de plus en plus populaires comme outils d'auto-évaluation pour mesurer l'expérience utilisateur. Par exemple, l'EmojiGrid a été proposé comme outil d'auto-évaluation pour l'évaluation des émotions évoquées par la RV [47]. Pour plus de détails sur l'évaluation de l'état émotionnel/affectif de l'utilisateur en RV, le lecteur est invité à consulter [48, 49, 50].

0.2.2 Évaluation instrumentale des EMI/FIHs

L'évaluation instrumentale des EMI/FIHs offre une évaluation quantitative des expériences des utilisateurs, en utilisant des méthodes comportementales et psychophysiologiques pour contrôler en temps réel des facteurs tels que l'engagement, l'attention et le cybermalaise. Ces méthodes, améliorées par les progrès de la technologie des capteurs et des dispositifs portables, s'appuient initialement sur des méthodes subjectives pour les étiquettes de référence de base, mais finissent par fonctionner de manière indépendante. Les sections suivantes présentent une revue de la littérature de 2015 à 2021, en mettant l'accent sur les méthodes psychophysiologiques.

Méthodes comportementales

Les méthodes comportementales ont pour objectif d'évaluer si le comportement des participants dans un environnement virtuel est similaire à celui qu'ils auraient dans un environnement physique réel, incluant les mouvements physiques et les interactions sociales [51]. Des comportements tels que le toucher du casque de RV peuvent indiquer un inconfort, tandis que les sourires peuvent signaler une expérience positive [52]. L'analyse des expressions faciales est un bon indicateur de l'état émotionnel de l'utilisateur. Des technologies récentes permettent de reconnaître 11 expressions faciales différentes avec une précision de 85% grâce à des capteurs placés autour des yeux [53, 54]. Le suivi du regard, quant à lui, donne des informations sur la focalisation de l'attention des utilisateurs, sur les variations de la taille de la pupille, sur la fréquence des clignements des yeux, et sur les mouvements oculaires qui peuvent indiquer des niveaux de stress, d'attention et la présence dans un environnement immersif [55, 56, 57, 58, 59, 60]. Il est proposé d'utiliser des capteurs EOG intégrés directement dans le casque de réalité virtuelle pour suivre les mouvements des yeux [61, 62]. Enfin, les mouvements du corps et les gestes peuvent également être indicatifs de l'expérience immersive. Des corrélations ont été trouvées entre les mouvements de la tête et les états émotionnels des utilisateurs [63, 64]. La stabilité posturale peut également prédire la probabilité de cybermalaise [65], et des mouvements limités peuvent réduire le sentiment de présence [34]. La reconnaissance des gestes de la main est généralement basée sur des contrôleurs de RV équipés de capteurs, mais des systèmes basés sur des caméras ont également émergé pour un suivi sans contrôleur. Cependant, une étude récente a montré que les interactions basées sur un contrôleur étaient moins exigeantes pour les participants et entraînaient moins d'erreurs, améliorant ainsi l'expérience immersive globale [66]. Pour une vue d'ensemble des interactions gestuelles en RV, voir [67].

Méthodes psychophysiologiques

Les méthodes psychophysiologiques utilisent les réactions corporelles pour comprendre nos états internes. Ces réactions peuvent inclure l'augmentation du rythme cardiaque lors de l'excitation ou du stress, la transpiration des paumes lors de la nervosité ou du mal des transports, et de la respiration lors de l'engagement. Ces mesures sont devenues possibles grâce à l'évolution des technologies de biosenseurs et à la popularité croissante des appareils portables.

L'ECG et la photopléthysmographie (PPG) sont couramment utilisés pour mesurer la fréquence cardiaque (FC) et la variabilité de la fréquence cardiaque (VFC) dans les environnements virtuels immersifs. L'ECG enregistre l'activité électrique du cœur, tandis que le PPG mesure les variations du volume sanguin en utilisant des capteurs optiques. Les deux méthodes fournissent des informations sur le rythme cardiaque, le PPG étant le plus utilisée dans les appareils portables, car les capteurs peuvent facilement être intégrés dans des bracelets et des montres. L'analyse de la VFC peut se faire dans les domaines temporel et fréquentiel, ainsi qu'avec des méthodes non linéaires. Des paramètres dans le domaine temporel reposent sur des statistiques calculées directement à partir de la série RR, tandis que les méthodes du domaine fréquentiel se basent sur la densité spectrale de puissance (DSP) de la série RR. Cette DSP est ensuite divisée en différentes bandes de fréquence, qui représentent différents aspects du système nerveux autonome sympathique et parasympathique [68]. Plusieurs études ont utilisé les mesures FC et VFC pour quantifier différents aspects de l'EMI (Table 2.5). L'évaluation du stress est l'un des objectifs principaux de ces études. Une augmentation de la FC est couramment observée en fonction du niveau de difficulté du jeu ou des séquences stressantes [69, 70]. De plus, une corrélation significative a été démontrée entre la valence et la VFC [71, 72]. Une augmentation de la FC a également été observée lors des dernières minutes lorsque l'utilisateur signalait un cybermalaise [73]. La majorité des dispositifs utilisés étaient basés sur des appareils portables, permettant à l'utilisateur de se déplacer pendant l'expérience de RV immersive. Il convient de noter que dans la plupart des cas, des systèmes multimodaux ont été utilisés en complément de la FC/VFC ; notamment l'activité électrodermale (AED) [74, 75, 76, 70, 77, 78, 79, 71, 80].

Les mesures de l'AED, ou de réponse galvanique de la peau (RGP), qui évaluent les variations de la conductance électrique de la peau en réponse à la sécrétion de sueur, sont liées à l'attention, au traitement de l'information, à l'émotion et au stress. Trois types de mesures électrodermales sont couramment utilisés : le niveau de conductivité cutanée (NCC), les réponses non spécifiques de la conductance cutanée, et les réponses de conductance cutanée [81]. L'AED a été utilisée pour évaluer l'expérience utilisateur, la présence et les émotions. Par exemple, un haut degré de présence a entraîné significativement plus de pics d'AED par minute [82]. De plus, des augmentations lentes et régulières de NCC ont été corrélées à l'activité cognitive [79]. L'AED peut également être attribuée à une augmentation de la charge de travail mentale ou du stress et est fortement corrélée aux états d'arousal [55]. Enfin, lors des événements de cybermalaise, une relation positive entre les réponses AED et les effets de saccade élevés a été observée [76] [Table 2.6].

Les EEG capturent l'activité électrique corticale par le biais d'électrodes positionnées sur le cuir chevelu, fournissant des informations sur l'activité neuronale et la connectivité des régions du cerveau, utiles pour l'analyse des états affectifs [83] et la modélisation de la qualité de l'expérience vocale [84]. Le placement cohérent des électrodes est assuré par le système international 10-20, avec la possibilité d'utiliser jusqu'à 64 électrodes ou plus pour des mesures à plus haute résolution. Les positions des électrodes sont identifiées par des lettres (zone du cerveau) et des chiffres (côté gauche ou droit de la tête). La figure 2.4 illustre cette disposition des électrodes. Les EEG classent les ondes cérébrales en fonction de leur fréquence et de leur amplitude, reflétant ainsi les différents processus cognitifs et états mentaux. Les catégories sont les suivantes : Les ondes delta (δ ; 0,5-4 Hz) associées au sommeil profond et au traitement inconscient des informations ; les ondes thêta

(θ ; 4-8 Hz) observées pendant le sommeil léger et liées à la créativité et à la consolidation de la mémoire ; les ondes alpha (α ; 8-12 Hz) indiquant le calme, la concentration et la créativité ; les ondes bêta (β ; 12-30 Hz) prévalant pendant la réflexion active et la prise de décision, mais pouvant induire du stress ; les ondes gamma (γ ; 30-45 Hz) associées aux fonctions cognitives supérieures et à l'intégration de l'information. Des études récentes ont exploré l'EEG pour la recherche liée à l'EMI, en utilisant diverses caractéristiques de l'EEG comme corrélats des paramètres de l'EMI et du cybermalaise (voir Tableaux es 2.7 et 2.8) avec des classificateurs atteignant une précision de détection de 84% [85, 86, 87].

De plus, avec l'évolution de l'internet tactile et de l'internet des sens, d'autres sens sont sollicités dans les applications, créant ainsi un média multisensoriel, qui améliore le réalisme et l'immersion dans les systèmes de RV [88, 89]. L'intégration des sensations olfactives [90, 91] et haptiques [92] améliore l'immersion, l'haptique fournissant des indices physiques sur un objet, augmentant ainsi le réalisme [93, 94]. Le retour vibrotactile améliore le réalisme des interactions avec les dispositifs virtuels [95, 96]. L'évaluation de la qualité de l'expérience multimédia à l'aide de méthodes psychophysiologiques est en train d'émerger 2.9. Par exemple, une forte modulation d'amplitude ou des signaux de potentiels liés aux évènements ont été observés lorsque les participants utilisaient des gants haptiques pour interagir avec des objets virtuels, et les conflits haptiques ont entraîné des changements significatifs dans le potentiel lié aux évènements [97]. Bien que les stimuli olfactifs augmentent le sens de la présence, ils ne modifient pas significativement l'AED [98], ce qui suggère la nécessité d'utiliser d'autres modalités. Bien que cette revue couvre les articles de 2015-2021, de nombreux travaux antérieurs contribuent également au domaine multisensoriel, détaillé dans [99].

0.2.3 Discussion

La surveillance du comportement humain et des signaux psychophysiologiques en RV permet d'élaborer des modèles de FIHs, notamment pour détecter et prédire le cybermalaise, surveiller la perception d'immersion et le sentiment de présence de l'utilisateur, ainsi que l'expérience globale des médias immersifs [100]. La mesure la plus utilisée de l'EMI de l'utilisateur reste l'évaluation subjective, malgré ses limites, telles que la nécessité d'une évaluation hors ligne, la possible partialité des réponses des sujets [101], et l'impact potentiel sur l'expérience utilisateur [102]. Des alternatives comme les questionnaires basés sur la RV sont en cours de développement, mais leur validité à long terme reste à vérifier [20, 21].

Le cybermalaise, qui affecte de manière disproportionnée les femmes, les enfants [103, 104] et les fumeurs [105], est un obstacle majeur à l'EMI. Des stratégies d'atténuation, comme l'ajout de modalités sensorielles supplémentaires [106], pourraient être mises en place si le cybermalaise peut être prédit en début de session de RV. Cependant, il existe encore peu de travaux sur la prédiction de cybermalaise, ouvrant la voie à de nouvelles recherches [107, 108, 109].

De plus, avec l'émergence des communications sans fil 5G et 6G, des applications de RV totalement portables se développent, entraînant de nouveaux défis en matière de qualité des signaux psychophysiologiques et d'évaluation des FIHs [110]. De nouveaux algorithmes adaptatifs et des caractéristiques robustes aux artefacts de mouvement seront nécessaires [111, 112]. Les systèmes multimodaux pourraient être utiles dans de telles conditions mobiles [113]. Avec l'amélioration des largeurs de bande et des couvertures de communication sans fil, et la réduction de la latence, des technologies de nouvelle génération, comme l'internet tactile [114] et l'internet des sens [115], vont devenir courantes. Ces technologies stimuleront plusieurs sens, améliorant ainsi l'EMI. Les effets de tels stimuli multisensoriels sur les signaux comportementaux et psychophysiologiques restent cependant mal compris, et peu d'études ont exploré cette direction.

Enfin, l'EMI est multifacette. La plupart des travaux n'ont examiné que quelques facteurs d'influence, offrant ainsi une vue partielle de ce qui peut être réalisé avec l'évaluation de l'EMI [7]. Un questionnaire unifié sur l'expérience utilisateur a donc été proposé, qui mesure la présence, l'engagement, l'immersion, le flow, l'utilisabilité, la compétence, l'émotion, le cybermalaise, le jugement, et l'adoption de la technologie [116]. Les futures études devraient explorer l'utilisation de mesures comportementales et psychophysiologiques pour mesurer chacun de ces composants et leur contribution individuelle à l'EMI globale. Des premiers pas dans cette direction ont été faits pour la parole [84], l'image [117], et les applications vidéo [118], où plus d'un facteur d'influence a été exploré et combiné. Cependant, il existe encore peu de travaux sur les applications immersives et multisensorielles. Le futur devrait se concentrer sur une meilleure compréhension de ces aspects et sur l'impact global des médias multisensoriels sur l'EMI, y compris le possible décalage de temps entre différentes modalités.

0.2.4 Conclusion

Ce chapitre a présenté le contexte de l'évaluation de l'EMI en mettant l'accent sur les FIHs. Tout d'abord, les différentes méthodes d'évaluation, y compris les mesures subjectives, comportementales et psychophysiologiques, ont été examinées, en mettant en évidence leurs dernières tendances, innovations et limites. Ensuite, nous nous sommes penchés sur les applications de nouvelle génération qui intègrent de multiples modalités sensorielles afin d'améliorer le réalisme et l'immersion des environnements virtuels. Enfin, nous avons engagé une brève discussion sur les limites identifiées tout au long de notre examen de la littérature, en soulignant les domaines de recherche future et les améliorations potentielles dans l'évaluation de l'EMI et des FIHs. Dans l'ensemble, ce chapitre offre une synthèse approfondie des connaissances actuelles, posant les fondations de la recherche et du développement dans ce domaine en constante évolution. Il jette ainsi les bases de cette thèse.

0.3 Chapitre 3: Instrumentation d'un casque de RV pour la surveillance quantitative de FIHs

Ce chapitre traite de la création, de l'essai et de l'utilisation d'un casque de RV doté d'un bioamplifieur sans fil intégré, conçu pour mesurer les FIHs. Il décrit tout d'abord l'évolution du casque, y compris ses différentes générations et l'intégration de différents capteurs comme l'EEG, l'ECG, l'EOG et l'électromyogramme (EMG) facial. Il souligne également l'importance d'une acquisition précise des données et d'un retour d'information en temps réel dans les applications mobiles de RV. Puis, il couvre les modules d'extraction de caractéristiques utilisés pour mesurer les différents FIHs, en incorporant des caractéristiques de référence fréquemment observées dans la littérature. Enfin, le chapitre valide chacune des quatre modalités de signal (EEG, EOG, ECG et EMG).

0.3.1 Développement d'un casque de RV instrumenté

Le casque de RV instrumenté mis au point comprend un module amplificateur de biopotentiel sans fil pour l'acquisition et la transmission de signaux physiologiques et des électrodes sèches pour la détection des potentiels physiologique. Pour favoriser la reproductibilité, le système a utilisé des composants disponibles sur le marché avec un minimum de modifications.

Module d'amplification du biopotentiel

Le module d'amplification du biopotentiel, essentiel pour les applications mobiles, devait acquérir différentes modalités physiologiques, être portable, peu coûteux, léger et doté d'une capacité de communication sans fil. La solution retenue a été la carte Cyton d'OpenBCI, équipée d'une carte Daisy supplémentaire, offrant 16 canaux d'entrée entièrement différentiels, programmables indépendamment, à gain élevé et à faible bruit, conçus pour des modalités multiples telles que l'ECG, l'EOG, l'EEG et l'EMG [119]. Pour faciliter l'utilisation d'une variété d'électrodes standard, des câbles à extrémités encliquetables ont été utilisés. Une batterie au lithium polymère de 1000 mA @ 3,7 V alimente les cartes OpenBCI. Tous ces composants, ainsi qu'un chargeur USB, ont été logés dans un boîtier personnalisé imprimé en 3D, conçu pour protéger l'électronique tout en préservant la modularité des cartes OpenBCI. Les caractéristiques de l'amplificateur biopotentiel OpenBCI sont les suivantes : un seul amplificateur pour plusieurs modalités physiologiques (EEG, ECG, EOG, EMG), communication sans fil, 8 ou 16 canaux configurables, canaux entièrement différentiels ou à référence unique, gain programmable pour chaque canal, conception légère (86 g pour la configuration à 16 canaux et 70 g pour la configuration à 8 canaux), et 12 heures de fonctionnement pour la configuration à 16 canaux.

Casque de RV prêt à l'emploi

Le système a été initialement intégré dans un Oculus Rift (kit de développement 2) avec une fréquence d'images de 75 Hz et un champ de vision de 100 degrés. Les sangles originales du casque, qui couvrent les régions cérébrales, ont été utilisées pour placer des électrodes sèches flexibles, des sangles supplémentaires ayant été ajoutées pour une surveillance plus large des régions cérébrales. L'amplificateur de biopotentiel a également été placé sur les sangles du casque.

Électrodes sèches

Les électrodes sèches ont été sélectionnées en fonction de la qualité du signal, de la praticité et du confort [120]. En fonction de leur emplacement dans le casque de RV, trois types d'électrodes ont été utilisés : flexibles, plates et jetables. Les électrodes flexibles Ag/AgCl sèches ont été utilisées pour mesurer l'EEG dans les zones couvertes de cheveux, les électrodes plates Ag/AgCl sèches ont été utilisées lorsqu'un contact avec la peau nue était nécessaire et que l'électrode était soutenue par le casque (par exemple, autour de la pièce faciale pour l'enregistrement des signaux EOG, EMG EEG frontal), et les électrodes jetables standard Ag/AgCl ont été utilisées sur la peau lorsqu'il n'y avait pas de support pour les électrodes, comme au niveau des mastoïdes (référence) et sur la clavicule gauche (pour l'acquisition de l'ECG).

Integration du matériel

Dans la configuration à 16 canaux, l'objectif était d'enregistrer les signaux EEG, EOG, ECG et EMG du visage. Cela impliquait l'acquisition de 11 signaux EEG à partir d'électrodes situées dans les zones frontale, centrale et occipitale. Les signaux EOG ont été dérivés des électrodes EEG de la zone frontale ainsi que de deux électrodes verticales et deux électrodes horizontales placées sur la pièce faciale du casque de RV. Les signaux EMG faciaux ont également été acquis à partir des électrodes de la pièce faciale, et une électrode a été placée sur la clavicule de l'utilisateur pour l'acquisition des signaux ECG. Les terminaux Bias et SRB ont été placés sur les mastoïdes. L'emplacement des électrodes pour cette configuration à 16 canaux est illustré à la figure 3.3a, et les capteurs de la pièce faciale sont illustrés à la figure 3.3b. La configuration peut être facilement modifiée en fonction du protocole expérimental. Le premier prototype est représenté sur la figure 3.4.

Évolution et améliorations du casque de RV instrumenté au fil du temps

Le casque de RV, initialement doté d'électrodes fixées par Velcro (Figure 3.4), a fait l'objet de diverses améliorations entre 2019 et 2022. Les principales améliorations comprennent le remplacement de l'électrode ECG jetable par un capteur PPG intégré dans le casque, le passage d'électrodes

EEG sèches flexibles à des électrodes supérieures de Datwyler, le passage d'électrodes mastoïdiennes jetables à des électrodes à clip auriculaire pour un enregistrement EEG stable, et la refonte de la sangle de tête pour un meilleur confort et une meilleure répartition du poids. L'instrumentation a également été adaptée à différents modèles de casque de RV, notamment HTC Vive Pro Eye (Fig. 3.6), HP Reverb G2 (Fig. 3.7), Meta Quest 2 (Fig. 3.8), Meta Quest 1 (Fig. 3.9), et Pico Neo 3 (Fig. 3.9). Ces améliorations ont considérablement accru la praticité du casque pour diverses applications de RV, en offrant une expérience plus immersive et en permettant une utilisation prolongée.

Intégration du logiciel

La gamme de produits OpenBCI, soutenue par une philosophie de recherche ouverte, permet une intégration avec un large éventail de langages de programmation, de protocoles de communication tels que *Lab Streaming Layer* (LSL), et d'outils ouverts, notamment OpenViBE, et le serveur EEG MuSAE Lab développé en interne (MuLES) (Figure 3.10) [1]. MuLES, un serveur code ouvert d'acquisition et de streaming EEG, vise à simplifier le développement d'applications en fournissant une interface commune pour les appareils EEG portables et une interface graphique minimaliste pour une interaction facile avec divers appareils EEG grand public.

0.3.2 Prétraitement et extraction de caractéristiques pour l'évaluation des FIHs

Le casque de RV instrumenté recueille divers signaux physiologiques, notamment l'EEG, la fréquence cardiaque, la VFC, le clignement des yeux, le suivi du regard et l'EMG facial, ce qui permet d'extraire des caractéristiques qui fournissent des informations précieuses sur l'expérience de l'utilisateur pendant les applications de RV (Figure 3.12). Cependant, il est essentiel de prétraiter les données brutes de biosignaux pour garantir une représentation précise et interprétable de l'activité neuronale sous-jacente. Le prétraitement des données EEG est crucial et implique généralement des étapes telles que la suppression des mauvais canaux, le filtrage, le re-référencement et la suppression du bruit et des artefacts [121, 122, 123]. Les mauvais canaux dans les données EEG, qui peuvent résulter d'un mauvais fonctionnement de l'équipement, d'un mauvais positionnement des électrodes ou d'électrodes saturées, sont identifiés et traités pour maintenir l'intégrité des données [122]. Cela peut se faire par une inspection visuelle ou à l'aide d'algorithmes automatisés [124, 121, 125]. Les techniques de filtrage sont mises en œuvre pour isoler des bandes de fréquences spécifiques et réduire le bruit, ce qui rend les données EEG plus faciles à interpréter [126, 127]. Les quatre principaux types de filtres utilisés dans l'analyse des données EEG sont les filtres passe-bas, passe-haut, passe-bande et les filtres à encoche [128]. Le re-référencement est une autre étape importante qui consiste à ajuster les électrodes de référence à un emplacement qui influence le moins possible les signaux d'intérêt [129]. Plusieurs choix de référence sont possibles en fonction de la question de recherche spécifique et du résultat souhaité de l'analyse [130, 131]. Enfin, le rejet et la correction des artefacts permettent d'identifier et de supprimer les signaux qui ne proviennent pas du cerveau, à l'aide de techniques telles que l'analyse en composantes indépendantes (ACI) et la reconstruction du sous-espace des artefacts (RSA) [132, 133]. Par exemple, la RSA est efficace pour éliminer les artefacts tels que les mouvements de la tête, les clignements des yeux et les mouvements des yeux, comme le montre la figure 3.13. Ces étapes de prétraitement garantissent l'intégrité des données pour l'analyse ultérieure et l'extraction des caractéristiques, jetant ainsi les bases d'une interprétation précise et significative de l'activité neuronale pendant les applications de RV.

0.3.3 Extraction de caractéristiques de référence

Cette section détaille les caractéristiques de référence dérivées des modalités de biosignal, comprenant les données EEG, EOG, ECG et accéléromètre, collectées via un système de RV instrumenté.

Premièrement, nous avons évalué l'expérience utilisateur en analysant plusieurs paramètres EEG et puissances de fréquence des sous-bandes EEG, tels que delta (δ), thêta (θ), alpha (α), bêta (β) et gamma (γ), comme recommandé par des études précédentes [134, 135, 136, 137]. Ensuite, nous avons utilisé une mesure EEG pour quantifier l'engagement cognitif ou l'effort mental, basée sur les données de l'électrode Fp1 [138]. Pour calculer cette mesure, nous avons mis en œuvre des techniques comme la transformée de Fourier rapide et le calcul des puissances relatives. Par la suite, nous avons intégré les indices d'arousal et de valence comme mesures de l'état émotionnel de l'utilisateur, car ils sont liés au niveau d'immersion perçue [139]. Nous avons également employé l'indice d'asymétrie alpha frontale (AAF) comme une mesure supplémentaire de plaisir, qui prend en compte les différences de puissance de la bande alpha entre les régions frontales droite et gauche [140]. Pour continuer, nous avons intégré la cohérence spectrale de phase et de magnitude (CSPM) comme une mesure de la connectivité entre les régions corticales. Les caractéristiques CSPM révèlent l'interaction entre les processus cognitifs, émotionnels et attentionnels [141]. Nous avons mis l'accent sur l'importance de CSPM pour évaluer la charge de travail mental dans les environnements virtuels immersifs [142, 143]. Enfin, nous avons introduit les caractéristiques de cohérence spectrale de phase et de magnitude des caractéristiques de modulation d'amplitude (CSPM-MA) comme une extension des caractéristiques CSPM. Celles-ci fournissent des informations sur le taux de changement de sous-bandes de fréquences spécifiques et leur utilisation potentielle pour prédire l'arousal et la valence [144]. Nous avons également étudié l'utilisation potentielle de ces caractéristiques pour comprendre la corrélation avec la perception du temps [145, 146].

Pour l'EOG, la gamme de fréquences du signal est comprise entre 0,1 et 50 Hz et l'amplitude se situe entre 100 et 3500 μV [147]. Les mesures des taux de clignement des yeux et de saccade et leurs durées sont extraites des signaux EOG [148]. Ces mesures ont été associées à la frustration de l'utilisateur et au sentiment de présence dans les environnements de RV [149, 150, 59]. L'utilité des signaux EOG pour le suivi des mouvements oculaires sans caméra est également explorée, avec le calcul des caractéristiques de la pente pour la détermination de la position du regard [151].

Concernant l'ECG, les caractéristiques sont extraites à l'aide d'une boîte à outils MATLAB à source ouverte, ce qui permet d'obtenir 15 caractéristiques de FC et de VFC. L'analyse de la VFC est divisée en domaines temporel et fréquentiel et en méthodes non linéaires, ce qui permet de mieux comprendre la variabilité de la fréquence cardiaque pendant les sessions de jeu en RV.

Enfin, les données de l'accéléromètre fournissent des informations sur le mouvement et l'orientation de la tête. Des mesures statistiques sont extraites pour l'accélération, la vitesse et le déplacement le long des axes x, y et z, fournissant des informations précieuses sur les mouvements de la tête de l'utilisateur pendant l'expérience de RV [152, 153].

0.3.4 Validation initiale du casque de RV instrumenté développé

La section traite de la validation initiale du casque de RV instrumenté développé en utilisant différents scénarios de validation pour chaque modalité acquise, avec cinq participants recrutés pour ces tests préliminaires.

Pour la validation du signal EEG, des potentiels évoqués visuels à l'état stable (PEVES) ont été enregistrés pendant trois étapes de 30 secondes : yeux ouverts, présentation d'une sphère clignotante à 12,5 Hz et yeux fermés [154]. Le rapport signal-bruit (RSB) a été calculé pour chaque étape, l'étape PEVES enregistrant un RSB plus élevé que les deux autres, validant la modalité EEG (Figure 3.14). La validation du signal ECG a été réalisée en plaçant une électrode ECG sur la clavicule gauche, un emplacement non traditionnel qui a néanmoins fourni des mesures précises de la crête R, permettant ainsi de calculer la FC et la VFC [155]. Les signaux ECG du casque et d'un autre système ECG de niveau recherche ont été acquis simultanément pendant 10 minutes, montrant une forte corrélation et validant ainsi la modalité ECG (Figure 3.15). La validation du signal EOG a nécessité l'utilisation de sept électrodes plates placées dans la plaque frontale du casque de RV. Les participants ont été invités à suivre une cible dans l'environnement virtuel se déplaçant dans huit directions. Les formes d'onde acquises présentaient différents modèles en fonction du mouvement oculaire effectué, validant ainsi la modalité EOG (Figure 3.16) [156, 157, 158]. Les signaux EMG faciaux ont également été validés. Les participants ont reçu des indices leur permettant d'exprimer quatre expressions faciales : neutre, en colère, surpris et heureux. Les différentes expressions faciales ont suscité une activité EMG différente sur les groupes d'électrodes, de sorte que les signaux EMG peuvent être utilisés pour classer les gestes faciaux, comme le montre [159] (Figure 3.17).

Cette validation est préliminaire et le test de validation ultime pour le casque sera son utilisation dans un cadre hautement écologique. Ce chapitre traite du développement et de l'évaluation du casque de RV instrumenté sans fil qui peut capturer plusieurs signaux physiologiques comme l'EEG, l'ECG, l'EOG et l'EMG facial dans des applications mobiles de RV. Le système mis au point permet un retour d'information en temps réel, la mesure des FIHs pertinents tels que le sentiment de présence, le cybermalaise, l'attention et d'autres. En incorporant les signaux physiologiques disponibles et les étapes de prétraitement d'amélioration discutées dans ce chapitre, une large gamme de caractéristiques de référence peut être extraite, offrant des informations précieuses sur l'expérience de l'utilisateur dans les environnements virtuels immersifs. Le chapitre suivant se penchera sur l'utilisation des signaux collectés pour la surveillance du regard dans la RV.

0.4 Chapitre 4: Mesure du regard via un casque RV instrumenté

Au cours des dernières années, le suivi des yeux est devenu une modalité clé pour améliorer l'immersion dans la RV. L'EOG, méthode peu coûteuse permettant de mesurer les mouvements oculaires, notamment les saccades, a été utilisée pour améliorer l'interaction en RV [160, 161, 162, 163, 164, 165, 166, 167, 59, 149]. Cependant, les systèmes EOG commerciaux restent chers, et une alternative *"do-it-yourself"* basée sur l'utilisation d'un openBCI est explorée dans ce chapitre [168, 169, 170, 166, 165, 171]. Deux méthodes d'extraction de caractéristiques: les caractéristiques de séries temporelles et la mesure de la pente du signal EOG, et trois classificateurs: le perceptron multicouche (PMC), le classificateur à vecteurs de support (MVS) et un nouvel arbre de classification hiérarchique, sont donc utilisés pour améliorer la performance de classification des mouvements oculaires. L'efficacité de cette approche est évaluée par un test sur quatre sujets mesurant les mouvements oculaires saccadiques de 10 degrés d'interval durant la pandémie de COVID-19. Cette solution pourrait offrir une alternative abordable pour améliorer l'expérience utilisateur en RV.

0.4.1 Méthodologie

Dans cette section, nous présentons notre approche pour la collecte des données expérimentales, le prétraitement, l'extraction des caractéristiques ExG, et la mise en œuvre de deux algorithmes d'apprentissage machine pour notre méthodologie de classification hiérarchique.

Pour la collecte des données, nous utilisons un casque de RV Oculus Rift équipé de sept capteurs. Ces capteurs capturent les signaux ExG à partir d'électrodes placées près des positions Fp1, Fpz et Fp2, ainsi que deux électrodes verticales et horizontales, tous intégrés dans la mousse du casque de réalité virtuelle [172]. Les signaux sont acquis à un taux d'échantillonnage de 250 Hz. Dans le cadre de notre expérimentation, nous avons développé une application en RV avec Python 3 et Unity3D. L'expérience implique que les participants suivent visuellement une cible qui se déplace du centre du champ de vision à l'une des 36 positions sur l'écran pendant une durée de 1,6 seconde. Ces 36 positions correspondent à des angles de 10 degrés répartis uniformément sur un cercle. Ensuite, les signaux sont prétraités et filtrés entre 25 et 125 Hz avant d'être normalisés. Les données sont ensuite séquencées en intervalles de 1,6 seconde, correspondant à la durée de la saccade. Une variété de caractéristiques sont extraites à partir de ces données. Nous utilisons la boîte à outils HCTSA pour extraire 7664 caractéristiques de séries temporelles statistiques à partir des séquences ExG [171].

L'algorithme mRMR est utilisé pour classer ces caractéristiques et sélectionner les sept principales pour notre tâche [173]. Nous explorons également les caractéristiques basées sur la pente, motivées par [165]. Nous proposons une méthodologie de classification hiérarchique en quatre étapes. Les trois premiers niveaux impliquent une série de tâches de classification binaire, tandis que le dernier niveau implique une tâche de classification à 4 ou 5 classes. Cette approche vise à classer la direction du regard des utilisateurs avec une précision de 10 degrés. Enfin, nous explorons l'utilisation de deux classificateurs différents, MVS et PMC, pour notre tâche de classification [174, 175]. Pour chacun des classificateurs, nous effectuons une validation croisée à quatre reprises, où 75% des données sont utilisées pour l'entraînement et 25% pour les tests.

0.4.2 Résultats et discussion

Importance des caractéristiques

Comme mentionné précédemment, pour l'approche de classification hiérarchique proposée, les 7 caractéristiques principales pour chacun des 14 classificateurs ont été sélectionnées parmi les 7664 caractéristiques statistiques à l'aide de l'algorithme de sélection de caractéristiques mRMR. La Figure 4.6 montre l'importance relative des 20 caractéristiques les plus souvent sélectionnées. Pour une description complète de ce que représente chaque caractéristique, le lecteur intéressé est invité à se référer à [171]. Les trois caractéristiques les plus importantes sont les statistiques sur les segments locaux, l'autocorrélation non linéaire normalisée et la variation des propriétés des séries temporelles, présentes respectivement dans 12, 11 et 7 des 14 classificateurs. Les statistiques sur les segments locaux se sont avérées toujours importantes pour les canaux H EOG gauche et V EOG gauche. Elles sont basées sur des fenêtres glissantes le long de la série temporelle, mesurant certaines quantités, comme la moyenne, l'écart type ou l'entropie, dans chaque fenêtre, et produisant un résumé de cet ensemble d'estimations locales de ces quantités. Les caractéristiques d'autocorrélation non linéaire normalisée se sont avérées les plus pertinentes pour les canaux V EOG droit, Fp1, Fp2 et Fpz. Cette quantité est souvent utilisée comme statistique de non-linéarité dans les données de substitution [176]. En revanche, la variation des propriétés des séries temporelles a toujours montré son importance pour les canaux Fp1, Fp2 et Fpz. Elle applique une transformation de prétraitement donnée à la série temporelle (détrendage polynomial ou sinusoidal) et renvoie des statistiques sur la manière dont diverses propriétés des séries temporelles changent en conséquence.

Précision de la classification

Dans cette étude, nous avons comparé l'approche de classification hiérarchique proposée à une méthode non hiérarchique. Le Tableau 4.1 présente la précision moyenne de la classification et l'écart type obtenus à chaque essai de validation croisée pour tous les participants. Dans le Tableau, pour l'approche hiérarchique, les niveaux 1, 2, 3 et 4 correspondent à la précision cumulée des classificateurs à chacun des quatre niveaux. Les résultats sont présentés pour chaque type de caractéristique séparément, ainsi que combinés via la fusion des caractéristiques. Dans l'approche non hiérarchique, à son tour, les résultats présentés pour les niveaux 1 à 4 correspondent respectivement aux tâches à 2, 4, 8 et 36 classes en utilisant soit un classificateur MVS, soit un PMC. Pour comparer la précision finale à 36 classes, il faut utiliser les résultats du niveau 4. Enfin, conscients qu'une erreur de 10 degrés peut ne pas poser de grave problème pour la surveillance du regard dans les applications de RV, nous explorons davantage un scénario dans lequel les erreurs qui sont décalées de seulement 10 degrés ne sont pas comptées comme des erreurs. Dans le Tableau 4.1, cela est indiqué comme "Niveau 4*".

Comme on peut le voir, le classificateur MVS a toujours surpassé le PMC pour tous les types de caractéristiques et les niveaux de classification. En général, les caractéristiques basées sur la pente ont presque toujours surpassé les caractéristiques top-HCTSA. De plus, dans l'approche hiérarchique, les erreurs des niveaux précédents étaient propagées vers le bas, bien que la précision finale soit restée supérieure à celle des approches conventionnelles à 36 classes (c'est-à-dire non hiérarchiques). La fusion des caractéristiques a montré qu'elle améliore la précision de la classification, suggérant ainsi une complémentarité des caractéristiques. Après une enquête approfondie sur les erreurs, il a été constaté que la majorité des erreurs commises étaient avec des classes voisines d'un pas. Pour les applications RV, une erreur de détection du regard de moins de 10 degrés peut ne pas être cruciale. Comme approche alternative, nous avons considéré le scénario où de telles erreurs n'étaient pas comptées. Comme on peut le voir dans le Tableau 4.1 sous les lignes intitulées "Niveau 4*", les niveaux de précision ont augmenté de manière substantielle pour tous les types de caractéristiques et de classificateurs. La méthode hiérarchique avec les classificateurs MVS et l'ensemble de caractéristiques fusionnées s'est avérée être la meilleure approche, atteignant une précision de 76,51%. Enfin, les faibles valeurs de l'écart type indiquées dans le Tableau suggèrent que la méthode proposée est assez insensible à la partition des données et à la variabilité inter-sujets. Ceci est un facteur important pour les applications pratiques.

Dans ce chapitre, nous avons présenté une approche de classification hiérarchique pour classer avec précision les mouvements oculaires saccadiques en 36 directions en utilisant une solution à faible coût basée sur l'incorporation de 7 capteurs ExG directement dans la face avant d'un casque de réalité virtuelle. Nous avons exploré deux types de caractéristiques (individuellement et fusionnées) et deux classificateurs conventionnels (MVS et PMC). Il a été constaté qu'avec aussi peu que sept électrodes ExG, sept caractéristiques, et une série de classificateurs MVS linéaires simples, une précision de 76,51% pourrait être atteinte sur le problème de classification à 36 classes. Ces résultats sont encourageants et suggèrent que les mouvements oculaires saccadiques précis peuvent être suivis de manière peu coûteuse et avec des exigences de calcul négligeables, deux facteurs importants pour les applications réelles. Dans le Chapitre 6, nous explorerons davantage l'utilisation de ces caractéristiques pour la classification de la perception du temps. En examinant la relation entre les mouvements oculaires saccadiques et la perception du temps, nous visons à découvrir des informations supplémentaires sur le processus cognitif humain et l'impact de la RV sur notre perception du temps.

0.5 Chapitre 5: Validation hautement écologique du casque : Surveillance des FIHs des joueurs à distance

Dans ce chapitre, nous décrivons un système permettant de recueillir des signaux physiologiques multimodaux à partir d'un casque de RV instrumenté, décrit dans le Chapitre 3. Ce système, livré aux participants avec un ordinateur portable pour les jeux et un autre pour le streaming des données biosignaux, comprend 16 capteurs ExG, incluant EEG, ECG, et EOG. Un bioamplificateur portable et sans fil est utilisé pour collecter, diffuser et stocker les signaux en temps réel. Nous cherchons à répondre à deux questions principales de recherche (QRs) : (1) Est-ce que le casque instrumenté proposé peut être utilisé dans des contextes hautement écologiques avec une intervention minimale de l'expérimentateur? et (2) Les signaux physiologiques mesurés peuvent-ils être utilisés comme des corrélats des FIHs des joueurs? Notre travail s'appuie sur l'étude précédente de [177], où nous proposons l'extraction de plusieurs mesures liées aux FIHs à partir des signaux ExG et leur corrélation avec les évaluations de l'expérience rapportées par les joueurs.

0.5.1 Méthodologie

Dans cette section, le protocole expérimental détaillé inclut la collecte de données à distance, le prétraitement des signaux, l'analyse et la mesure des FIHs.

Un casque de RV instrumenté, le HTC VIVE Pro Eye, a été utilisé pour acquérir 11 signaux EEG situés dans trois zones : frontale, centrale et occipitale, comme illustré dans la Figure 5.1. Les signaux EOG sont quant à eux obtenus à partir des électrodes EEG situées sur la zone frontale et de quatre autres électrodes placées directement dans la mousse du casque de RV. Les données ont été transmises sans fil à l'aide de l'interface utilisateur OpenBCI vers un ordinateur portable à proximité. Une électrode jetable est placée sur la clavicule gauche de l'utilisateur pour enregistrer l'ECG, une position reconnue pour son confort et sa fiabilité.

Huit participants ont accepté de prendre part à cette expérience (5 hommes et 3 femmes, âge moyen de 28,9 ans avec un écart type de 2,9 ans). Ces participants, adultes consentants, possédaient une audition normale, une vision normale ou corrigée, et n'avaient pas de problèmes connus avec la RV, comme le cybermalaise. Les participants n'avaient aucune expérience au préalable avec le jeu Half-Life: Alyx. Ils ont passé deux conditions de jeu : "référence" et "exploration/combat". Une fois ces deux sessions terminées, les participants étaient invités à remettre tout le matériel dans la boîte. Afin de mesurer l'impact des FIHs liés aux médias immersifs sur l'expérience utilisateur des joueurs, nous avons utilisé le questionnaire unifié proposé par [178]. Le questionnaire comprend 87 éléments différents, compilés à partir de 10 échelles différentes. Pour le prétraitement des signaux, plusieurs caractéristiques des signaux EEG, EOG et ECG ont été extraites. Pour les signaux EEG, nous avons examiné plusieurs métriques, en particulier le score d'engagement (SE), les indices d'arousal et de valence (IA et IV) et l'asymétrie alpha frontale (AAF). Pour les signaux EOG, nous avons extrait les taux de clignotement des yeux et de saccade et leurs durées. Pour le traitement du signal ECG, nous avons extrait 15 caractéristiques liées à la FC et à la VFC. Finalement, afin de répondre aux questions de recherche, des tests t ont été menés pour comparer les conditions de référence et d'exploration/combat. De plus, une corrélation de Pearson a été utilisée entre les signaux physiologiques mesurés et les évaluations subjectives pour explorer quelles mesures corrélaient le mieux avec chaque FIH.

0.5.2 Résultats

Dans cette section, nous discutons des résultats obtenus à partir des différentes questions subjectives et des mesures physiologiques. Le Tableau 5.1 répertorie 21 questions subjectives, parmi les 87 possibles, qui ont montré une différence significative entre les conditions de référence et d'exploration/combat pour tous les sujets. Huit des dix catégories ont montré une différence significative, les catégories d'"utilisabilité" et d'"adoption de la technologie" n'ayant pas montré de différence significative. Dans l'ensemble, les scènes d'exploration/combat ont montré une augmentation du sentiment de présence, de flow, d'immersion et d'émotions, mais également des symptômes de cybermalaise légèrement plus élevés. Ces résultats contribuent à répondre à la première question de recherche (QR1).

Nous examinons ensuite les changements observés dans les signaux physiologiques mesurés entre les deux conditions. Le Tableau 5.2 montre la différence entre la moyenne des mesures dans la condition d'exploration/combat par rapport à la moyenne de la condition de référence, représentée par un symbole Δ, pour chacun des huit sujets, ainsi que la moyenne entre les sujets. Nous observons une augmentation de la fréquence cardiaque d'environ 12 battements par minute dans la condition de d'exploration/combat, ainsi qu'une augmentation de 23 saccades par minute. Ensuite, pour tester l'importance de ces changements, le Tableau 5.3 présente les résultats du test statistique. Comme on peut le voir, la fréquence cardiaque a montré une différence significative tandis que les changements dans les saccades étaient modérément significatifs. Pour étudier l'évolution temporelle de chaque mesure physiologique, la Figure 5.6 représente les moyennes des mesures présentées en fonction du temps pour tous les participants pendant les conditions de référence et d'exploration/combat. La fréquence cardiaque est restée constamment plus élevée dans la condition de combat, comme prévu, car il s'agit d'une condition plus stressante. Le nombre de saccades par minute était également constamment plus élevé dans la condition d'exploration. Enfin, la Figure 5.7 montre les corrélations de Pearson obtenues entre toutes les mesures physiologiques et les 21 échelles subjectives du Tableau 5.1 avec des valeurs concaténées pour les deux conditions. Les corrélations sont codées en couleur en fonction de la force des corrélations, allant de forte (par exemple, supérieure à 0,7), à modérée (entre 0,3 et 0,7) à faible (inférieure à 0,3). Ces résultats nous aident à répondre à la deuxième question de recherche (QR2).

0.5.3 Discussion

L'étude démontre que le dispositif de RV instrumenté peut être utilisé efficacement dans des environnements domestiques avec une intervention minimale de l'expérimentateur. Les données recueillies à partir de le système ont montré des modifications significatives à la fois dans les réponses subjectives et les mesures physiologiques entre les phases d'exploration et de combat dans un jeu vidéo. Les réponses subjectives, indiquées dans le Tableau 5.1, montrent des différences notables entre les deux phases. Les scores étaient généralement plus élevés pendant la phase de combat, indiquant un engagement accru des participants. Ce niveau d'engagement élevé pourrait être dû à la succession des phases - exploration suivie de combat - et à l'augmentation du défi représenté par les combats. Cependant, une fatigue visuelle est apparue après 15-20 minutes de jeu, comme indiqué par les participants.

En termes de mesures physiologiques, les signaux capturés ont validé l'utilisation appropriée du casque de RV instrumenté. L'ECG a montré une augmentation du rythme cardiaque, et les signaux EOG ont révélé une augmentation du nombre de clignements d'yeux et de saccades pendant la phase de combat, comme présenté dans le Tableau 5.2. Ces augmentations correspondent à une augmentation de l'implication du joueur et à une fatigue visuelle, comme le suggèrent Kuwahara et al. [179]. Les signaux EEG, analysés ensuite, ont montré un plus grand engagement et une diminution de l'indice de valence lors des événements de mort dans le jeu. Cela est attendu, car les situations de mort sont généralement stressantes et engendrent des émotions négatives, comme le démontrent McMahan et al. [139]. Par ailleurs, la mesure AAF a indiqué des niveaux de peur plus élevés, ce qui est conforme aux attentes lors de situations de combat.

En conclusion, l'étude a confirmé que les mesures physiologiques collectées suivaient les comportements attendus, indiquant que des signaux de haute qualité ont été mesurés à domicile. De plus, comme le montre la Figure 5.6, ces mesures se sont avérées pertinentes pour évaluer la qualité de l'expérience du joueur. Elles démontrent le potentiel du casque de RV instrumenté pour le suivi en temps réel du comportement du joueur, une capacité essentielle pour le développement de jeux adaptatifs à domicile.

0.6 Chapitre 6: Quantification multimodale de la perception du temps des joueurs

Ce chapitre explore l'utilisation de diverses modalités biométriques pour surveiller la perception du temps lors de l'immersion d'un utilisateur dans des expériences de RV. Les chercheurs et les développeurs se sont intéressés à comprendre les facteurs psychologiques et physiologiques qui influencent la qualité de l'expérience immersive de l'utilisateur, tels que le sentiment de présence, l'immersion, l'engagement et la perception du temps. Cependant, très peu de travaux ont été présentés à ce jour sur la caractérisation de la perception du temps de l'utilisateur et le rôle qu'elle joue dans la qualité globale de l'expérience des médias immersifs.

Le chapitre mettra l'accent sur l'utilisation de dispositifs portables et de biosignaux pour mesurer, en temps réel, les états cognitifs et affectifs des utilisateurs pendant qu'ils sont immergés dans des expériences de RV. En particulier, l'étude montrera l'importance de différentes modalités pour la surveillance de la perception du temps, y compris les caractéristiques extraites de l'EEG, les modèles de regard dérivés des signaux EOG, les mesures de fréquence cardiaque calculées à partir de l'ECG, et les informations sur les mouvements de la tête extraites des signaux de l'accéléromètre tri-axial du casque. L'objectif de cette étude est de contribuer au développement de nouvelles méthodes pour surveiller la perception du temps à partir de biosignaux, ouvrant ainsi la voie à des systèmes adaptatifs futurs qui maximisent l'expérience de l'utilisateur en RV sur une base individuelle.

0.6.1 Méthodologie

Dans cette section, nous détaillons le protocole expérimental suivi, y compris le jeu de données utilisé au Chapitre 5, le prétraitement des signaux, les méthodes d'extraction et de sélection des caractéristiques, ainsi que la méthode de régression utilisée.

Le jeu de données utilisé dans cette étude a été décrit en détail au Chapitre 5. Dans notre travail, nous avons combiné les deux tâches (conditions de référence et d'exploration/combat) et avons exploré l'utilisation des biosignaux pour surveiller les deux évaluations fournies en réponse à deux questions, provenant du questionnaire unifié, liées à la perception du temps : Q1 - *Le temps semblait s'écouler différemment que d'habitude"* et Q2 - *J'ai perdu la notion du temps"*. Dans notre analyse, diverses caractéristiques ont été extraites à partir des signaux EEG, EOG, ECG, et des données d'accéléromètre. Pour les signaux EEG, 20 caractéristiques ont été obtenues à partir des bandes de fréquences, avec 12 caractéristiques supplémentaires pour analyser les états mentaux des participants (le score d'engagement, l'indices d'arousal et valence, et l'indice d'asymétrie frontale alpha), ainsi que 550 caractéristiques CSPM et 1540 caractéristiques CSPM-MA [144]. Pour les signaux EOG, nous avons extrait 4 caractéristiques principales et 31 caractéristiques supplémentaires, ainsi que deux caractéristiques liées aux changements de regard entre les quadrants du champ de vision du casque de RV [180, 181]. Pour les signaux ECG, 15 caractéristiques liées à la FC et à la variabilité de la VFC ont été extraites (Section 3.4.2.3). En ce qui concerne l'accéléromètre, 117 caractéristiques ont été extraites pour offrir des informations sur le mouvement et l'orientation de la tête lors de l'expérience en RV (Section 3.4.2.4).

La sélection de caractéristiques est une étape essentielle qui a impliqué la suppression de caractéristiques non pertinentes ou redondantes. Pour ce faire, nous avons utilisé le coefficient de corrélation de Spearman pour mesurer la relation entre les caractéristiques physiologiques et les évaluations de Q1 et Q2. Par la suite, nous avons appliqué l'algorithme mRMR pour identifier les caractéristiques les plus informatives tout en minimisant la redondance [182, 183]. Ce processus a abouti à un ensemble de 18 caractéristiques principales. Pour prédire les deux évaluations de la perception du temps, nous avons utilisé un régresseur de processus gaussien (RPG) avec un noyau quadratique rationnel [184]. La performance du modèle a été évaluée en utilisant une méthodologie de test par bootstrap, en utilisant l'erreur quadratique moyenne (EQM), l'erreur absolue moyenne (EAM), et le coefficient de détermination (R^2). Enfin, nous avons vérifié si les résultats obtenus étaient significativement meilleurs que le hasard en utilisant un "régresseur aléatoire", et un test de Kruskal-Wallis pour chaque indicateur (EQM, EAM, R^2).

0.6.2 Résultats et discussion

Cette étude explore la perception du temps dans un environnement de RV, plus précisément dans un jeu vidéo hautement immersif. Les participants ont donné des évaluations (Q1 et Q2) liées à leur perception du temps, dont les distributions sont présentées dans les Figures 6.3 A et B. Les résultats suggèrent que la plupart des participants étaient fortement d'accord avec l'idée que le temps semblait s'écouler différemment que d'habitude et qu'ils avaient perdu la notion du temps pendant le jeu. Ces résultats sont cohérents avec des recherches antérieures [185, 186].

Au total, 2254 caractéristiques ont été extraites des signaux EEG, EOG, ECG et d'un accéléromètre. Après deux étapes de classement des caractéristiques (Section 6.4.3), 18 caractéristiques principales ont été identifiées pour chacune des deux évaluations de perception du temps. Les Figures 6.4 A et B montrent ces caractéristiques pour Q1 et Q2, respectivement, en ordre croissant d'importance. Les mouvements de la tête et les mesures liées à la VFC étaient parmi les caractéristiques les plus importantes. D'autres caractéristiques importantes étaient liées à des mesures d'EEG de cohérence entre différents sites d'électrodes. Le Tableau 6.1 présente l'impact de l'inclusion de ces caractéristiques sur la précision du régresseur. Il a été déterminé que l'ajout de 7 caractéristiques pour Q1 et de 8 caractéristiques pour Q2 était optimal. Les accélérations des mouvements de la tête le long de l'axe x, qui peuvent indiquer l'incarnation dans le jeu, étaient parmi les 7 premières caractéristiques pour Q1. De plus, la VFC des joueurs, caractérisée par SDNN, a été liée à des états émotionnels [187], au stress [188, 189], et à la charge mentale [190], qui ont également été montrés pour moduler la perception du temps. En ce qui concerne Q2, parmi les 8 caractéristiques principales, quatre étaient communes à celles de Q1, ce qui souligne leur importance pour la surveillance de la perception du temps. Les quatre autres donnent des vues alternatives des modulations de VFC et d'EEG. Par exemple, pNN50 de la VFC a été montré comme un corrélat de la concentration [191], un facteur crucial pour perdre la notion du temps en RV [192].

Enfin, les Figures 6.5 A et B montrent des diagrammes de dispersion des évaluations subjectives prédites par rapport aux vraies pour Q1 et Q2, respectivement, en utilisant les 7 et 8 caractéristiques principales mentionnées ci-dessus. Une corrélation significative a été observée entre les évaluations prédites et réelles pour Q1 (0.95) et Q2 (0.90). Les Figures 6.6 A et B montrent que les mesures d'erreur du régresseur par hasard sont presque trois fois plus élevées que celles de la méthode proposée. De plus, un test de Kruskal-Wallis a montré une différence R^2, suggérant que les régresseurs proposés ont performé significativement mieux que le hasard.

Cette étude souligne l'importance d'un système multimodal, utilisant l'EEG, l'ECG, l'EOG et l'accéléromètre, pour caractériser la perception du temps dans un environnement de RV. Les résultats suggèrent que les caractéristiques liées aux mouvements de la tête et à la VFC peuvent efficacement surveiller la perte de la notion du temps en RV. Les résultats démontrent également l'efficacité d'un casque de RV instrumenté pour suivre la qualité de l'expérience immersive. De plus, l'expérimentation a révélé que les participants subissaient une distorsion du temps significative en jouant au jeu. Les modèles de prédiction basés sur un régresseur à processus gaussien ont été efficaces pour caractériser la perception du temps des joueurs, avec une performance significativement supérieure au hasard. Ces résultats peuvent contribuer à une meilleure compréhension de la relation entre immersion et perception du temps dans les environnements de RV, et à l'amélioration des expériences de médias immersifs.

0.7 Chapitre 7: Conclusion

Dans cette thèse de doctorat, les défis associés à l'utilisation d'EMI et de FIHs dans les environnements de RV ont été examinés, en mettant l'accent sur l'évaluation de l'expérience utilisateur, des réponses physiologiques et de la perception du temps. Pour relever ces défis, trois domaines principaux ont été explorés : l'évaluation des méthodes EMIs actuelles, la mise au point d'un casque de RV instrumenté sans fil pour la collecte de signaux physiologiques multimodaux, et l'établissement de marqueurs pour divers FIHs à partir des données physiologiques recueillies.

Plusieurs contributions majeures ont été réalisées. Tout d'abord, un examen complet des méthodes d'évaluation de l'EMI et des FIHs actuels a permis de comprendre leurs tendances, innovations et limitations. Ensuite, un nouveau système de casque de RV instrumenté a été développé, capable de recueillir des signaux physiologiques multimodaux en temps réel lors des applications en RV mobiles. Enfin, des marqueurs pour différents FIHs ont été établis à partir des données physiologiques recueillies, permettant une meilleure compréhension des expériences des utilisateurs dans les environnements de RV. Plusieurs pistes de recherche futures ont été identifiées. Les études pourraient intégrer des modalités physiologiques supplémentaires comme l'AED et le taux de respiration. Des travaux supplémentaires devraient également se concentrer sur des tâches plus complexes de suivi des yeux et d'extraction de caractéristiques, impliquant un plus grand nombre de sujets et l'utilisation de méthodes avancées d'apprentissage automatique. De plus, l'extension des capacités multisensorielles du casque de RV et le développement de contenus adaptatifs dans les environnements de RV sont d'autres directions de recherche prometteuses.

En conclusion, cette thèse offre des contributions significatives à l'évaluation des EMIs et des FIHs dans les environnements de RV. Ces travaux devraient aider à stimuler la recherche dans le domaine des expériences de RV immersives et encourager le développement d'applications innovantes exploitant les avancées de l'acquisition, de l'analyse des signaux physiologiques et de l'intégration des informations multisensorielles.

Chapter 1

Introduction

1.1 Methods and tools for human influential factors assessment

It is predicted that the global virtual reality VR market will reach US$227.34 billion by 2029 [3] through steady and continuous growth of new mobile applications and the appearance of the fifth-generation (5G) wireless networks worldwide. 5G networks promise faster speeds, lower latency, wider coverage, and more stable connections. Applications across multiple verticals are projected, including entertainment and media, gaming, healthcare, automobile, aerospace and defense, manufacturing, retail, and education, to name a few. In fact, as recently emphasized by Qualcomm, 5G coupled with VR will be essential for the development of next-generation immersive experiences and will enable applications, such as six degrees of freedom immersive content, automotive video streaming, crowded event sharing, remote control, and the tactile internet. In 2022, VR users grew to over 171 million users [4]. VR is a cutting-edge technology that enables users to experience and interact with computer-generated environments in real-time. VR systems typically consist of a head-mounted display (HMD) that tracks the user's head movements and displays 3D graphics, providing a sense of presence and immersion. The HMDs often incorporate built-in audio and, in some cases, haptic feedback to create a multisensory experience. Additionally, advanced VR systems may include external sensors or cameras to track body movements, as well as hand-held controllers or gloves for more precise and natural interactions with the virtual environment. Recent advancements in VR headsets include the HTC Vive XR Elite, the Sony PlayStation VR 2, and the Varjo XR-3 which have introduced improvements in display resolution, tracking capabilities, and platform compatibility. These innovations contribute to a more immersive and enhanced user experience. To fully unlock this potential, however, the effectiveness of these emerging applications will not only depend on their technical capabilities but also on the quality of experience (QoE) they provide to the user [5].

More generally, QoE refers to the “degree of delight or annoyance of applications or services resulting from the fulfillment of his or her expectations with respect to the utility and/or enjoyment of the application or service in the light of the users personality and current state” [6]. When it comes to immersive media and content, immersive media experiences (IMEx) [7] build on the QoE concept by also including factors such as sense of presence and immersion, as well as motion sickness (cybersickness), to name a few. In fact, QoE and IMEx are driven by three influential factors (IFs): system, context, and the (human) user:

1. System IFs: Within immersive experiences, devices play a significant role as system influential factors [7]. The capability of accurately tracking the user’s behaviors (e.g., body/head position, movements, eye tracking) affects the interaction quality and the sense of presence and immersion [8]. Device design, including portability, usability, field-of-view, visual quality, and ergonomics, also impacts the user experience [193, 194]. Furthermore, multisensory experiences involving audiovisual media combined with haptic, olfactory, and gustatory stimuli in VR can dramatically influence the overall IMEx [88]. Advanced rendering techniques, such as real-time ray tracing and foveated rendering, contribute to higher visual fidelity, while improvements in haptic feedback systems provide more accurate and realistic touch sensations.
2. Context IFs: As highlighted in [7], context IFs describe the user’s environment, encompassing physical, temporal, social, economic, task, and technical characteristics. Physical context may include the user’s surroundings, ambient noise, and lighting conditions, while temporal context refers to the time of day or the user’s available time for the experience. Social context involves the presence of others during the VR experience, either as co-located spectators or participants in multi-user scenarios. Economic context could be related to the cost of the VR system and content, whereas task context refers to the user’s goals, objectives, and motivations for using VR. Finally, technical context encompasses aspects such as network conditions, available processing power, and hardware compatibility. Sometimes it is difficult to separate system and context completely and they are evaluated together.

3. Human IFs: Human influential factors (HIFs) include "any variant or invariant property or characteristic of a human user," such as emotional state, expectations, and attention [6]. As emphasized in [7], "the fact that not every human becomes equally immersed in the same book, movie, or game illustrates that human IFs are of very high relevance for an IMEx." Additionally, each user's sensitivity to incongruency and timing differences between perceptual modalities can lead to discomfort, visual fatigue, and cybersickness. Cybersickness has been reported to affect between 30% and 80% of users, with symptoms potentially lasting several hours post-VR exposure. Individual differences in cognitive and perceptual abilities, as well as prior VR experience, also play a role in shaping the IMEx.

In order to continuously improve VR technology, constant evaluation is needed to measure IMEx, taking all three IFs into account. This comprehensive approach allows researchers and developers to identify areas for improvement and deliver more engaging and satisfying immersive experiences, ultimately driving the widespread adoption of VR across various industries and applications. While system and context have been widely explored, the impact of human influential factors on IMEx is a less studied topic, thus will be the focus of this dissertation. In particular, two assessment methods have been commonly used for this purpose, namely: subjective and instrumental. The latter can be further classified as behavioural and psycho-physiological.

Conventionally, subjective methods consist of questionnaires, administered after the VR experience, that measure certain aspects of the human experience itself [9, 10, 11, 12, 13]. These methods can have several disadvantages [195]. First, it is difficult for naive users to convert human judgment into a quantifiable assessment of final quality. Second, the post-experience questionnaires typically provide only a snapshot of the perceived overall experience, lacking real-time insights to improve IMEx. Third, continuous quality evaluation experiments, while addressing this limitation, often result in additional cognitive workload and excessive fatigue for users, which can compromise the media experience itself, leading to a loss of immersion in VR/AR applications. Lastly, subjective methods can be influenced by biases and may not accurately represent the actual experience of the user. On the other hand, (instrumental) behavioral HIFs assessment is based on tracking user behaviors, such as facial expressions, body gestures, and social interaction. These responses, including reflexive actions like blinking or instinctual facial expressions, can occur in an involuntary, automatic manner, often without conscious introspection, unlike the processes involved in subjective methods. Advances in computer vision and machine learning have enabled automated analysis of these behaviors, providing real-time insights into user experiences, which can be leveraged to improve IMEx. Furthermore, behavioral assessment can also include analysis of gaze patterns, head movements, and navigation data, which can help identify areas of interest and potential issues within the VR environment.

Over the last few years, developments in biosensors [14] have allowed for numerous HIFs to be monitored in real-time in immersive environments [15]. As such, (instrumental) psycho-physiological methods have emerged and aim to find correlates between perceptual QoE/IMEx features and physiological metrics [16]. Physiological signals have been used, for instance, to measure stress [196], engagement [197], emotions [144], sense of presence [198], immersion [199], and overall experience [200, 84], thus can play a key role in advancing VR applications. Several physiological signals have shown great potential in assessing user experiences in immersive environments. These include the electroencephalogram (EEG), which records electrical brain activity and offers insights into cognitive processes, emotional states, and attention levels; the electrocardiogram (ECG) and heart rate (HR) or heart rate variability (HRV), which measure the electrical activity of the heart and provide information on emotional arousal, stress, and relaxation; the electrooculogram (EOG) and eye blink, which track electrical activity associated with eye movements, giving indications of visual attention, areas of interest, and fatigue; electrodermal activity (EDA), which evaluates changes in skin conductance due to sweat gland activity, reflecting emotional arousal, stress, and cognitive load; and cerebral blood flow measured via near-infrared spectroscopy (NIRS), a non-invasive technique for monitoring brain activity that can assess cognitive workload, attention, and emotional states [17, 18, 19].

The development of psycho-physiological methods is still in its infancy and much work is still needed in pre-processing the obtained signals. Unlike conventional video QoE assessment where users are sitting and static [6], VR experiments have users moving around and exploring the virtual environment, hence hampering the signal quality and overall human IF measurement. Ultimately, monitoring human biosignals while immersed in virtual reality will allow us to characterize factors such as cybersickness, perception of immersion, and overall experience, thus allowing for experiences to be adapted in real-time to maximize the IMEx. As VR technology continues to grow in popularity, the assessment of IMEx becomes increasingly important for the development of immersive applications that cater to a wide audience. The integration of biosensors into VR systems and the refinement of psycho-physiological methods have the potential to revolutionize the way we evaluate and enhance virtual experiences. Such advances open doors for more personalized and adaptive VR systems, leading to more engaging and enjoyable experiences for users. As such, the feasibility of these systems should be explored and their potential impact on the future of immersive media experiences fully realized.

1.2 Thesis contributions

The overarching goal of this doctoral research is to develop various tools that allow the assessment of QoE in immersive virtual applications by focusing on HIFs and utilizing physiological signals in more ecologically valid settings. To achieve this goal, several innovations had to be developed, thus constituting the main contributions of this thesis. More specifically, three main innovations were conceptualized, developed, and evaluated.

1. **Development of an instrumented VR headset:** To monitor physiological signals related to QoE, an instrumented VR headset with several biosensors was designed and built. Sensors included EEG, EOG, and ECG. This allowed the collection and analysis of physiological data in more ecologically valid settings and the development of objective measures of QoE in VR environments.
2. **Development of an eye gaze tracking system from physiological signals:** Commercial headsets with eye-tracking capability typically only grant access to the eye gaze data to custom-built applications. Here, we showed the potential of the instrumented headset to track eye gaze using the recorded physiological signals. The gaze data could then be used to extract features related to IMEx.
3. **Development of user experience markers from multimodal signals:** By leveraging the collected physiological data, different neurophysioligical correlates were found for different HIFs. In particular, a multimodal correlate of time perception was developed to provide cues about the sense of presence, immersion, and engagement in VR.

These innovations have been described in several manuscripts, as listed below in chronological order. Where appropriate, the chapters of this thesis in which these publications appear are also specified.

1.3 Publications derived from the thesis

Publications included in the thesis

Articles published in refereed journals

- “Neural interface instrumented virtual reality headsets: Toward next-generation immersive applications”, Cassani, R., **Moinnereau, M.A.**, Ivanescu, L., Rosanne, O. & Falk, T.H., (2020), *IEEE Systems, Man, and Cybernetics Magazine, 6(3), 20-28* [201] [Chapter 3]

- “Immersive media experience: a survey of existing methods and tools for human influential factors assessment”, **Moinnereau, M.A.**, de Oliveira Jr, A.A., & Falk, T.H., (2022), *Quality and User Experience, 7(1), 5*, [202] [Chapter 2]

- “Instrumenting a Virtual Reality Headset for At-Home Gamer Experience Monitoring and Behavioural Assessment”, **Moinnereau, M.A.**, de Oliveira Jr, A.A., & Falk, T.H., (2022), *Frontiers in Virtual Reality, Vol. 3, 156*, [203] [Chapter 5]

- “Quantifying time perception during virtual reality gameplay using a multimodal biosensor-instrumented headset: a feasibility study”, **Moinnereau, M.A.**, de Oliveira Jr, A.A., & Falk, T.H., (2023), *Frontiers in Neuroergonomics*, [204] [Chapter 6]

Conference proceedings and abstracts

- “A Neurophysiological Sensor-Equipped Head-Mounted Display for Instrumental QoE Assessment of Immersive Multimedia”, Cassani, R., **Moinnereau, M.A.** & Falk, T. H. (2018), *Tenth International Conference on Quality of Multimedia Experience (QoMEX), 1-6* [205] **** Winner of the Best Paper Award ****

- “Saccadic eye movement classification using ExG sensors embedded into a virtual reality headset”, **Moinnereau, M.A.**, de Oliveira Jr, A.A., & Falk, T.H., (2020), *In 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC), 3494-3498. IEEE* [151] [Chapter 4] **** Winner of the Best Student Paper Award ****

- "Measuring Human Influential Factors During VR Gaming at Home: Towards Optimized Per-User Gaming Experiences", **Moinnereau, M.A.**, de Oliveira Jr, A.A., & Falk, T.H., (2022), *Human Factors in Virtual Environments and Game Design, AHFE, 50, 15* [177]

- "Human Influential Factors Assessment During At-Home Gaming with an Instrumented VR Headset", **Moinnereau, M.A.**, de Oliveira Jr, A.A., & Falk, T.H., (2022), *In 2022 14th International Conference on Quality of Multimedia Experience (QoMEX), 1-4* [206]

Other publications

Conference proceedings and abstracts

- "EEG Artifact Removal for Improved Automated Lane Change Detection while Driving", **Moinnereau, M.A.**, Karimian-Azari, S., Sakuma, T., Boutani, H., Gheorghe, L. & Falk, T. H. (2018), *IEEE International Conference on Systems, Man, and Cybernetics (SMC), 1076-1080* [207]
- "Nat(UR)e: Quantifying the Relaxation Potential of Ultra-Reality Multisensory Nature Walk Experiences", Lopes, M. K. S., de Jesus, B. J., **Moinnereau, M.A.**, Gougeh, R. A., Rosanne, O., Schubert, W., de Oliveira Jr, A.A. & Falk, T. H. (2022), *IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE), 459-464* [208]
- "Quantifying User Behaviour in Multisensory Immersive Experiences", Gougeh, R. A., de Jesus, B. J., Lopes, M. K. S., **Moinnereau, M.A.**, Schubert, W. & Falk, T. H. (2022), *IEEE International Conference on Metrology for Extended Reality, Artificial Intelligence and Neural Engineering (MetroXRAINE), 64-68* [209]
- "Quantifying Multisensory Immersive Experiences using Wearables: Is (Stimulating) More (Senses) Always Merrier? ", de Jesus, B. J., Lopes, M. K. S., **Moinnereau, M.A.**, Reza Gougeh, R. A., Rosanne, O., Schubert, W., de Oliveira Jr, A.A. & Falk, T. H. (2022), *In Proceedings of the 2nd Workshop on Multisensory Experiences - SensoryX'22* [210]

1.4 Thesis organization

While this introductory chapter has presented the challenges with QoE assessment in immersive virtual applications and laid out the foundation for the contributions described herein, the remainder of this dissertation is structured as follows. Chapter 2 provides an overview of the state-of-the-art methods in QoE assessment and HIFs in immersive virtual environments. Chapter 3 presents the development of an instrumented VR headset capable of monitoring physiological signals, such as EEG, EOG, and ECG, and potential extracted features. Next, Chapter 4 explores the tracking of new eye gaze measures from the instrumented headset, including the use of the classifier to detect eye gaze measures. Following this, Chapter 5 describes the ecological study of the instrumented VR headset, including data collection and the features extracted. In Chapter 6, the quantification of time perception relevant to the senses of presence and immersion in virtual reality is explored, including the latest research in this area and potential future directions for research. Lastly, Chapter 7 provides the general conclusions of this thesis, as well as future research areas.

Chapter 2

Background and related work

2.1 Preamble

This chapter is compiled from material extracted from the manuscript published in the journal *Quality and User Experience* [202].

2.2 Introduction

As highlighted in Chapter 1, in the study of IMEx the assessment of HIFs plays a crucial role. Utilizing psycho-physiological methods to evaluate these factors offers several advantages compared to traditional subjective approaches, such as:

1. **Objectivity**. Psycho-physiological methods provide quantitative and objective measures of human influential factors, eliminating the need for self-reporting, which may be prone to biases and inaccuracies.
2. **Real-time assessment**. By continuously monitoring physiological signals, these methods enable the real-time evaluation of user experiences in virtual reality, allowing for adaptive content delivery and optimization of the immersive media experience.

3. **Unobtrusive measurement**. Psycho-physiological methods can be integrated seamlessly into VR headsets, ensuring a non-intrusive user experience while still collecting valuable data on human influential factors.

This chapter presents a comprehensive survey of the literature on IMEx assessment, with a particular focus on the assessment of human influential factors, in order to identify the latest trends and innovations in the field. We begin by examining existing subjective methods that concentrate on users' sense of presence, perception of immersion, cybersickness, emotional state, and overall experience. Subsequently, we shift our attention to behavioral and psycho-physiological measures, detailing the most recent biosensors and tools employed in the assessment. Although the primary emphasis is on psycho-physiological assessment, we also provide a succinct summary of alternative methods and direct the reader toward available review papers that cover these topics in greater depth. Additionally, we explore next-generation applications that encompass multiple sensory modalities beyond audio-visual, in order to enhance realism and immersion in virtual environments. To conclude, we engage in a brief discussion regarding the limitations identified throughout the review of the literature, outlining areas for future research and potential improvements in the assessment of IMEx and human influential factors.

2.3 Subjective IMEx Assessment

Subjective evaluations are the most common method for IMEx/HIFs assessment. They are usually applied shortly after the end of an experiment through questionnaires or rating scales. Their composition can vary according to the purposes of a specific experiment or application, or could be more generic and applicable across several contexts. Moreover, due to the lack of a common understanding and definition of the terms presence and immersion, a plenitude of different questionnaires have been developed. Recently, questionnaires that have proven their effectiveness via pen-and-paper assessments have also been integrated into virtual reality [20, 21, 22], hence reducing study duration and discomfort to the users [23]. Here, we focused on four aspects of IMEx measured from subjective assessments, including: sense of presence and perception of immersion, user quality of experience, cybersickness, and mental/affective state.

2.3.1 Questionnaires for presence assessment

Presence within the context of virtual reality is defined as one's sense of being in the virtual world. One of the fundamental aspects of VR is the ability to create and maximize the sense of presence of the user [24, 25, 26], hence making them feel like they are present in the virtual world. While sense of presence and immersion are closely related, numerous studies have categorized presence [27] based on what is being measured [28, 29, 30, 31, 10, 26]. For example, [32] lists three types of presence in VR, namely personal presence (also called self-presence), i.e., the feeling of "being there," social presence (also called co-presence), i.e., the sense of "being there with others," and environmental presence (also called physical, telepresence or spatial presence), where participants feel immersed physically in the virtual environment and interact with virtual objects.

In other words, the sense of presence is influenced by a range of elements including equipment factors (as physical barriers and device awareness), user's subjective factors (personality traits or immersion propensity), social factors (interactions with VR characters), and affective state [33], such as the emotions about self (anxiety, paranoid ideation, detachment), emotions about others (loneliness, retrospective emotions, recognition of self), thoughts about self (memories, social judgement), thoughts about others (paranoid ideation, narrative), physiological reactions (anxiety, cybersickness), behaviour of avatars (narrative, duration of interaction, characteristics), interactivity with environment (movement, familiarity), and environmental characteristics (restrictions) [34].

Here, we present the most common questionnaires that have been created to measure sense of presence in VR. Table 2.1 lists the questionnaires, how many subjects they were validated on, subscales used, rating scale, number of items rated, as well as which media they are applicable to, namely: virtual environment (VE), cross-media (CM), shared virtual environment (SVE), and 2D screens. Moreover, citation numbers were taken from Google scholar and latest numbers were confirmed at the date of paper submission, which was June 15, 2022.. As can be seen, most of the questionnaires were created more than 20 years ago. The most popular and most widely used to date is the Presence Questionnaire (PQ) [26] that has been cited over 5250 times and measures involvement, sensory fidelity, adaptation/immersion, and the interface quality. The GlobalED Questionnaire [35] is the most popular for social presence, with over 2500 citations, and the Igroup Presence Questionnaire [28] for spatial presence, involvement, and the experienced realism. Although PQ continues to be the standard in virtual reality research, it has been argued that the instrument does not provide a measure of presence, but of the individual's responses to various aspects of the virtual reality system, through a series of questions that involve the expression of the respondent's opinion about the evaluated factors (i.e., control, sensory, distraction, and realism factors) [29]. The interested reader is referred to [211, 212, 213] for a complete in-depth review on subjective presence questionnaires.

2.3.2 Questionnaires for user experience assessment

User experience is defined as perceptions and responses resulting from the use of a system. It is assessed by various measures of involvement such as engagement, flow, immersion, and encapsulates the user's preferences and behaviour during use. Immersion represents the instrumental level of sensory fidelity provided by a VR system, and in applications requiring a certain level of suspension of disbelief; it plays a crucial role in overall experience. Immersion also modulates user engagement and can result in achieving a flow state where the perception of time seems to warp. In VR, sensory immersion is defined as "the degree in which the range of sensory channels are engaged by the virtual simulation" [36]. Moreover, flow experience is often considered as an important standard of ideal user experience and keeping users in the flow state is considered as one important goal in VR system design [214]. Here, we list the most commonly used user experience questionnaires in Table 2.2, alongside how many subjects they were validated on, the subscales used, rating scale, number of items rated, as well as which media they are applicable to, i.e., VE, SVE, CM, or 2D screens. The interested reader is referred to [37] for a complete in-depth review on subjective user experience questionnaires.

Table 2.1: List of commonly used presence questionnaires for subjective IMEx assessment. VE stands for Virtual Environment, CM represents Cross-Media, and SVE denotes Shared Virtual Environment.

Reference	Questionnaires	Subject	Subscale	Rating scale	Citations	Items	Media
[215]	Barfield et al. Questionnaire 1	86	Personal presence	0-100	329	2	VE
[216]	Barfield et al. Questionnaire 2	12	Monoscopic vs stereoscopic display, head-tracking, field-of-view	5-point	409	3	VE
[217]	Memory characteristic Questionnaire (MCQ)	90	Presence, Judgment, Attention, Coherence, and Field-of-view	7-point	1257	21	SVE
[31]	Slater-Usoh-Steed Questionnaire (SUS)	24	Presence from internal/external factors	7-point	908	6	VE
[218]	Lombard & Ditton Questionnaire	600	Social presence, Realism, Transportation, and Immersion	N/D	332	103	CM
[35]	GlobalED Questionnaire	50	Social presence	5-point	2560	14	SVE
[219]	Kim & Biocca Questionnaire	96	Physical, Virtual or imaginary presence	8-point	860	8	2D screen
[220]	Reality Judgment and Presence Questionnaire (RJPQ)	124	Reality judgment, and Attention	10-point	225	18	VE
[26]	Presence Questionnaire (PQ)	152	Presence, Involvement, and Immersion	7-point	5254	32	VE
[221]	Thie & Van Wijk Questionnaire	48	Social presence	N/D	38	N/D	VE
[222]	Presence & Realism	N/D	Virtual art exhibits	4-point	8	10	
[223]	Dinh et al. Questionnaire	322	Visual, Olfactory, Auditory, and Tactile	0-100	537	14	VE
[224]	Murray et al. Questionnaire	10	Impact of the sound on the sense of presence	5-point	56	5	
[225]	Nichols et al. Questionnaire	24	Influence of the headset, and Auditory stimuli	7-point	231	9	VE
[226]	Basdogan et al. Questionnaire	10	Social presence	7-point	497	8	SVE

[227]	ITC - Sense of Presence Inventory (ITC-SOPI)	604	Sense of Physical space, Engagement, Ecological validity, and Negative effects	N/D	1121	44	CM
[228]	IPO Social Presence Questionnaire (IPO-SPQ)	34	Social presence	7-point	151	17	2S screen
[229]	Gerhard et al. Questionnaire	27	Immersion, Communication, Involvement, Awareness, Nature of the environment, and User interface	7-point	82	19	SVE
[230]	Krauss et al. Questionnaire	165	Presence	Rating scale	14	42	VE
[28]	Igroup Presence Questionnaire (IPQ)	246	Spatial Presence, Involvement, and Realism	5-point	1283	14	SVE
[231]	Swedish Viewer-User Presence Questionnaire (SVUP)	32	Enjoyment, Sound quality, Presence, and Cybersickness	5-point	72	19	VE
[232]	Schroeder et Al. Questionnaire	132	Physical and Social presence	5-point	177	11	SVE
[233]	Bailenson et al. Questionnaire	50	Social presence	7-point	493	5	VE
[234]	CMC Questionnaire/Social presence and Privacy Questionnaire (SPPQ)	310	Social presence	5-point	592	17	CM
[235]	Networked Minds	76	Co-presence, Psychological Involvement, and Behavioral Engagement	7-point	405	40/38	SVE
[236]	E^2I Questionnaire	10	Presence, and Enjoyment	7-point	451	14	VE
[237]	Nowak & Biocca Questionnaire	134	Telepresence, Copresence, and Social presence	7-point	833	29	SVE
[238]	Cho et al. Questionnaire	32	Visual realism, and Presence	0-100	40	4	VE
[239]	MEC-SPQ	N/D	Spatial presence, and Attention	5-Point	206	8	VE

[240]	Temple Presence Inventory	46	Satial presence, Social presence-actor, Passive social presence, Active social presence, Presence as engagement, Presence as social richness, Presence as social realism, and Presence as perceptual realism	7-point	223	42	CM
[241]	Tendency Toward Presence Inventory	499	Cognitive Involvement (active and passive), Spatial Orientation, Introversion, Ability to Construct Mental Models, and Empathy	5-point	57	41	VE
[242]	The German VR Simulation Realism Scale	151	Visual Realism, Audience Behavior and Appearance, and Sound Realism	5-point	18	14	VE
[243]	Multimodal Presence Scale (MPS)	161/118	Physical, Social, and Self presence	5-point	62	38/15	VE
[244]	Short QoE questionnaire	36	Perceptual quality, Presence, Acceptability, and Cybersicknes	5-point	84	5	VE

Table 2.2: List of commonly used user experience questionnaires for subjective IMEx assessment. VE stands for Virtual Environment, CM represents Cross-Media, and SVE denotes Shared Virtual Environment.

Reference	Questionnaires	Subject	Subscale	Rating scale	Citations	Items	Media
[245]	Immersive Experience Questionnaire (IEQ)	244	Cognitive, Involvement, Emotional involvement, World dissociation, and Challenge	5-point	1791	31	CM
[246]	GameFlow Questionnaire	N/D	Concentration, Player Skills, Control, Challenge, Feedback, Clear goals, Immersion, and Social Interaction.	GameFlow criteria	2715	35	CM
[247]	EGameFlow Questionnaire	N/D	Concentration, Control, Knowledge Management, Challenge, Goal clarity, Immersion, Feedback, and Social Interaction	0-100	786	42	CM
[248]	Game Engagement Questionnaire (GengQ)	153	Immersion, Flow, Presence and Absorption	5-point	982	19	CM
[249]	Game Experience Questionnaire (GexpQ)	N/D	Immersion, Competence, Flow, Negative effect, Positive effect, and Challenge	5-point	396	33	CM
[250]	EVE-GP questionnaire	2182	Multidimensional UX in video games	7-point	33	180	CM
[251]	Narrative game questionnaire	340	Curiosity, Concentration, Control, Challenge, Comprehension, and Empathy	7-point	266	27	CM
[252]	SCI Model Questionnaire 10	234	Sensory immersion, Challenge-based immersion, Imaginative immersion	5-point	1395	18	CM

[253]	Core Elements of the Gaming Experience (CEGE) questionnaire	15	Enjoyment, Frustration, Control, Puppetry, Facilitators, Ownership, Gameplay, and Environment	7-point	252	38	CM
[116]	Unified questionnaire on User eXperience in Immersive Virtual Environment	116	Presence, Engagement, Immersion, Flow, Usability, Skill, Emotion, Experience consequence, Judgement, and Technology adoption	10-point	76	87	VE
[254]	Presence-Flow-Framework (PFF)	68	Perceptual experience, Situational involvement, and Competence	7-point	165	124	VE
[255]	Presence-Involvement-Flow Framework2(PIFF2)	91	Presence, Involvement, and Flow	7-point	79	139	VE
[256]	Virtual Reality Neuroscience Questionnaire (VRNQ)	40	QoE, Game mechanics, and In-game assistance	7-point	29	20	VE
[257]	User Experience Questionnaire (UEQ)	144	Attractiveness, Perspicuity, Efficiency, Dependability, Stimulation, and Novelty	7-point	1297	26	CM

2.3.3 Questionnaires for cybersickness assessment

The term "cybersickness", though often used, can be misleading as it suggests a disease. However, as highlighted by the work of [258] and [259], cybersickness is not a disease but refers to the negative side effects experienced during VR immersion. Some even consider certain side effects to be positive, as seen in vestibular system rehabilitation [260]. Cybersickness is one of the main limitations of VR as it induces physiological changes that affect the users' sympathetic and parasympathetic activities. Reports suggest that cybersickness can affect between 30% and 80% of users and that symptoms can last for several hours [38]. The most common hypothesis to explain cybersickness is the sensory conflict theory. Indeed, cybersickness is the result of conflicts between three sensory systems: visual, vestibular and proprioceptive. Cybersickness is a complex phenomenon and, although motion cues play a primary role, multiple factors are known to contribute to the occurrence of sickness. These include factors related to the characteristics of the stimuli (e.g., spatial frequency, reactivity of the system, wideness of the field-of-view) and factors related to predispositions of the user (e.g., gender, age, predisposition to migraines) [261]. The most evident symptom of cybersickness is nausea, but there are also others, including general discomfort, headache, disorientation, and eye strain. Symptom intensity and duration are quite variable and depend on the characteristic of the stimulus, as well as user predisposition to cybersickness. In the majority of cases, the symptoms disappear a few minutes after the end of the stimulation. In more rare cases, the symptoms could still be present 6 hours after the VR experience [39].

There have been a number of questionnaires developed to evaluate cybersickness, as shown in Table 2.3. Although the Simulator Sickness Questionnaire (SSQ) is widely used in VR research, it was originally developed to measure motion sickness in simulators [262]. It has been criticized for its psychometric qualities and applicability in VR as a measure cybersickness [40]. Recent questionnaires have since been developed specifically for HMDs, such as the Virtual Reality Symptom Questionnaire (VRSQ) [41], and have shown better indicators of validity [42]. Moreover, there are questionnaires that also focus on the severity of cybersickness [263]. These questionnaires have been regarded as being too long, so shorter versions have also been explored and validated, such as the Motion Sickness Susceptibility Questionnaire-Short (MSSQ-Short) [264], and the Simplified SSQ [265]. The interested reader is referred to [43, 44, 40] for an in-depth review on cybersickness assessment in VR.

Table 2.3: List of commonly used cybersickness questionnaires for subjective IMEx assessment. VE stands for Virtual Environment, and CM represents Cross-Media.

Reference	Questionnaires	Subject	Subscale	Rating scale	Citations	Items	Media
[262]	Simulator Sickness Questionnaire (SSQ)	N/D	Nausea, Oculomotor, and Disorientation	4-point	4206	16	CM
[266]	Motion Sickness Assessment Questionnaire (MASQ)	310	Motion-sickness	9-point	297	16	CM
[264]	Motion Sickness Susceptibility Questionnaire-Short (MSSQ-Short)	257	Motion-sickness	4-point	273	18	VE
[263]	Fast Motion Sickness Scale (FMS)	126	Motion-sickness	0-20	277	1	VE
[41]	Virtual Reality Sickness Questionnaire (VRSQ)	24	Oculomotor, and Disorientation	4-point	212	9	VE
[267]	Misery Scale (MISC)	24	Motion-sickness	0-10	161	1	VE
[268]	Symptom Questionnaire	16	Motion-sickness	0-6	155	13	VE
[269]	Refactored SSQ	371	Nausea, and Oculomotor	4-point	140	16	VE
[265]	Simplified Simulator Sickness Questionnaire	158	Uneasiness, Visual Discomfort and Loss of Balance	5-point	2	9	CM

2.3.4 Questionnaires for affective/mental state monitoring

The word "experience" in the *user experience* expression implies that there is emotional involvement when users explore immersive media content. For example, users may feel happy, satisfied, frustrated, overjoyed, or disappointed by the experience. In general, emotional experiences can be characterized by three fundamental components: valence, arousal, and dominance. Valence refers to the degree of pleasantness associated with a stimulus, arousal denotes the intensity of the emotion elicited by a stimulus, and dominance indicates the extent of control exerted by a stimulus. The arousal-valence model is the most widely recognized framework for describing emotional states. In this model, each emotional state is positioned on a two-dimensional plane, with valence and arousal as the horizontal and vertical axes, respectively. Arousal ranges from inactive states, such as boredom and disinterest, to active states like alertness and excitement. Valence, on the other

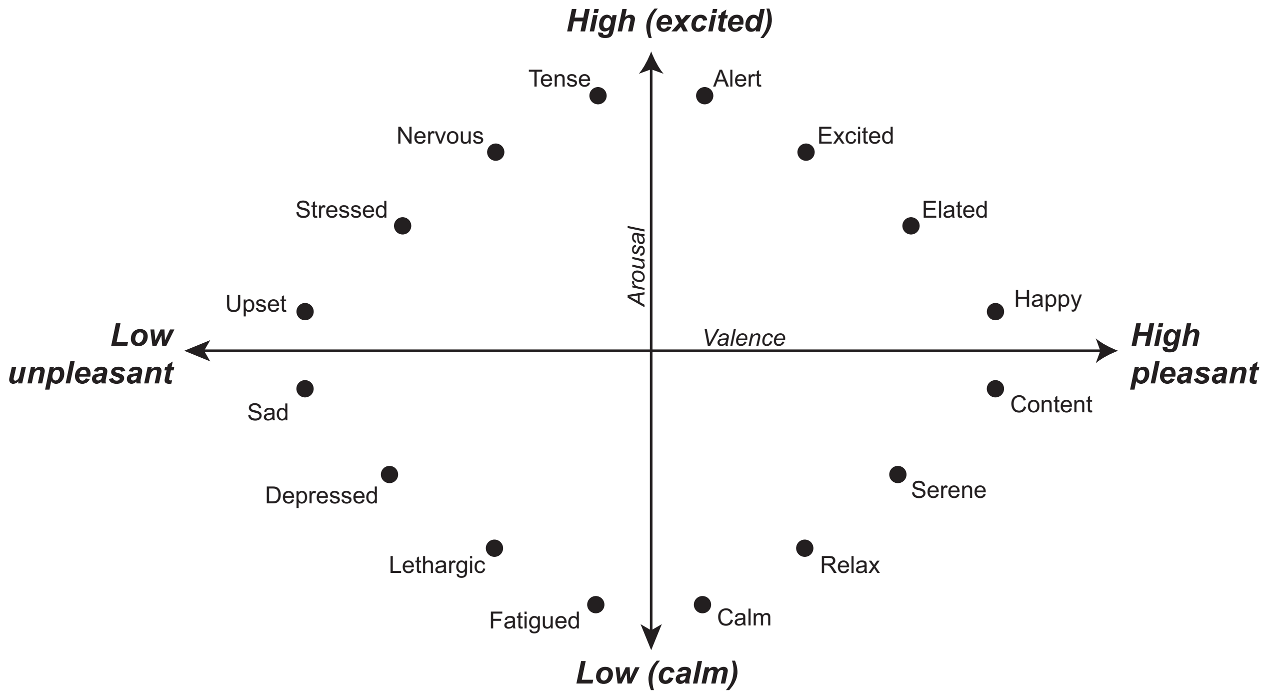


Figure 2.1: Mapping of emotions on the valence-arousal scale.

hand, spans from unpleasant emotions, like sadness and stress, to pleasant ones, such as happiness and elation. Figure 2.1 illustrates various emotions and their locations on this scale. While the majority of emotional variations can be explained using this two-dimensional plane, a third dimension, dominance, has been introduced. Dominance encompasses feelings from helplessness and weakness (lack of control) to empowerment and control over one's surroundings. The Self-Assessment Manikin (SAM) is typically employed to evaluate these three distinct dimensions [45]. The SAMs for valence, arousal, and dominance are shown in Fig.2.2. Graphical tools allow users to report their feelings efficiently and intuitively by indicating or rating the part of the figure that best represents their current affective state. Graphical self-report instruments are appealing for the measurement of affective experiences since they do not require the users to verbalize their emotions. Instead, they rely on the human ability to intuitively and reliably attribute emotional meaning to (simple) graphical elements. However, the user may not be able to easily interpret the pictorials and therefore may have difficulty identifying with them [46]. More recently, a variant was proposed based on emojis (e.g., smiling or frowning faces). Emojis are pictographs or ideograms representing emotions, concepts, and ideas. Emoji-based rating tools are increasingly becoming popular tools as self-report instruments to measure user and consumer experience. The EmojiGrid, for example, has been proposed as a self-report tool for the assessment of VR-evoked emotions [47]. The interested reader is referred to [48, 49, 50] for more details on user emotional/affective state assessment in VR.

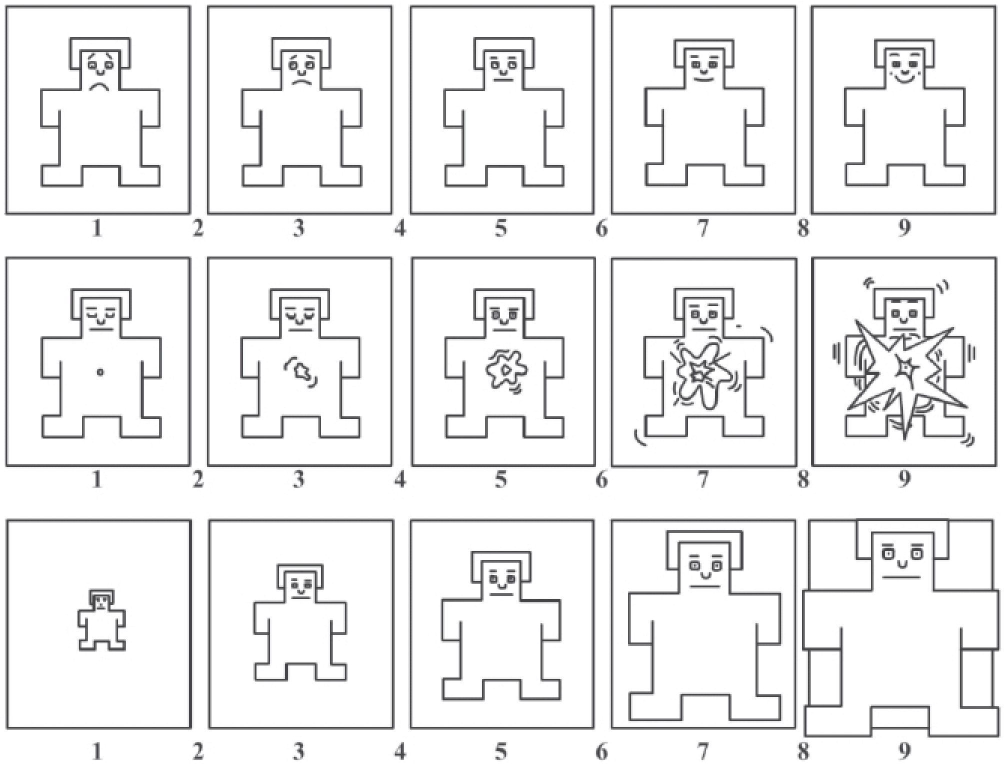


Figure 2.2: SAM illustrations for valence, arousal, and dominance dimensions (top to bottom).

2.4 Instrumental IMEx/HIFs Assessment

While subjective assessment methods aim to collect *qualitative* feedback from the users concerning their experiences, instrumental methods aim to measure them in a *quantitative* manner, thus allowing for easier replication and real-time (or quasi real-time) IMEx/HIFs monitoring. For example, behavioural measures can track the user's facial expressions, movements, and eye gaze to monitor user reactions without the need for conscious introspection. Psycho-physiological methods, in turn, can be used to measure correlates of experience factors, such as engagement, attention, and cybersickness, to name a few. Commonly, instrumental methods rely on ground-truth labels obtained via subjective methods in order to build accurate and reliable models. Once the models are built, however, subjective methods are no longer required and real-time assessment can be achieved. With advances in sensor technology and wearable devices, instrumental methods are burgeoning. In the sections to follow, we present the findings from a survey of the literature spanning the years of 2015-2021, with particular focus placed on psycho-physiological methods, as the existing literature lacks a survey in this aspect.

2.4.1 Behavioural methods

With behavioural methods, the main goal is to assess whether the participants behave in the virtual environment as they would under similar conditions in the physical environment. For example, are the user's physical movement and social interactions inline with those expected in the real world. Recent studies suggest that this can indeed be the case and participants can express verbal and bodily reactions in virtual reality in manners very similar to real situations [51]. Behaviors can provide subconscious cues about user experiences. A smile on one's face typically indicates good user experience, while touching the HMD could imply poor fit or discomfort, and sweating and nausea typically indicates signs of cybersickness. In [52], for example, statistics showed that almost 50% of subjects touched their HMD at least once, suggesting discomfort and reduced sense of immersion. Over 76% of the participants, in turn, smiled at least once during the experiment, suggesting a positive reaction to the virtual content. Finally, roughly 10% of the participants reported sweating and nausea symptoms, suggesting visual fatigue and signs of motion sickness. The next sections report the various methods in which researchers have proposed to measure behaviours and what they represent in terms of IMEx.

2.4.1.1 Facial expressions

Facial expressions can tell a lot about the current emotional state of the user. Moreover, real-time facial expression recognition can improve the realism of virtual avatars, which can play a key role in user experience [53]. Recently, facial EMGs were placed in a transparent adhesive plastic film identical in shape and size to the actual HMD and placed around the eyes prior to donning the HMD [54]. Such a system was used to recognize 11 different facial expressions and on a sample size of 42 participants, an average expression recognition rate of 85% was achieved with eight sensors.

2.4.1.2 Eye tracking

Eye tracking provides information not only on where the users are focusing their attention at any particular point in time, but also on pupil dilation, blink rates, and eye movements indicative of e.g., cybersickness. Indeed, increases in pupil size reflect arousal associated with increased sympathetic activity [55]. In [56], a stressful experiment was conducted and showed that pupil dilatation and heart rate changes showed differences with stress. Furthermore, eye blink rate has a close direct relationship with dopamine activity in the brain, hence could be related to valence [57]. Moreover, increased attention levels have been shown to reduce blink frequency [58], as have more positive affective states [55]. Eye gaze information has also been linked to concentration levels and sense of presence in immersive environments [59]. More recently, pupillometry (more specifically, pupil dilation) was used to assess cognitive load in VR with uncontrolled scene lighting [60].

Eye tracking is typically achieved with costly infrared cameras embedded into the HMD. Alternatively, in this thesis we propose to use EOG sensors embedded directly into the VR headset to track eye movements [61] and blink rates. Real-time knowledge of where the user is looking can also provide virtual environment developers cues about what captures users' attention, what elements were more calming or stressful, and can allow for adaptive systems to be developed to make experiences more realistic (e.g., have an avatar look at you when you look at them), hence maximizing IMEx. More recently, eye movement information has also been shown to correlate with cybersickness, where atypical eye movements were indicative of motion sickness [62].

2.4.1.3 Movements and gestures

Body and head movements, along with arm gestures can also be indicative of IMEx related factors. For example, the work in [63, 64] showed correlations between head movements and user reports of valence, arousal, and emotional states. The work in [270], in turn, showed that different types of head movements (i.e., rotations and left/right tilts) could affect cybersickness. Postural instability was also shown to predict the likelihood of cybersickness in [65] and constrained movement was shown to reduce the sense of presence [34]. Commonly, hand tracking and gesture recognition has relied on VR controllers equipped with sensors. More recently, camera based systems have emerged that have allowed for controller-free hand/arm gesture tracking. While intuitively one would expect the controller-free setting to be more realistic, hence improve the overall IMEx, a recent study showed that controller-based interactions in VR were less demanding for the participants and resulted in fewer errors, thus in an overall improved IMEx [66]. The authors attributed this finding to the camera-based technology still being in its infancy (hence, not very reliable) and the learning curve of the user's to a new technology. The interested reader is referred to [67] for an overview of gesture interactions in VR.

2.4.2 Psycho-physiological methods

Our bodies are an excellent canvas to convey our internal states. For example, our faces turn red when we are embarrassed, our heart rates go up when we are excited and/or stressed, our palms become sweaty when we are nervous or suffering from motion sickness, our heart rates and breathing rates synchronize when we are engaged. As biosensor technologies evolve and wearable devices become mainstream, psycho-physiological measurement has become a reality and has been incorporated into instrumental IMEx/HIFs assessment. In the sections to follow, we highlight methods that have been proposed in the literature over the last six years separated by biosensor modality. As the existing literature lacks a comprehensive survey of such instrumental methods, we aim to fill this gap.

2.4.2.1 Electrocardiogram and photoplethysmogram

Electrocardiogram (ECG) and photoplethysmogram (PPG) have become increasingly popular for studies in immersive virtual environments where a user's heart rate (HR) and heart rate variability (HRV) need to be measured. While an ECG records the electrical activity of the heart, a PPG measures blood volume changes using optical sensors that measure changes in light absorption. Both methods provide information about heart rate, with PPG being the most widely used modality in wearables, as sensors can be easily embedded into bracelets and watch form factors. In both methods, it is common for a so-called RR time series to be derived from the interbeat/interpulse intervals and HR/HRV analysis is typically done on this heart rate series signal. Figure 2.3 presents a visual representation of the RR interval in a heartbeat data sample.

HRV analysis can be done in the time and frequency domains, as well as with nonlinear methods. Time-domain parameters rely on statistics computed directly from the RR series, such as

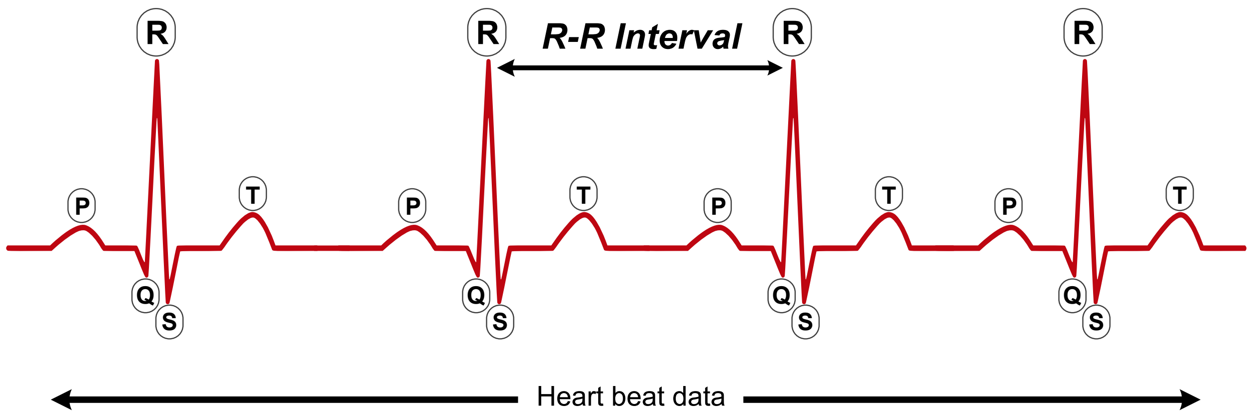


Figure 2.3: RR interval representation of a heartbeat data sample.

standard deviation over certain window sizes. Frequency domain methods, in turn, rely on the power spectral density (PSD) of the RR time series, computed either via nonparametric (e.g., fast Fourier transform) or parametric (e.g., autoregressive models) methods. The PSD is then divided into different frequency bands, such as very low frequency (VLF: 0-0.04 Hz), low frequency (LF: 0.04-0.15 Hz), and high frequency (HF: 0.15-0.4 Hz), as these have shown to represent different aspects of the sympathetic and parasympathetic autonomic nervous systems. Commonly, absolute, relative, or normalized powers in the VLF, LF and HF bands, as well as their ratios, have been used to characterize heart rate variability. Lastly, as the RR time series exhibits complex non-linear behavior, non-linear measures have also been explored [68].

Table 2.5 presents a list of studies that have relied on HR and HRV measures to quantify different aspects of IMEx. As can be seen, measurement of stress is one of the leading aims. Dependent on the difficulty level of the game or the stressful sequences, an increase of HR is commonly observed [69, 70]. Moreover, a significant correlation between the valence emotional primitive and HRV has been demonstrated [71, 72]. An increase in HR was also seen during the last minutes when the user reported motion sickness [73]. The majority of the devices used were wearables-based, thus allowing the user to move during the immersive VR experience. It should also be noted that in the majority of the cases, multimodal systems were utilized, with HR/HRV coupled with other modalities; EDA being the most prevalent [74, 75, 76, 70, 77, 78, 79, 71, 80]. The next sub-section is dedicated to the measurement IMEx correlates from the EDA.

2.4.2.2 Electrodermal activity

EDA, also known as galvanic skin response (GSR), measures the variation of the electrical conductance of the skin in response to sweat secretion. In the past, EDA has been associated with various aspects of psychological functioning, such as mechanisms underlying attention, information processing, emotion and stress. Several methods can be used to measure EDA, but a typical procedure consists of applying a constant voltage between two electrodes (commonly placed on the fingers, but also possible in other parts of the body, such as wrists and feet) to record conductivity variations, expressed in microsiemens (μS). Three types of electrodermal measures are commonly used [81]: skin conductance level (SCL), representing a baseline measure of electrodermal conductance; nonspecific skin conductance responses (NS-SCRs), representing the frequency of spontaneous and momentarily changes in conductance, which are independent of external stimuli; and skin conductance responses (SCRs), which are momentary changes, similar to the NS-SCRs, but specifically elicited by external stimuli.

Table 2.6 lists the works that have relied on EDA signals for IMEx-related assessment. As can be seen, SCL peaks and amplitudes (and statistical measures over time) have been used to assess user experience, presence, and emotions. In particular, high sense of presence has shown to result in significantly more EDA peaks per minute than environment eliciting lower sense of presence [82]. Moreover, slow and steady increases in SCR have been shown to be correlated with cognitive activity [79]. EDA can also be attributed to an increase in mental workload or stress, as well as as significantly positively correlated with arousal states [55]. Lastly, during cybersickness events, researchers were able to observe a positive relationship between EDA responses and high jerk effects [76].

2.4.2.3 Electroencephalograms

Electroencephalograms (EEG) measure electrical activity of the cortex using electrodes placed on the scalp. EEGs can be used to measure (cortical) neural activity in different parts of the brain, as well as connectivity patterns between different brain regions, which could be indicative of different affective states [83]. In fact, so-called affective EEG brain-computer interfaces have been used to model human influential factors for speech QoE modeling [84].

Table 2.4: Identification of electrodes

Letter	Brain Area
A	Auricular
AF	Anterio-Frontal
C	Central
CP	Parieto-central
F	Frontal
FC	Fronto-central
FT	Fronto-temporal
Fp	Frontopolar
Iz	Inion
Nz	Nasion
O	Occipital
P	Parietal
PO	Parieto-occipital
T	Temporal
Z	Midline

The international 10-20 sensor placement system has been developed to ensure accurate and consistent electrode placement across individuals and studies. Although the original system consists of 21 electrodes, it can be extended to include up to 64 electrodes or more, providing higher spatial resolution and more detailed measurements. Each electrode position is identified by a combination of letters and numbers. The letters represent the brain area in which the electrode is located (see Table 2.4for electrode identification), while the numbers indicate whether the electrode is on the left (odd numbers) or right (even numbers) side of the head. For example, “F3” would represent an electrode positioned in the frontal area on the left side, and “T4” would indicate an electrode in the temporal area on the right side.

The spatial representation of the EEG channels according to the international 10-20 system can be visualized in Figure 2.4. This figure illustrates the arrangement of the electrodes on the scalp, allowing for a better understanding of the brain regions being measured and the connectivity patterns that can be analyzed with EEG. The flexibility of the 10-20 system to accommodate a varying number of electrodes enables researchers and clinicians to tailor their EEG setups to specific study requirements and obtain more comprehensive data on brain activity.

In the context of EEGs, different types of brain waves have been described and represented based on what frequency range they are in and what amplitude levels that have, thus helping characterize

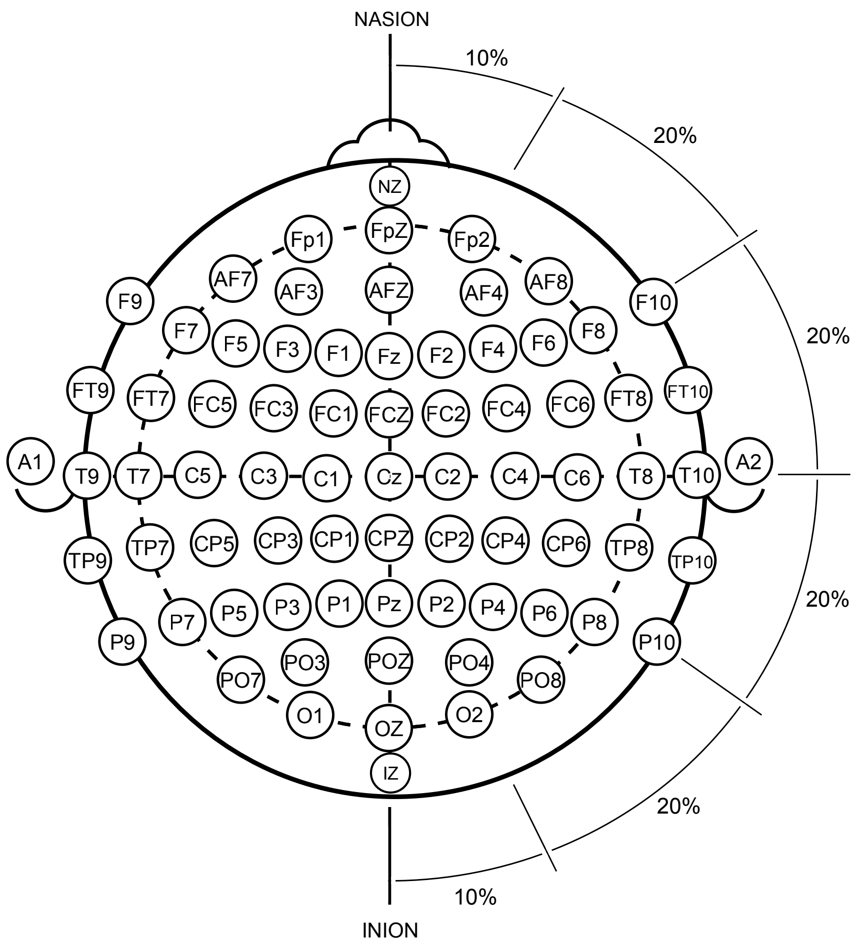


Figure 2.4: The international 10-20 system for EEG electrode placement.

the roles they play in various cognitive processes and mental states. The main brain wave categories are:

- Delta waves (δ; 0.5–4 Hz): These slow waves have the highest amplitude, typically ranging from 20 to 200 µV. They are predominant during deep sleep and are essential for restorative sleep and the processing of subconscious information. Delta waves are also associated with healing and regeneration processes.

- Theta waves (θ; 4–8 Hz): With amplitudes between 5 and 100 µV, theta waves are typically observed during light sleep, meditation, and drowsiness. They are associated with creativity, intuition, and the integration of emotional experiences. Theta waves are also linked to memory consolidation and the processing of complex information.

- Alpha waves (α; 8–12 Hz): Present during relaxed wakefulness, alpha waves have amplitudes of 20 to 60 µV and are an indicator of a calm and relaxed state of mind. They are associated with focused attention, enhanced creativity, and reduced anxiety. Alpha waves are often considered a bridge between the conscious and subconscious mind.

- Beta waves (β; 12–30 Hz): These faster waves have amplitudes between 2 and 20 µV and are prevalent during active thinking, problem-solving, and focused concentration. Beta waves are associated with alertness, logical thinking, and decision-making. However, excessive beta activity can lead to stress, anxiety, and restlessness.

- Gamma waves (γ; 30–45 Hz): The fastest brain waves, gamma waves have the smallest amplitude, typically around 1 to 5 µV. They are associated with higher cognitive functions such as perception, learning, and information processing. Gamma waves are thought to facilitate the integration of information across different brain regions, enabling complex cognitive tasks and heightened awareness.

In recent years, several studies have explored the use of EEG for IMEx-related research. Tables 2.7 and 2.8, for example, list studies that have used different EEG features as correlates of IMEx parameters and cybersickness, in particular, respectively. As can be seen, event-related potential (ERP), ratio between the event-related desynchronization (ERD) and event-related synchronization (ERS), and statistical features such as the mean, the power of all frequency bands, and even the standard deviation of the EEG time series have been explored. EEG electrodes are typically positioned in the frontal, parietal, central, occipital, and temporal areas. Researchers have observed strong significant correlations between the subjective experience of presence and i) the N1 ERP component (a large negative peak occurring roughly 80-120ms post visual stimulus presentation) and ii) the mismatch negativity (MMN), an ERP component resulting from the presentation of an odd stimulus in a sequence of stimuli, regardless of whether the subject is paying attention to the sequence or not [82]. Moreover, the total band power in the frontal and frontal-left regions decreased with sense of presence and relative beta and delta powers increased in temporal and temporal right regions, respectively [75].

EEGs have also been used to measure arousal states while in VR, especially via the use of the so-called frontal alpha asymmetry (FAA) index [271]. Alpha power changes were also seen with changes in attention levels in a target-response paradigm [272, 273]. Moreover, the ratios of theta, alpha and beta were used to assess alertness levels [274]. In [71], in turn, a fearful experiment showed significant correlations between arousal and the higher end of the gamma band powers and between arousal and (lower end) beta band power; the sensation of fear was shown to be correlated with the power in the lower end of the gamma band. In turn, dominance was shown to be correlated with theta band power. When fear was not induced valence, arousal, and dominance levels showed some correlations but only with the higher end of the gamma frequency band. Correlates of engagement in VR have also been proposed and they typically correspond to the ratio of the beta frequency band power to the combined power in the alpha and theta ranges [275, 276]. Lastly, the measurement of cybersickness using EEG has been proposed recently and deep neural network classifiers have been explored [85]. A sickness index relying on alpha, theta, and beta frequency subbands showed to achieved 84% in detecting cybersickness [86, 87].

Table 2.5: **List of works relying on HR/HRV measurement for user IMEx assessment.**

Ref.	Sub.	Device	Measurement	Processing	Results	Questionnaire
[69]	21	AliveCor Kardia	Engagement, Concentration, Stress, Relaxation, and Emotion	HR	A low HR for Relaxation, an elevated HR for concentration, and an increase of HR during stress	PQ, and SUS
[277]	60	MP30 from Biopac System	Stress	Average of LF/HF ratio	Significant differences in the average ratios of LF/HF, as a function of plan configuration	N/A
[74]	18	e-Health Sensor Platform V2.0	QoE in terms of Quality, Frame-rate and Texture	Statistical features from HR: mean, min, max, median, std;	For Quality, no impact on the physiological responses	ACR, and SSQ
[75]	20	E4 from Empatica	Presence	Statistical features from HR: mean, LF, HF;	ECG features did not significantly vary between the presence and lack of factors of presence	PQ
[76]	33	g.USBamp and g.TRIGbox from g.tec	Mental immersion	Mean HR, and HRV;	HRV turned out to be significantly affected by network condition. Significant relationships between HRV and IEQ and gaming QoE	IEQ, Gaming QoE, and Video quality
[276]	10	Polar H10	User Experience	HRV, Time elapsed between two successive R-waves of the QRS signal (R-to-R interval), HF, LF, and VLF	HR and HRV are significantly different during resting once compared with the easy, medium, and hard difficulties	SSQ, Simulation performance, and Post-session interview

[77]	24	E4 from Empatica	Emotional responses	Mean HR, and std HR, root square of R-to-R, LF, and HF;	Higher classification accuracy of cognitive load against the HR data of 82.78%	N/A
[70]	24	ProComp Infinity from T&T	Gaming experience	Mean HR, and LF/HF ratio	all considered measures reported statistically significant increases due to playing in VR,	Demographics, System Usability Score, Visual Analogue Scale; SUS PQ
[78]	49	Brainproducts V-AMP 16	Fear effect on presence	Mean HR	Physiological responses in virtual heights leads to higher presence	Acrophobia Questionnaire, State-trait Anxiety Inventory, SSQ, MEC spatial, and PQ
[278]	33	E4 from Empatica	Influence of jerk on cybersickness	Inter-beat interval; HR	Lower HR with a high jerk effect. Correlation betweem HRs during collision periods and SS scores	IPQ, System Usability Scale, NASA task load assessment, SAM, and SSQ

[79]	600	Fitbit Charge	QoE	HR	A minor increase is noted in the tablet group as the mean HR increases by 1.8% over the test duration. The VR group experienced a slightly larger increase of 3.33%. Lastly, the AR group experienced the highest increase of 5.7%	Post-Test Questionnaire; video quality, audio quality, and audiovisual quality Questionnaire
[71]	24	Fitbit Charge	Emotions	Variation of HR and median for HR	Significant correlation between valence and variation of HR	Pre-test questionnaire, User Engagement Scale (UES), and SAM
[72]	13	BiosignalsPlux Explorer	Emotions	Mean HR, Mean RR	High emotional levels of valence and exaltation (SAM)	Self-assessment Manikin
[279]		BIOPAC's MP150	Emotions	HRV, RR standard interval of the normal sinus of the human body, standard deviation of the difference between adjacent RR intervals	Mean and interval standard deviations of HR were equally significant in 2D and VR environments	SAM, Positive and Negative Affect Schedule, and SSQ
[73]	56	Biopac wireless sensors	Cybersickness	HF of HRV	augmentation of HF during the last minute	MSSQ
[80]	31	Zephyr OmniSense HR	SSQ			

Table 2.6: List of works relying on EDA measurement for user IMEx assessment.

Ref.	Sub.	Device	Measurement	Processing	Results	Questionnaire
[74]	18	e-Health Sensor Platform V2.0 for Arduino and Raspberry Pi	QoE in terms of Quality, Frame-rate and Texture	Peaks detection	For quality: no impact on the physiological responses	ACR, and SSQ
[75]	20	E4 from Empatica	Presence	Tonic and phasic decomposition	EDA features did not significantly vary between the presence and lack of factors of presence	PQ
[76]	30	g.USBamp, g.TRIGbox from g.tec hardware	Mental immersion	Peaks and amplitude in Skin Conductivity	No significantly effect of network condition and screen size on skin conductivity	IEQ, Gaming QoE, and Video quality
[77]	24	E4 from Empatica	Emotional responses	Mean, std, peak, strong peak, 20th percentile, 80th percentile, quartile deviation	EDA classification has returned low accuracy	N/D
[70]	24	ProComp Infinity from T&T	Gaming experience	Skin conductance response (SCR)	Effect size revealed a large SCR	Demographics, System Usability Score, Visual Analogue Scale; SUS, and PQ

[78]	49	Brainproducts	Fear effect on presence	SCL	Physiological responses in virtual heights leads to higher presence	Acrophobia Questionnaire, State-trait Anxiety Inventory, SSQ, MEC spatial, and PQ
[278]	33	E4 from Empatica	Influence of jerk on cybersickness	Amplitude of SCR	Positive EDA responses with a high jerk effect	IPQ, System Usability Scale, NASA task load assessment, SAM, and SSQ
[79]	600	Pip Biosensor	QoE	SCL	Slow and steady increase in SCR can be correlated with an increase in cognitive activity, EDA can be attributed to an increase in mental workload or stress	Post-Test Questionnaire; video quality, audio quality and audiovisual quality Questionnaire
[55]	18	Shimmer3 Consensys	Determining affective responses	Skin conductance	Conductivity is significantly positively correlated with Arousal	Physical Activity Readiness Questionnaire (PAR-Q)
[82]	34	Shimmer3	Presence in video games	EDA amplitude and peak	High presence group had significant more EDA peaks/min than the low presence group	Demographics, MPS, SAM, and Emotional experiences questionnaire

[71]	24	N/D	Emotions	Median and its variation	Fear situation: arousal is correlated with median of EDA	Pre-test questionnaire, UES, SAM
[80]	31	NeuLog EDA	Cybersickness	Average, percentage of change, min, and max of EDA	CNN-LSTM model can detect and predict cybersickness only the last two minutes of data with an accuracy of 97.44% and 87.38%	SSQ

In order to better understand the role of each brain region shown to correlate with sense of presence, some researchers have relied on functional magnetic resonance imaging or functional near-infrared spectroscopy to get a snapshot of which brain regions become active while in VR. In [280], for example, frontal, parietal and occipital regions showed involvement during free virtual navigation and activation in the dorsolateral prefrontal cortex was shown to be negatively correlated to sense of presence, hence corroborating some of the EEG findings. In turn, brain regions responsible for balance and vestibular (located in the cerebellum) inputs were shown to be active during cybersickness events [281].

2.4.2.4 Multiple-sensorial media applications

The majority of current applications stimulate only one (visual) or two senses (audio-visual). As the tactile Internet and Internet of Senses revolutions emerge, additional senses will be stimulated, including olfactory and somatosensory. Such media has been termed multiple-sensorial media, or mulsemedia, and within a VR framework, could lead to next-generation immersive systems with increased sense of realism and immersion [88, 89]. For example, inclusion of smells [90, 91] and haptics [92] have shown to improve sense of immersion. Haptics can be used to provide the user with cues about physical characteristics of an object (e.g., weight or texture) hence increase sense of realism [93, 94]. Vibrotactile feedback, in turn, provides feedback when interacting with virtual devices [95], thus also improving the sense of realism [96]. Table 2.9 lists some of the emerging work on mulsemedia QoE assessment via psycho-physiological methods. As an example, when using haptic gloves, a strong amplitude modulation or ERP signals occurred when the participants selected virtual objects and significant changes in the early negativity component of the ERP was seen during situations with haptic conflicts [97]. Moreover, while addition of olfactory stimuli showed a significant increase in sense of presence, it did not generate significant changes in EDA [98], hence suggesting that alternate modalities may be needed. It is important to emphasize that while our search period encompassed papers from 2015-2021, a great number of works in the mulsemedia domain appeared prior to 2015. The interested reader could refer to [99] for a detailed review of mulsemedia systems proposed prior to 2015.

2.5 Discussion

Monitoring of human behaviour and psycho-physiological signals while immersed in virtual reality will allow models of human influential factors to be built, including to e.g., detect and even predict cybersickness, monitor the user's perception of immersion and sense of presence, as well as overall immersive media experience. Ultimately, this information will allow for virtual environments and applications to be adjusted per user, thus maximizing the user experience. As emphasized by [100], the success or failure of any system for immersive communication will rely on the user experience that it provides and not necessarily on the technology it uses. Building IMEx systems that take into account system, context, and human influential factors will be crucial for the development of the field.

Today, the most widely used measure of user IMEx remains subjective assessment. While subjective assessment can directly target specific IMEx dimensions (e.g., presence, immersion, cybersickness) with high validity, it requires offline evaluation, can be biased by subject responses [101], can be disruptive to the user experience with constant prompts, which, in turn, can increase the user's cognitive load and indirectly affect the experience. Disruptions to answer subjective questionnaires can break the immersive experience and studies have reported that it can take some time before the sense of immersion is recovered post interruption [102]. Moreover, while VR-based questionnaires have been developed to replace paper-and-pencil ones (e.g., [20, 21]), their validity over time has yet to be confirmed. Future studies should explore this.

Furthermore, it is known that VR sickness drastically hampers IMEx. Studies have reported that women and children are more susceptible to cybersickness than men [103, 104], mostly due to a poor fit of their interpupillary distance to the VR headset [282]. More recently, an effect of smoking has also been reported [105]. While exposure and habituation to VR can drastically reduce the prevalence and severity of cybersickness symptoms [107], especially over multiple sessions [108], getting through the first 20 minutes is crucial [109]. As such, being able to predict cybersickness at the beginning of a VR session could allow for mitigation strategies to be put in place "on the fly", such as bringing in additional sensory modalities [106], hence improving the overall IMEx. Psycho-physiological measures are crucial for such real-time cybersickness evaluation. As shown here, however, only few works exist that have focused on cybersickness prediction, hence there is ample room for research. In particular, the methods relying on EEG signals have mostly used standalone EEG systems worn under the VR headset. This could lead to discomfort, hence indirectly affecting the IMEx. Future works should explore tools with sensors directly embedded into the VR headset. Moreover, the developed tools have mostly relied on deep neural networks, which could be power and storage hungry [283, 284], thus not suitable for untethered applications in which the user is truly mobile. As such, future work should explore the use of feature engineering to find more robust features that can be coupled with simpler machine learning algorithms, as shown in [285].

As 5G and 6G wireless communications become more widespread, truly portable VR applications are emerging where the user is completely mobile and untethered to a computer [110]. Movement is known to generate artifacts that affect psycho-physiological signal quality and hamper human influential factors assessment. Existing enhancement algorithms, however, especially those developed for EEG signals, have not been tailored to such artifacts [111], hence new algorithms and movement artifact robust features will need to be developed. Adaptive systems are already starting to emerge (e.g., [112]) but further work is needed. Moreover, multimodal systems have shown to be useful in such mobile conditions where multiple signal modalities can account for certain confounding factors (e.g., fatigue on HRV) [113], but such systems within a portable immersive application are still needed to learn what confounding factors exist within an IMEx (e.g., how does fatigue effects on HRV affect the presence-related HRV features?). Future work should focus on better understanding these confounds.

And as wireless communication bandwidths and coverage increase, and latency decreases, future generation technologies, such as the tactile internet [114] or the Internet of Senses [115] will become the mainstream. In such scenarios, multiple senses will be stimulated, including olfactory, taste, and somatosensory systems, hence drastically improving the IMEx. As highlighted in [106], smells have already been explored and shown to reduce cybersickness symptoms, as have pleasant songs. Haptic feedback, in the form of vibrations and airflow time-aligned with visual cues, have also helped increase overall experience. The effect that such multisensory stimuli has on behavioural and psycho-physiological signals is still not well understood and only a few works have explored this direction (see Table 2.9). Future work should focus on multi-sensorial media and the overall impact it has on IMEx, including possible timing mismatch between different modalities.

Lastly, as highlighted by [7], IMEx is multi-faceted. Most of the works surveyed have touched only one or a few of the influential factors, hence only show a snapshot of what can be achieved with IMEx assessment. 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 [116]. Future studies should explore the use of behavioural and psycho-physiological metrics to measure each of these components and measure their individual contributions to overall IMEx. Initial steps in this direction have been taken for speech (e.g., [84]), image [117], and video applications [118] where more than one influential factor has been explored and combined. Limited work exists, however, with immersive and mulsemedia applications.

Table 2.7: List of works relying on EEG measurement for user IMEx assessment (excluding cybersickness).

Ref.	Sub.	Device	Electrode location	Measurement	Processing	Results	Questionnaire
[271]	36	8 channels LXE5208	Fp1, Fp2, F3, F4	Presence on affective responses and attitude	Arousal = Absolute β wave during stimulus - Absolute β wave during rest; level of arousal: Band-to-band β power	Increase in presence positively affected physiological arousal. Significantly higher arousal and attitude towards luge	N/D
[82]	34	Advanced Brain Monitoring	Fz, F3, F4, Cz, C3, C4, POz, P3 and P4	Presence in video games	ERPv	Strong significant correlation between the subjective experience of presence and the early ERP components of N1 and MMN	Demographics, MPS, SAM, and Emotional experiences questionnaire
[275]	25	Mindwave	Fp1	Patient engagement	Banpowers; Engagement index: absolute power of $\beta/(\alpha+\theta)$	θ power in simulation conditions correlated with PQ scores to measure engagement an Increase of θ power and a decrease in α power	PQ
[276]	10	Biocybernetic Loop Engine	TP9, Fp1, Fp2, and TP10	Stress level	Absolute bandpowers; Engagement index; Frontal asymmetry index	Frontal θ values were significantly different between easy and hard difficulty levels	SSQ, Simulation performance, and Post-session interview

[69]	21	MyndPlay BrainBand	Fp1	User engagement, Concentration, Stress, Relaxation, and Level of emotion	Mean α, β, and θ	An elevated θ level and reduced α level for stress, and an elevated α level for relaxation, an elevated β level for concentration/focus,	PQ, and SUS
[286]	12	BrainVision 32 channel amplifier system	Fp1/2, F7/8, F3/4, Fz, FT7/8, FC3/4, T7/8, C3/4, Cz, TP7/8, CP3/4, CPz, P7/8, P3/4,Pz, O1/2, Oz and referenced to FCz	Spatial Presence	Eye blinks and muscles artefacts removal. Power of the α band. (ERD/ERS) = [(band-power reference x band power test)/(band power reference)] x 100.	Strong spatial presence experiences are associated with increased ERD (cortical activity) in parietal/occipital areas of the brain together with decreased activity in frontal structures	Annett handedness questionnaire, and MEC-SPQ

[71]	24	N/D	N/D	Emotions	Median for all EEG bands	With Fear case: significant correlation between arousal and high γ and low β band and sensation of fear with with low γ band. Dominance is correlated with θ band. No fear case: user's valence, arousal, and dominance, all of them with High-Gamma band	Pre-test questionnaire, UES, and SAM
[75]	20	g.HIamp amplifier with the g.GAMMAcap2 EEG cap and g.SCARABEO active electrodes	F3, F4, T7, C3, C4, T8, P3, P4, PO7, PO8	Presence	Mean of EEG signal, Std of EEG signal, Signal power all frequency bands, Asymmetry index	band power in the frontal and frontalleft regions were decreased. The relative β and δ powers shows a significant increase in temporal and temporal right regions respectively	PQ

[287]	15	Neuroelectrics Enobio 32 using 8 gel-based AgCl electrodes	Fpz, F3, F4, Fz, P3, P4, Pz, Oz	Presence, Engagement, and Immersion	α and θ band power in frontal and parietal EEG	Increased α and θ band power following the VR exposure, θ band power significantly higher compare to baseline, α power increase reached statistical significance in the initial phase	NASA-TLX, and VR UX

Table 2.8: List of works relying on EEG measurement for cybersickness assessment.

Ref.	Sub.	Device	Electrode location	Measurement	Processing	Results	Questionnaire
[85]	130	Neurosky Mindwave Mobile	Fp1	Cybersikness	Low α, high α, low β, high β, θ, δ, low γ, and high γ waves, sickness detection including attention and meditation, and the sickness index: $\frac{\sum\alpha+\sum\theta}{\sum\beta}$ as input of binary LSTM network	Around 84% of accuracy for a window of 1, 5, and 10 mins	N/A
[283]	25	Emotiv Epoc+	AF3, F7, F3, FC5, T7, P7, O1, O2, P8, T8, FC6, F4, F8, AF4	Cybersickness	Image generation process of EEG data for an input to the CNN and DNN algorithms	Both algorithms gave 98% accuracy	N/A
[284]	202	N/D	Fp1, Fp2, F3, F4, T3, T4, P3, P4	Cybersickness	Inter-correlation of the EEG channels and intra-correlation over the spectral and temporal information in each spectrogram as an input to a CNN	87% accuracy	SSQ

[288]	44	Emotiv Epoc EEG	AF3, AF4, F3, F4, F7, F8, FC5, FC6, T7, T8, P7, P8, O1, O2	Cybersickness	EEG spectral power	Increase in spectral power, with respect to a baseline recording, is indicative of the onset of cybersickness	SSQ
[87]	18	OpenBCI system	FP1, FP2, C3, C4, P3, P4, O1 and O2	Cybersickness	Wavelet packet transform for EEG rhythm energy ratios of δ, θ, α and β	The average cybersickness recognition accuracy for single subject reaches 92.85%, and the cybersickness recognition accuracy to 18 subjects is also up to 79.25%	N/A
[86]	28	64-channel cap from AntNeuro	64-channel	Cybersickness	Relative power of each frequency band	Beta and LG showed significance only for the individuals suffering from headache, fullness of head, and blurred vision, while no other significances were found for an EEG parameter	MSSQ

Table 2.9: List of works using psycho-physiological measurements to assess QoE of immersive mulsemedia applications.

Ref.	Sub.	Modality	Sense	Device	Measurement	Processing	Results	Questionnaire
[289]	27	ECG, EDA	Olfactory, Haptics, Thermal, Wind	Ambiotherm	Presence	HR, and SCL	A rise in HR was observed at the onset of the different wind/thermal stimuli and towards the end of the olfactory stimuli. Higher EDA values, which represent high arousal, have been noted to correlate with Negative Affect	Game experience Q, and PQ
[98]	60	EDA	Olfactory	Mindware MW3000A, Dreamreapers Inc.	Augment the exposure therapy process	Event related SCR	Olfactory stimuli increase presence but not EDA	IPQ, Quick Smell Identification Test, State-Trait Anxiety Inventory, Immersive Tendencies Questionnaire, Presence Visual-Analogue Scale
[97]	11	EEG	Haptics gloves	Model308-100, Brain-Products 64 chan	Detect conflicts in visuo-haptic sensory integration	ERPs	Strong amplitude modulation occurring when selection of objects; The early negativity component of the ERP is more pronounced during situations with haptic conflicts	N/A

2.6 Conclusion

This chapter presented the background of IMEx assessment with a focus on human influential factors. First, the various assessment methods, including subjective, behavioral, and psychophysiological measures, were discussed, highlighting their latest trends, innovations, and limitations. Next, we delved into next-generation applications that incorporate multiple sensory modalities to enhance the realism and immersion of virtual environments. Finally, we engaged in a brief discussion regarding the limitations identified throughout our review of the literature, outlining areas for future research and potential improvements in the assessment of IMEx and human influential factors. Overall, this chapter provides a comprehensive overview of the current state of the art, laying the foundation for further research and development in this rapidly evolving field, thus setting the foundations for this thesis work.

Chapter 3

Instrumenting a VR headset for quantitative HIF monitoring

3.1 Preamble

This Chapter is compiled from material extracted from the manuscripts published in the journal *IEEE Systems, Man, & Cybernetics Magazine* [201], and *Frontiers in Virtual Reality* [203], and in the conferences *Applied Human Factors and Ergonomics Conference (AHFE 2022)* [177], and *2022 14th International Conference on Quality of Multimedia Experience (QoMEX)* [206]. As the second author in [201], my role involved designing the initial version of the instrumented headset based on the Oculus Development Kit 2, participating in data recording sessions with participants, and contributing to the signal analysis.

3.2 Introduction

Over the last decade, advances in computational power, computer graphics, and sensors have brought to the market a diverse array of consumer-grade HMD for VR applications. Representative examples include the Meta Quest Pro, HTC Vive Pro 2, and PlayStation VR 2, among others [290]. These devices have brought immersive applications to the general public. Moreover, the near future of VR applications looks promising with the arrival of improved real-time tracking due to the use of cameras on the HMDs, as well as standalone HMDs such as the Oculus Quest [290]. In addition to gaming applications aimed at the mass market, VR applications are also burgeoning in rehabilitation [291], medical training [292, 293], education [294], work training [295], and to treat different disorders and phobias [296].

However, despite advances in hardware and software, VR applications have not yet achieved fully credible simulations of real experiences [297]. Users often experience challenges such as limited immersion or presence and cybersickness affecting between 30%-80% of users [297]. QoE is a complex concept related to three groups of influential factors: technological, contextual, and human [298]. As highlighted in Chapter 2, traditional subjective testing for measuring human perception in VR has its limitations. Recent research has shifted focus on biosensors technologies for characterizing users' cognitive states based on physiological signals. These interfaces have been used to measure various cognitive states, advancing VR applications and providing a more comprehensive understanding of cognitive process [299].

Recently, VR applications have started emerging within healthcare [300], neurorehabilitation [301], and educational programs [302], to name a few domains. In such scenarios, it is hard to gauge the effectiveness of such interventions in an objective, quantitative manner and subjective behavioural assessments or short/long-term outcomes are typically monitored (e.g., [303, 304]). Within such scenarios, physiological signals may also play a key role and could provide not only real-time feedback on e.g., student engagement [305] or stroke recovery [306], but also enable neurofeedback-based immersive applications [307].

As discussed in Chapter 2, various modalities monitor users' affective states in immersive environments. Although EEG provides accurate measures, it presents challenges such as complex setup and restricted mobility, particularly affecting mobile VR applications.

This Chapter presents the development, evaluation, and application of an instrumented VR headset with a focus on measuring HIFs using an integrated, wireless biomaplifier. The first part of this Chapter details the development of the headset, illustrating its evolution through various generations, and the incorporation of different sensors, including EEG, ECG, EOG, and facial EMG. It then delves into the signal pre-processing techniques, emphasizing the importance of accurate data acquisition and real-time feedback for mobile VR applications. The second part of the Chapter focuses on the feature extraction modules used as correlates of different HIFs, including benchmark features widely used in the literature. Finally, the Chapter showcases the validation of each of the four signal modalities (i.e., EEG, EOG, ECG, and EMG) and highlights potential use cases for these signals, such as eye movement tracking and real-time feedback during mobile VR applications. By providing an extensive overview of the instrumented VR headset and its potential applications, this Chapter demonstrates the potential of biosensor-embedded headsets in advancing VR applications by offering insights into the creation of objective outcome measures for different VR-based applications. This integrated HMD system aims to enhance the understanding of HIFs in immersive environments and to foster the development of next-generation immersive applications across multiple domains.

3.3 Instrumented HMD development

The developed instrumented HMD is comprised of three main parts: (i) a portable, wireless biopotential amplifier module to measure, record and transmit the physiological signals, (ii) an HMD-based VR system, and (iii) dry electrodes for the sensing of physiological potentials. With the aim of fostering reproducibility, off-the-shelf components were used with minimal modifications needed. The following subsections present these three parts in more detail.

3.3.1 Biopotential amplifier module

In order to enable practical mobile applications, the biopotential amplifier module needed to be suitable for acquiring different physiological modalities, portable, low-cost, light and have wireless communication capability. Given these requirements, we selected the OpenBCI Cyton board (comprised by eight fully-differential, independently programmable and high gain, low noise input channels), along with its optional Daisy board which provides eight extra input channels[1]. The analog front-end in both boards is the TI ADS1299 analog-to-digital converter for biopotentials, which is designed for multiple modalities such as ECG, EOG, EEG, EMG. The OpenBCI hardware has been shown to be an acceptable alternative to traditional research EEG amplifiers [119].

[1] https://shop.openbci.com/collections/frontpage/products/cyton-daisy-biosensing-boards-16-channel

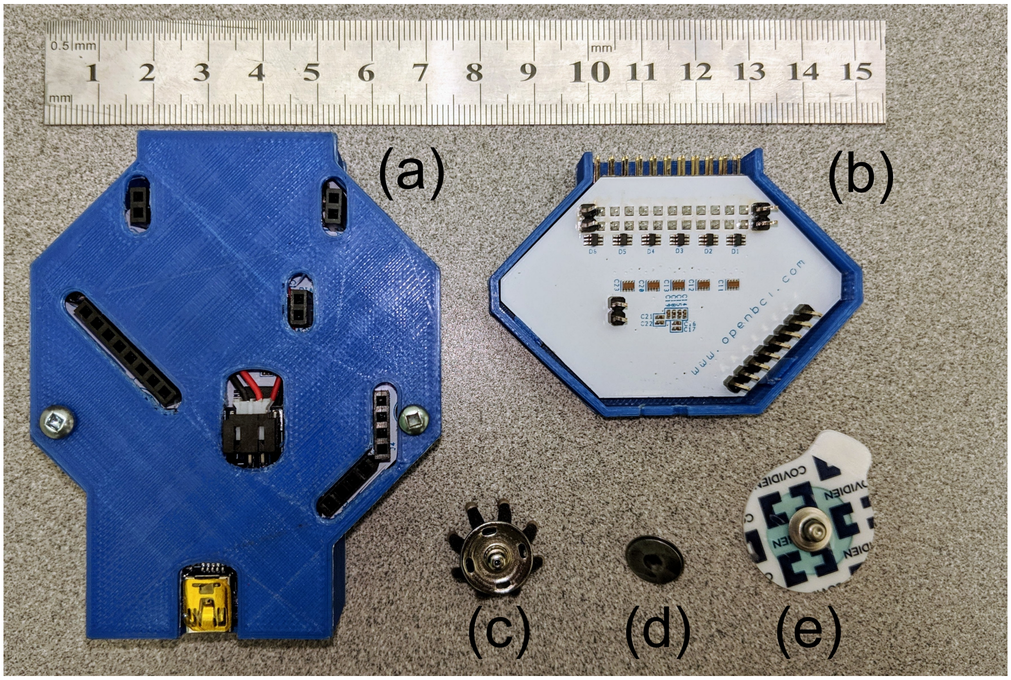


Figure 3.1: Biopotential amplifier module and electrodes: (a) case for OpenBCI cyton, battery and charger; (b) case for daisy board; (c) dry flexible electrode; (d) dry flat electrode; (e) disposable electrode.

Snap-ended cables[2] were used to support a great variety of standard electrodes. To power the OpenBCI boards, we used a 1000 mA @ 3.7 V Lithium polymer battery; the capacity of the battery was calculated to last 12 hours. Finally, the OpenBCI boards and the battery, as well as a USB charger[3] were placed in a custom designed, 3D printed case to host and protect the electronic components. To keep the modularity aspect of the OpenBCI boards, the case was divided into two parts. One part encloses the OpenBCI Cyton board along with the battery and charger (Fig. 3.1a), thus it can be used alone if only 8 channels are required. In turn, the second part hosts the Daisy board (Fig. 3.1b). The 3D model of the case has been made available online[4] to facilitate reproduction. Features of the OpenBCI biopotential amplifier include:

- Single amplifier for multiple physiological modalities: EEG, ECG, EOG and EMG
- Wireless communication using the OpenBCI USB dongle
- Configurable: 8 or 16 channels
- Each channel can be fully differential (bipolar), or single reference (monopolar)
- Programmable gain for each channel

[2] `https://shop.openbci.com/collections/frontpage/products/emg-ecg-snap-electrode-cables`
[3] `https://www.adafruit.com/product/259`
[4] `https://www.tinkercad.com/things/bvnf9isn9NS`

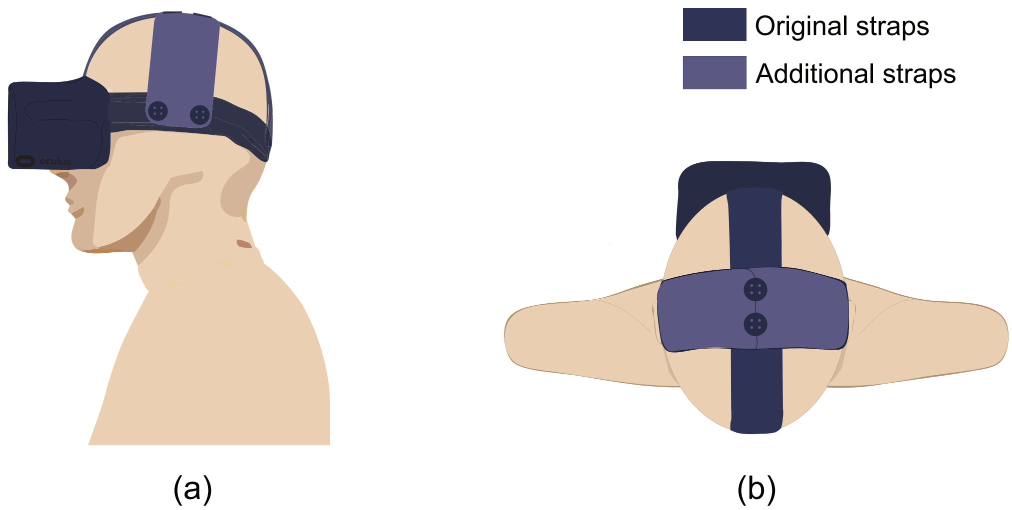


Figure 3.2: HMD head strap organization: (a) profile view; (b) top view.

- Light, 86 g for the 16-channel configuration, and 70 g for the 8-channel configuration
- 12 hours of operation for the 16-channel configuration

3.3.2 Off-the-shelf HMD

The initial integration of the system was carried out using an Oculus Rift (Development Kit 2) featuring a frame rate of 75 Hz and a field of view (FOV) of 100 degrees. The original head straps of the HMD are ideal spots to place dry flexible electrodes, as they cover relevant brain regions over the scalp (e.g., central, parietal, temporal, and occipital). Additional textile straps were also added to allow for more brain regions to be monitored. Figure 3.2 illustrates the original strap positions, as well as the additional ones. Note that the HMD straps also serve as support to place the biopotential amplifier.

3.3.3 Dry electrodes

The selection of the dry electrodes was based on three criteria: signal quality, practicality, and comfort [120]. Three different types of electrodes were used: flexible, flat, and sticker (disposable), depending on their location in the HMD. Ag/AgCl dry flexible electrodes[5] were used for EEG

[5]`http://cognionics.com/index.php/59-products/sensors`

measurement in locations with the presence of hair. Flat Ag/AgCl dry electrodes[6] were used in places where contact with the bare skin is needed and the electrode is physically supported by the HMD (i.e., around the face-piece to record EOG, facial EMG, and frontal EEG). Lastly, standard Ag/AgCl disposable sticker electrodes were used on the bare skin where there was no support for the electrodes, i.e., at the mastoids (reference) and on the left collarbone (for ECG acquisition). The three types of electrodes are shown in Figures 3.1 c-e, respectively.

3.3.4 Hardware integration

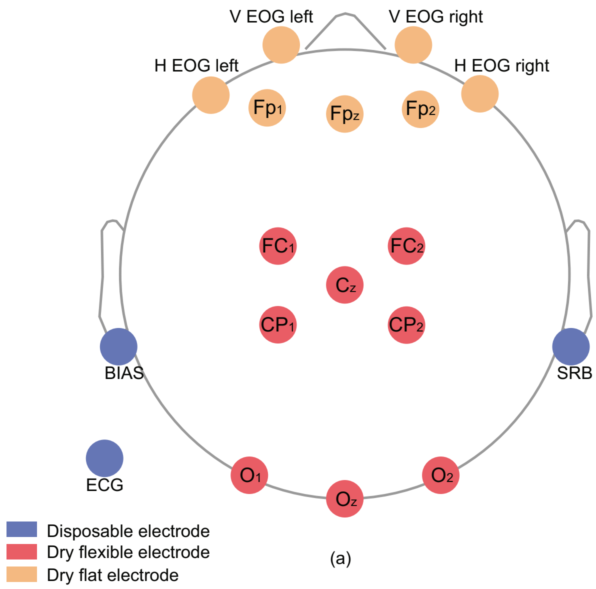
With the aim of using the 16-channel configuration to record EEG, EOG, ECG and facial EMG signals, we proposed to acquire 11 EEG signals from electrodes located in three areas: frontal (Fp1, Fpz and Fp2), central (FC1, FC2, Cz, CP1 and CP2), and occipital (O1, Oz and O2). The EOG signals were derived from the EEG electrodes on the frontal area, as well as two vertical and two horizontal electrodes placed on the face-piece of the HMD. Facial EMG signals were also acquired from the electrodes on the face-piece. Moreover, one electrode was placed on the user's collarbone with the goal of acquiring an ECG signal. Lastly, the Bias and SRB terminals were placed on the mastoids. For this proposed 16-channel configuration, the placement of the electrodes can be seen in the layout depicted in Figure 3.3a, where the face-piece sensors are further depicted by Figure 3.3b. The layout can be easily modified depending on the experimental protocol. The first prototype can be seen in Figure 3.4.

3.3.5 Evolution and enhancements of the instrumented VR headset over time

As shown in Figure 3.4, the first prototype had electrodes velcroed to the headset. As research evolved, different improvements were implemented for improved user experience and signal acquisition. Below is a description of the improvements implemented from 2019-2022 to the instrumented headset:

- The disposable electrode placed on the collarbone for ECG measurement was replaced with an integrated PPG sensor within the VR headset's frontal foam padding[7], eliminating the

[6] `http://thoughttechnology.com/index.php/cables-and-electrodes/ag-agcl-electrodes-x6.html`
[7] `https://shop.openbci.com/products/pulse-sensor`



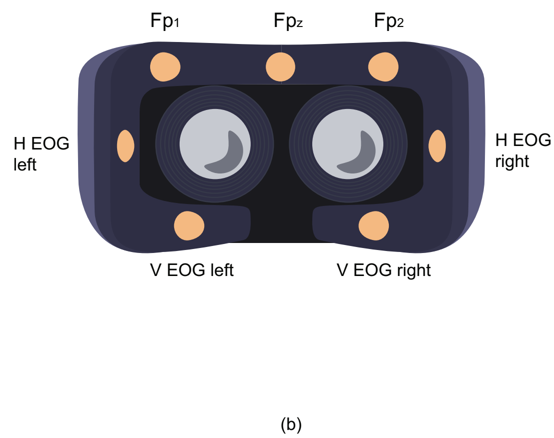


Figure 3.3: Proposed layout for the 16-channel configuration: (a) top view; (b) electrodes on the face-piece.

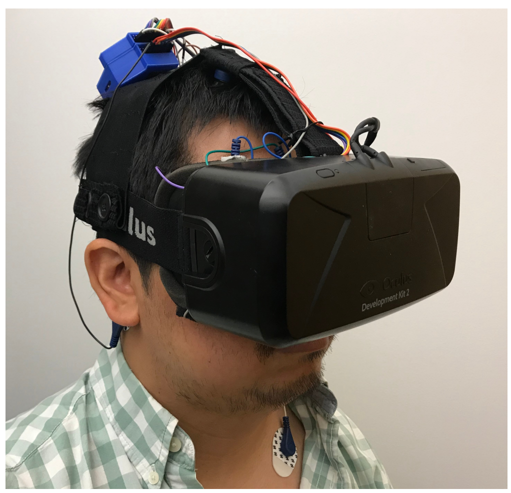


Figure 3.4: First prototype of the instrumented HMD system encompassing 16 multi-modality sensors and a wireless amplifier module attached to the top of the HMD straps.

need for an additional cable. The Pulse Sensor is capable of recording heart rate and heart rate variability (HRV), and it is plugged directly into the OpenBCI boards.

- The flexible dry EEG electrodes from Cognionics were replaced with rigid dry EEG electrodes from CGX, and later by Datwyler SoftPulse flexible dry EEG electrodes for enhanced performance and comfort[8].

[8] `https://datwyler.com/files/pages/data/downloads/softpulse-fact-sheet/25bf0c7737-1670401505/datwyler.com_softpulse_factsheet.en.pdf`

- In terms of reference electrodes, disposable electrodes positioned on the mastoids were replaced by an ear-clip electrode placed on the earlobes[9]. This electrode allows for a stable grounding signal while recording EEG data.
- The deluxe comfort strap with a spare Velcro kit was replaced by an ergonomically improved head strap design. This allowed for a more even distribution of the device's weight, making it easier and more comfortable to wear. The strap is made with soft, breathable synthetic leather foam, offering pressure resistance on the head and comfort for extended use without slipping. Figure 3.5 highlights the evolution made over time to enhance user experience and system performance. The latest version of the headset, for example, can now be comfortably worn for long periods of time without users experiencing any pain or discomfort.
- The instrumentation was adapted for various HMD models, including HTC Vive Pro Eye (Fig. 3.6), HP Reverb G2 (Fig. 3.7), Meta Quest 2 (Fig. 3.8), Meta Quest 1 (Fig. 3.9), and Pico Neo 3 (Fig. 3.9), showcasing the system's versatility and compatibility with different VR devices.

As can be seen, over the years there have been several key improvements to the instrumented VR headset, addressing various challenges and enhancing user comfort. This improvement has significantly enhanced the practicality and applicability of the headset for various VR applications, allowing for extended use and a more immersive experience.

3.3.6 Software integration

The open-research philosophy behind the OpenBCI product line facilitates the integration of the developed system with a myriad of programming languages and communication protocols, including lab streaming layer (LSL), as well as open tools, such as OpenViBE, MNE and our in-house developed MuSAE Lab EEG server (MuLES) [1]. MuLES is an open-source EEG acquisition and streaming server that aims to create a common interface for portable EEG devices, facilitating the development of device-agnostic applications as shown in Figure 3.10. It provides a minimalist Graphical User Interface (GUI) that allows quick and simple interfacing with different portable EEG consumer devices.

[9] `https://shop.openbci.com/products/earclip-electrode`

(a) (b)

Figure 3.5: A side-by-side comparison of the first and latest versions of the instrumented VR headset: (a) The initial version. (b) The latest version, showcasing the integrated PPG sensor for heart rate measurement and Datwyler SoftPulse flexible dry EEG electrodes.

Figure 3.6: Instrumented HTC Vive Pro Eye VR headset featuring CGX dry rigid EEG electrodes, flat EOG electrodes, and a single-channel disposable ECG electrode

The source code, installer, and examples are provided under the MIT license. MuLES is available as a GitHub repository[10]. MuLES features include:

- Simple GUI allowing recording and streaming of data with a few clicks, see Figure 3.11.
- Recording of EEG data in standard formats: CSV, EDF.
- Streaming of EEG data (from devices or files) using TCP/IP.
- Simultaneous multiple instances facilitating data synchronization across multiple devices.
- Clients for different programming languages provided MATLAB/Octave, Python, Unity.

[10]`https://github.com/MuSAELab/MuLES`

Figure 3.7: Instrumented HP Reverb G2 VR headset featuring dry EEG electrodes from Cognionics and flat EOG electrodes

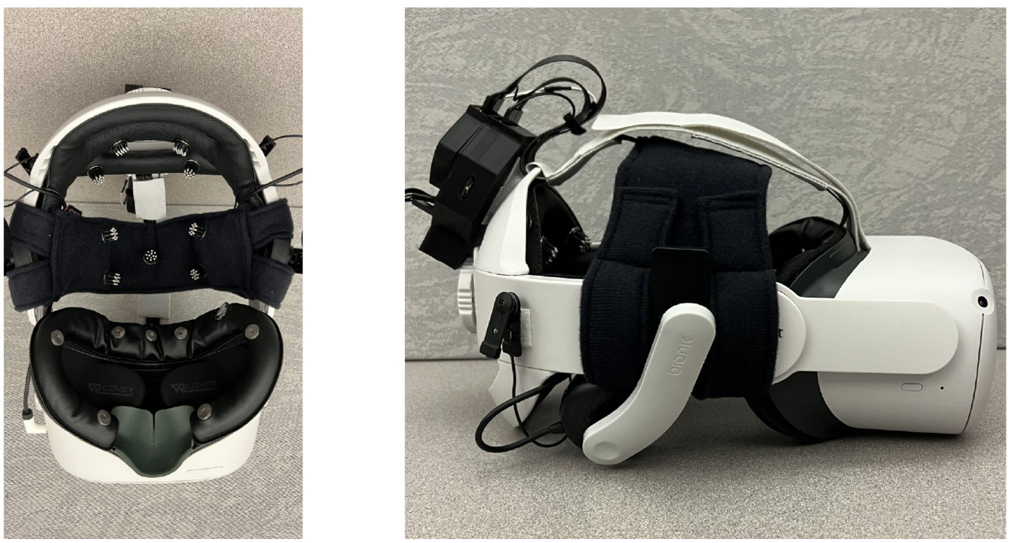


Figure 3.8: Instrumented Quest 2 VR headset featuring Datwyler flexible EEG electrodes, flat EOG electrodes, and pulse sensor

3.4 Pre-processing and feature extraction for HIFs assessment

The instrumented HMD system provides access to a wide range of physiological signals, including EEG, heart rate, heart rate variability, blinking, eye gaze tracking, and facial EMG. These signals enable us to extract various features that offer valuable insights into the user's experience during VR applications. However, before extracting these features, it is essential to pre-process the raw biosignal data to ensure a more accurate and interpretable representation of the underlying neural

Figure 3.9: Instrumented Quest VR headset (left) and Pico Neo 3 (right), showcasing the integration of multimodal physiological sensors.

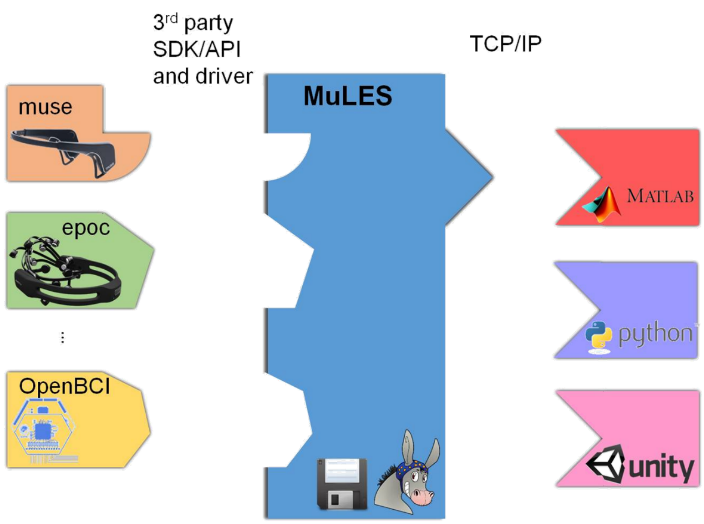


Figure 3.10: Architecture of MuLES: EEG devices are connected through their respective drivers, EEG data is recorded, and communication to external client applications is done using the Transmission Control Protocol/Internet Protocol (TCP/IP). Image taken from [1].

activity. Figure 3.12 illustrates the time series of ExG sensor data and accelerometer data obtained from the instrumented HMD system.

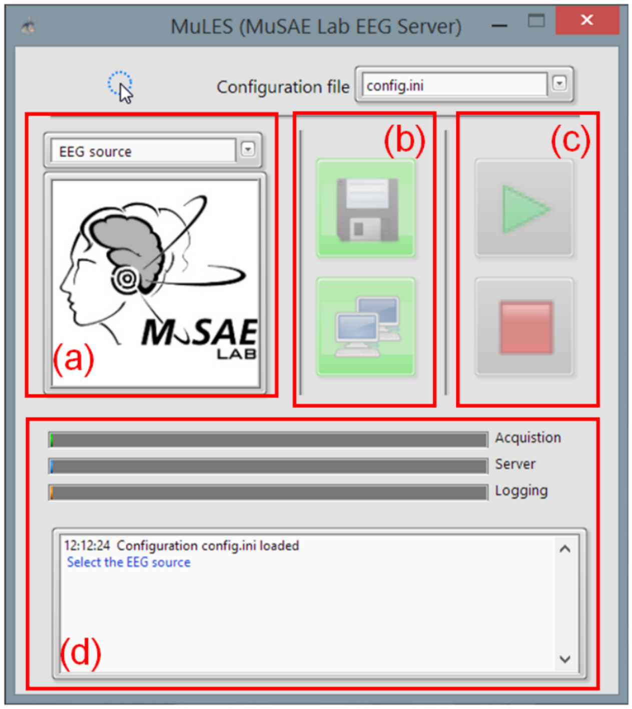


Figure 3.11: MuLES GUI and its sections: (a) input device selection, (b) recording and streaming controls, (c) start/stop acquisition, and (d) current server state information.

3.4.1 Pre-processing

Pre-processing is a vital step in transforming raw biosignal data into a format that is more suitable for further analysis and interpretation. Pre-processing of EEG data typically involves several key steps, such as removing bad channels, filtering, re-referencing, and removing noise and artifacts to reveal the underlying neural signals [121, 122]. This is crucial because spatial information can be lost when recording scalp signals, as EEG data often contains noise that can obscure weaker neural signals [123]. Furthermore, artifacts such as eye blinks and muscle movements can contaminate the data, distorting the overall signals [308, 309].

3.4.1.1 Bad channels

The process of identifying and eliminating bad channels is crucial for obtaining a more accurate representation of neural activity in EEG data. Bad channels can arise from various sources, including malfunctioning equipment, improper electrode placement, bridged channels, or saturated electrodes [122]. These issues can lead to the presence of high impedance, excessive noise, or flat-line signals in the data. Visual inspection can be an initial step in detecting problematic channels, as

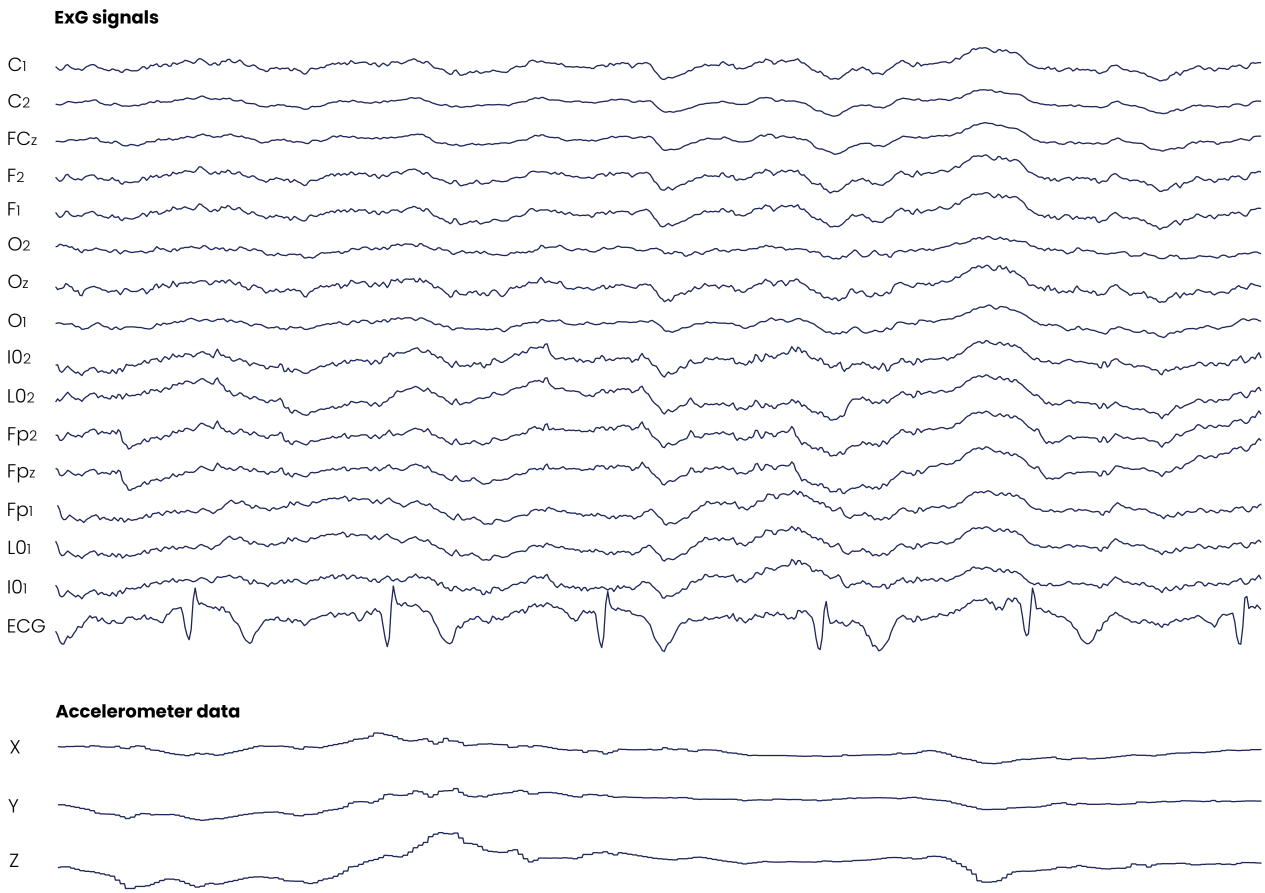


Figure 3.12: Example of ExG data recorded from the instrumented HMD system.

experienced researchers can often identify irregularities in the data by examining the recorded signal traces [124]. However, automated algorithms can also be employed to detect bad channels more objectively and efficiently [121, 125]. These algorithms may use criteria such as kurtosis, correlation, or standard deviation to flag channels with abnormal characteristics compared to the rest of the dataset [310]. Once identified, bad channels can be addressed through interpolation or exclusion [311, 312]. Interpolation involves estimating the missing or corrupted data by using information from the surrounding channels. On the other hand, excluding bad channels entirely from further analysis ensures that the remaining data is not contaminated by unreliable information, though it may lead to reduced spatial resolution. In either case, maintaining the integrity of the data and ensuring that only reliable channels are included in the analysis helps to reduce the risk of drawing erroneous conclusions from the data [123]. Thus, addressing bad channels is a vital step in the pre-processing of EEG data, laying the foundation for accurate and meaningful interpretation of the neural activity.

3.4.1.2 Filtering

Filtering techniques are essential for processing EEG data, as they enable the isolation of specific frequency bands and noise reduction, resulting in a more accurate and interpretable signal [126, 127]. The four main types of filters used in EEG analysis are low-pass, high-pass, band-pass, and notch filters, each with a unique purpose [128]. Low-pass filters retain slower brainwave activity by preserving frequencies below a specified cut-off value. They are particularly useful for investigating slow brain oscillations, such as delta and theta waves, which are typically associated with relaxation, sleep, or drowsiness [313]. High-pass filters, on the other hand, remove lower frequencies while retaining higher ones, making them ideal for examining faster brain oscillations. These filters are valuable for investigating brain activities such as beta and gamma waves, which are linked to active thinking, problem-solving, and high-level cognitive processing [314][315]. Analyzing these high-frequency brainwaves can also help reveal the user's cognitive engagement and immersion within a VR environment, providing feedback to enhance the VR experience [316]. Band-pass filters selectively permit frequencies within a specified range, which is particularly advantageous for isolating specific brain rhythms [128]. This type of filter is advantageous for targeting particular brain rhythms, such as alpha or mu rhythms, which are related to specific cognitive or behavioral events, such as attention shifts or sensorimotor processing [317]. Lastly, notch filters are designed to eliminate single, specific frequencies or narrow bands, making them ideal for removing electrical interference, which is typically at 50 or 60 Hz [126]. The presence of electrical noise can significantly impact the quality and interpretability of EEG data. Notch filters help to address this issue by effectively suppressing these artifacts while maintaining the integrity of the underlying neural signals [128].

3.4.1.3 Re-referencing

Re-referencing is an essential pre-processing step in EEG data analysis that aims to reduce the impact of neural activity at the reference electrode(s) on the overall signal [129]. This process involves adjusting the references electrodes to a location that has minimal influence on the signals of interest. Careful selection of the reference electrode(s) is critical to obtaining accurate and reliable results [131]. Several reference choices are available, including mastoids, earlobes, the central electrode (Cz), or the average of all electrodes (Common Average Reference) [130]. The mastoids are commonly used as reference electrodes due to their stable and well-defined electrical properties [318]. Earlobes are also a popular choice as they are relatively far from the scalp, reducing the likelihood of picking up local neural activity. Cz is often used as a reference electrode for motor and sensory tasks [319], while the Common Average Reference is used for analyses that require a stable baseline or comparisons between multiple subjects [320]. The selection of a reference electrode depends on the specific research question and the desired outcome of the analysis [131]. For example, the choice of reference may vary depending on the location of the cortical activity or the type of cognitive process being investigated. Without proper re-referencing, the interpretation of EEG results may be compromised, leading to inaccurate conclusions [318].

3.4.1.4 Artifact rejection and correction

Artifact rejection and correction is another critical step in EEG data analysis to identify and remove signals that do not originate from the brain. Environmental artifacts can occur due to power lines, electrode contact issues, or movement during the experiment, while biological artifacts may arise from blinks, eye movements, head movements, heartbeats, or muscle noise. Various techniques, such as Independent Component Analysis (ICA) [132] and Artifact Subspace Reconstruction (ASR) [133] can be used to separate and correct artifacts from the neural signal.

ICA, for example is a technique commonly used in EEG data analysis to separate the neural signals from various sources of artifacts. ICA is a blind source separation method that decomposes the EEG signal into a set of independent components that represent distinct sources of activity [321]. By isolating the sources of artifacts, ICA can effectively remove unwanted signals from the EEG data, making it a powerful tool for artifact rejection and correction [132]. In turn, ASR is an online, component-based method to effectively remove transient or large-amplitude artifacts [133]. The technique is capable of running in real-time and uses statistical anomaly detection to separate artifacts from EEG signals in multichannel data sets. It assumes that non-brain signals introduce a large amount of variance to the data set and can be detected via statistics. ASR decomposes short segments of EEG data and contrasts them to calibration data. Figure 3.13 depicts a 140 second signal excerpt recorded from Fp1 with different types of artifacts, including horizontal and vertical head motions, eye blinks and the eye movements. As can be seen, the ASR algorithm is able to remove such artifacts for posterior EEG feature extraction.

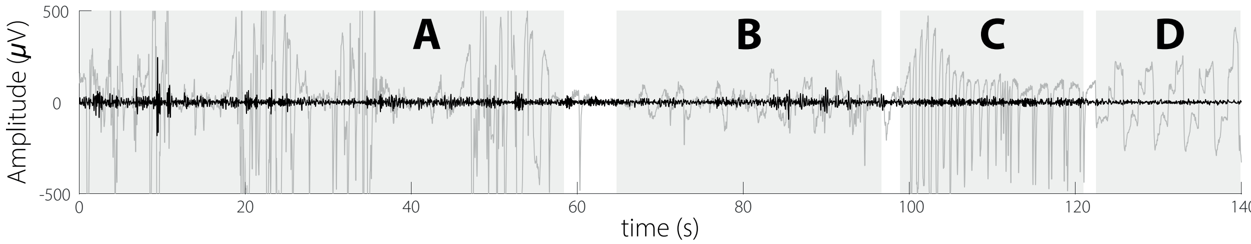


Figure 3.13: ASR applied on signal from Fp1 channel. Raw signal (grey) and enhanced signal (black). Artifacts A: horizontal head motions; B: vertical head motions; C: eye blinks; D: eye gaze.

The enhanced EEG data can then be used to extract valuable features to provide insights into the user's IMEx. In the next section, we will present some (benchmark) features extracted from biosignals that have demonstrated significant relevance in the literature for IMEx monitoring.

3.4.2 Benchmark feature extraction

In this section, we describe benchmark features extracted from various biosignal modalities, including EEG, EOG, ECG, and accelerometer data, collected using the instrumented HMD system. All of these features are summarized in Table 3.1.

3.4.2.1 EEG features

Power Spectral Features and ratios: The power distribution of the five EEG frequency bands was computed: delta (δ; 0.5–4 Hz), theta (θ; 4–8 Hz), alpha (α; 8–12 Hz), beta (β; 12–30 Hz), and gamma (γ; 30-44 Hz) using the Welch method. For each frequency band, the average power was calculated across all EEG channels, and 4 ratios were computed for each of the average power of each frequency band, resulting in 20 features. In the past, several studies have linked spectral powers to HIFs; for example, a link between VR video quality and alpha power was shown in the occipital and parietal regions [134], between immersion and θ/α and concentration and β/θ [135], stress regulation and δ/β [136], as well as sense of presence and θ/β [137].

In addition to the EEG band ratio features, we also examined several EEG metrics commonly referenced in the literature for measuring user experience. These metrics include the engagement score, arousal and valence indexes, and frontal alpha asymmetry.

Engagement score: Calculation of the engagement score (ES) from EEG relies on data collected from the Fp1 electrode. The engagement score is a metric that quantifies the level of cognitive engagement or mental effort of an individual during a particular task, by analyzing the neural activity in specific frequency bands (i.e., theta, alpha, and beta). This measure has been widely used in research related to cognitive workload, attention, and task engagement [138]. The EEG signals have to be segmented into 2-sec windows with 50% overlap using a Hamming window and transformed to the frequency domain via a fast Fourier transform, then magnitude squared, and averaged in order to obtain the power spectral density from which the absolute spectral power was estimated in theta, alpha, and beta bands. Relative powers were calculated by summing absolute power across the three bands to compute the total power, and then dividing the absolute power for each individual band by the total power, expressed as a percentage. Finally, the engagement score (ES) is computed as per [138]:

$$ES = \frac{\beta_{Fp1}}{\alpha_{Fp1} + \theta_{Fp1}}. \tag{3.1}$$

Arousal and valence indexes: To measure the emotional state of the user, we use the arousal (AI) and valence indexes (VI) proposed by [139]:

$$AI = \frac{\beta_{F3} + \beta_{F4}}{\alpha_{F3} + \alpha_{F4}}, \tag{3.2}$$

$$VI = \frac{\alpha_{F4}}{\beta_{F4}} - \frac{\alpha_{F3}}{\beta_{F3}}. \tag{3.3}$$

Engagement and arousal indexes have been shown to also correlate with perceived immersion levels [139], thus could provide useful cues for user experience measurement.

Frontal alpha asymmetry (FAA) index: FAA can be used as an additional measure of pleasantness. FAA is expressed as the alpha band power difference between right and left frontal regions, and can be computed by:

$$FAA = \ln \frac{\alpha_{F4}}{\alpha_{F3}}, \tag{3.4}$$

where ln corresponds to the natural log. A positive FAA index reflects greater left-sided frontal activity (alpha power has an inverse relationship with cortical activity) and may serve as an index of approach motivation or related emotion (e.g., anger and joy), whereas negative values indicate greater right-sided activity and may serve as an index of withdrawal motivation or related emotion, such as disgust, fear, and sadness [140].

Additionally, the skewness and kurtosis of each of these four indexes were also calculated, resulting in a total of 12 additional features for EEG modality.

Phase and Magnitude Spectral Coherence: To measure the connectivity between cortical regions, we used the Phase and Magnitude Spectral Coherence (PMSC) features, represented in Table 3.1 by *phc-band* and *msc-band* for phase coherence and magnitude spectral coherence respectively.. These features measure the co-variance of the phase and magnitude between two signals. In our case, with 15 electrodes, we computed PMSC for all possible pairs of electrodes for each of the five sub-bands (δ, θ, α, β, γ). Given that there are 55 unique electrode pairs and 5 sub-bands, this results in a total of 550 PMSC features. The interested reader is directed to [141] for a more detailed explanation of PMSC computation.

The use of PMSC for measuring human influence factors in immersive virtual environments is motivated by its effectiveness in capturing the complex interplay between cognitive, emotional, and attentional processes. As individuals navigate and interact with virtual environments, their brain activity reflects the dynamic changes in cognitive load, emotional valence, and attentional focus. PMSC, in combination with other EEG-derived metrics such as engagement score and frontal alpha asymmetry, can provide a rich, multidimensional representation of an individual's experience within the virtual environment.

PMSC has been shown to be sensitive to changes in mental workload, which is a crucial factor to consider in immersive virtual environments [142, 143]. As such, monitoring PMSC can help identify moments when cognitive load is too high or too low, which can then be used to adjust the environment, tasks, or interactions accordingly. This ensures that the individual remains engaged and challenged, without being overwhelmed or bored. Moreover, the use of PMSC allows for the examination of functional connectivity between different brain regions, which can provide insights into how individuals process and integrate information in virtual environments. This can help identify the neural mechanisms underlying successful interactions in immersive virtual experiences.

Phase and Magnitude Spectral Coherence of Amplitude Modulation Features: Moreover, we utilized the Phase and Magnitude Spectral Coherence of Amplitude Modulation (PMSC-AM) features which extend the capacity of PMSC features to amplitude modulations and provide information about the rate-of-change of specific frequency sub-bands. These interactions are represented by the notation *band_mband* and reveal interactions between different brain processes and long-range communication. These features have proven to be useful in predicting arousal and valence [144]. Given the established relationship between arousal and valence and time perception [145, 146], here we explore the potential use of these features as correlates of time perception in Chapter 6. The PMSC-AM features were calculated based on the modulated signals of each band, resulting in a total of fifteen signals per channel. The magnitude spectral coherence and phase coherence were then computed for all channel pairs, resulting in a total of 1540 features. More details about the PMSC and PMSC-AM features can be found in [144].

3.4.2.2 EOG features

The frequency range of EOG signal is 0.1 to 50 Hz and the amplitude lies between 100-3500 μV [147]. From the EOG signals, we extracted eye blink and saccade rate measures and their durations using the EOG event recognizer toolbox [148]. Eye blinks have been used to predict cybersickness [149] and saccades could be indicative of user frustration [150] and sense of presence in immersive virtual environment [59]. Saccades correspond to rapid and simultaneous movements of both eyes while fixing in the same direction. Additional details regarding saccades can be found in the next chapter. The blinks and saccades measurement algorithm relies on a probabilistic method that requires a short period of unsupervised training before the actual measurements. For this, the first 60 seconds of each session for each participant were used. The parameters of the Gaussian likelihoods were learned using an expectation maximization algorithm following the work of [148].

In Chapter 4, we illustrate the utility of EOG signals in tracking eye movements without requiring a camera, as first proposed in [151]. For each of the seven EOG electrodes embedded in the frontal foam of the virtual reality headset, we calculate the slope of the signal within 500ms windows, creating seven distinct slope features. These features feed into our classifiers, elaborated in the next Chapter, which determine the gaze position within the user's field of view. This classification process is binary, discerning either an up-down or left-right movement, thus necessitating the training of two separate classifiers. From these classifiers' outputs, we deduce the number of quadrant shifts, creating two additional features that represent the total number of gaze transitions between top-bottom and left-right quadrants. These features play a key role in our assessment of time perception, which will be further explored in Chapter 6.

3.4.2.3 ECG features

To extract ECG features, we utilized an open-source MATLAB toolbox to gather 15 features that relate to heart rate (HR) and HRV[11]. The analysis of HRV can be categorized into three methods: time-domain, frequency-domain, and nonlinear methods. The time-domain features measured the variation in time between two successive heartbeats, or interbeat intervals (IBI). We extracted the average IBI, the standard deviation of NN intervals (SDNN), the root mean square of successive RR interval differences (RMSSD), the number of pairs of successive RR intervals that differ by more than 50 ms, and the percentage of this difference (NN50 and pNN50, respectively). Frequency-domain analysis focuses on the power spectral density of the RR time series. We obtained the relative power of the LF band (0.04–0.15 Hz) and HF band (0.15–0.4 Hz), as well as their percentages. We also calculated the ratio of LF to HF and the total power, which is the sum of the four spectral bands, LF, HF, the absolute power of the ultra-low-frequency (ULF) band ($\leq$0.0003 Hz), and the absolute power of the VLF band (0.0033–0.04 Hz). Finally, nonlinear measurements were used to assess the unpredictability of a time series. We extracted the Pointcare plot standard deviation perpendicular to the line of identity (SD1) and along the line of identity (SD2). These features provide valuable insights into the variability of HR and HRV during the VR gameplay session.

3.4.2.4 Accelerometer features

The OpenBCI bioamplifier includes an accelerometer, which was placed towards the back of the VR headset. As such, analysis of the accelerometer data can provide insights into head motion and orientation. Since there is evidence that bodily movements can influence temporal perception and head movements differ based on arousal and valence states [153], we also extract features from the accelerometer data [152]. Specifically, we extracted statistical measures (i.e., mean, standard deviation, skewness, kurtosis, and energy) for acceleration, velocity, and displacement along the x,

[11] https://www.mathworks.com/matlabcentral/fileexchange/84692-ecg-class-for-heart-rate-variability-analysis

y, and z axes. This resulted in a total of 117 features that provide valuable information about the user's head movements during the VR experience.

3.5 Initial validation of the developed instrumented HMD

In order to validate the developed instrumented HMD, different validation scenarios were proposed for each of the acquired modalities. For this initial analysis, five participants were recruited. The VR applications were developed with Unity3D with synchronization using MuLES.

3.5.1 Validation of the EEG signals

A common paradigm in EEG experimentation is the recording of steady state visually evoked potentials (SSVEPs), which are elicited in the visual cortex when a user gazes at a target that flickers at a specific frequency. The spectral content of the SSVEPs corresponds to the frequency of the flickering target. As such, the validation scenario for the EEG modality consisted in three 30-second stages: (i) open eyes, (ii) presentation of a blinking sphere at 12.5 Hz, and (iii) closed eyes. The signal-to-noise ratio (SNR) was computed for the stimulus frequency (12.5 Hz) from the power spectrum as the ratio of the power at the stimulus frequency over the mean power of spectral components 2 Hz over and under the stimulus frequency for the three electrodes located in positions O1, Oz, and O2 [154]. Figure 3.14 presents the distributions of the average SNR values for each of the three stages. As expected, the SNR for the SSVEP is higher than the other two conditions, thus validating the EEG modality.

3.5.2 Validation of the ECG signal

In our initial experiments, the ECG electrode was placed on the left collarbone (see Fig. 3.4). While this location differs from standard ECG leads, it was shown to provide accurate R-peaks, thus allowing us to calculate heart rate (HR) and heart rate variability (HRV). Such metrics have been used often to measure different mental states, particularly in VR [155]. To validate the accurate registration of the R-peaks, a research-grade ECG monitor (Zephyr Bioharness3 chestband) was used alongside the developed HMD and both ECG signals were simultaneously acquired for 10

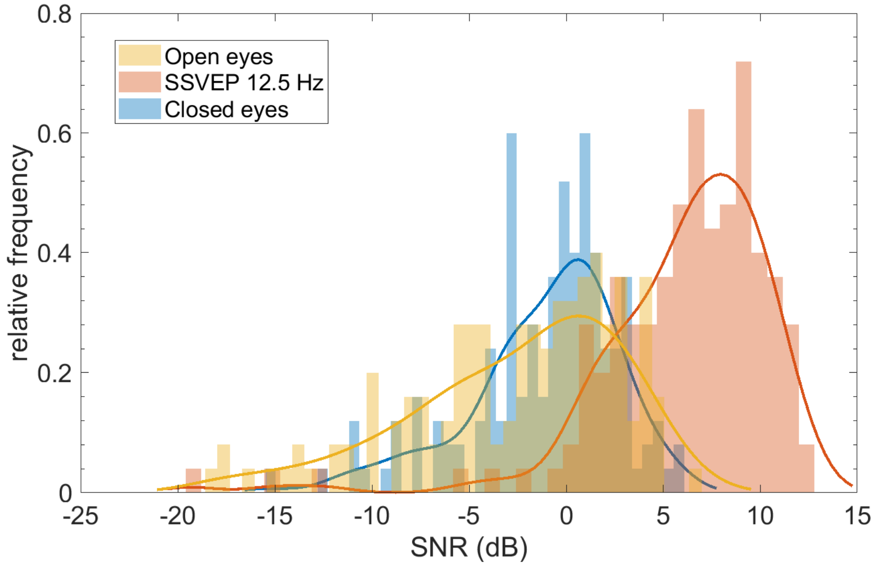


Figure 3.14: Distributions of the combined SNR values for the O1, Oz, and O2 electrodes for eyes-open (yellow), eyes-close (blue), and SSVEP (red) stages.

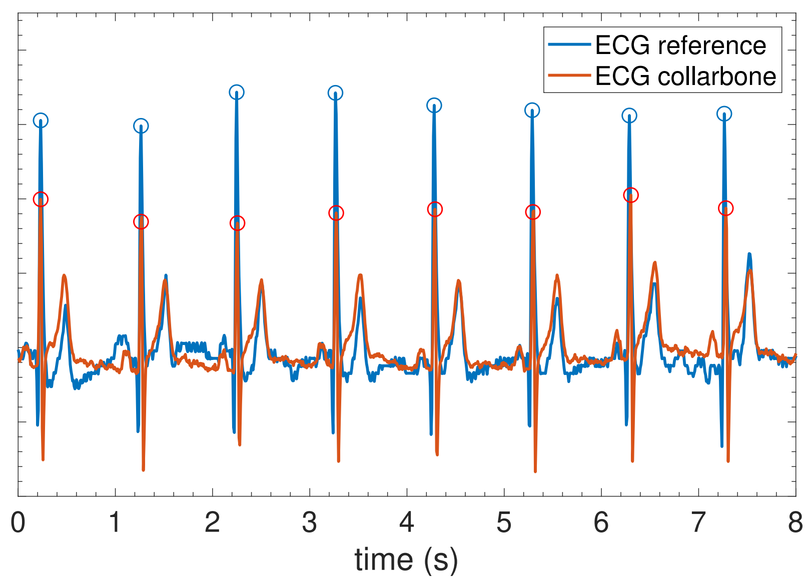


Figure 3.15: ECG signals for the reference (blue) and the prototype (red) devices. Location of detected R-peaks is indicated by a circle. Y-axis units are arbitrary.

minutes. Figure 3.15 depicts an 8-s segment of the ECG obtained via the collarbone sensors and the reference ECG signal. As can be seen, highly accurate cardiac measurement can be achieved and a correlation between the instantaneous HR derived from both sensors was of 0.996, thus validating the ECG modality.

3.5.3 Validation of the EOG signals

In this validation scenario, we used the acquired signals from the seven flat electrodes placed in the face plate of the HMD, as depicted in Figure 3.3b. Here, we are interested in identifying the direction of the eye movements, as well as blinks. Eye blinks have been shown to be useful in predicting cybersickness [156], whereas eye gaze detection could be particularly useful for foveated applications and gaze-adaptive content [157]. For this validation, users were asked to follow a target in the virtual environment for a duration of 5 minutes. The target moved from the center of the FOV to one of eight positions: right, right-up, up, left-up, left, left-down, down, and right-down; each position was repeated 12 times. Figure 3.16 depicts the average response over the 12 trials for each of the seven electrodes, for each of the eight eye gaze positions, as well as the average of a series of eye blinks. As can be seen in Figure 3.16b, the acquired waveforms present different patterns depending on the performed eye movement. For example, for the up and down directions, the horizontal EOG channels do not present changes, while the vertical EOG channels have opposite signs in those conditions. Similarly, a waveform sign change is observed in horizontal EOG channels for the left and right directions. In general, the acquired EOG waveforms follow the patterns reported in the literature [158], thus validating the EOG modalities.

3.5.4 Validation of the facial EMG signals

Facial EMG signals can be used to detect different facial expressions. While camera based systems have often been used for this purpose, with an HMD blocking the face, this becomes impossible. Facial expressions can not only provide information about different mental states, but can also be used to control remote avatars in embodied virtual applications. For this validation scenario, signals from the seven face-piece electrodes were used. The users were presented with one of four cues that indicate what facial expression to perform, namely: neutral, angry, surprised and happy. In this experiment, each expression was repeated 12 times over a duration of 5 minutes. For this analysis, the seven electrodes were re-referenced to Fpz, and grouped into three categories: vertical (V EOG left and right), horizontal (H EOG left and right), and frontal (Fp1 and Fp2). Figure 3.17 presents the average response in each of the three electrode groups for each of the four facial gestures. As can be seen, different facial expression evoke different EMG activity over the electrodes groups, thus EMG signals can be used to classify facial gestures, as shown in [159].

Ultimately, it is the use of the headset in a highly-ecological setting that will define the ultimate validation test for the headset. Before this evaluation is detailed in Chapter 5, the next chapter will detail a new eye gaze classifier mentioned in Section 3.4.2.2.

3.6 Conclusion

In this Chapter, we described the development and evaluation of a wireless, integrated instrumented HMD that enables the acquisition of multimodal physiological signals such as EEG, ECG, EOG, and facial EMG during mobile VR applications. The developed system allows for real-time feedback, measurement of relevant HIFs (e.g., sense of presence, cybersickness, attention, among others), and the creation of objective outcome measures for various VR-based applications. By incorporating the available physiological signals and the enhancement pre-processing stages described herein, a wide range of benchmark features can be extracted, providing valuable insights into the user's experience in immersive virtual environments. The next Chapter will explore how the collected signals can be used for eye gaze monitoring in VR.

Table 3.1: Computed features

Modality	Features group	Features
EEG	Frequency band and ratios (Computed on electrodes average)	delta, theta, alpha, beta, gamma delta/theta, delta/alpha, delta/beta, delta/gamma theta/delta, theta/alpha, theta/beta, theta/gamma alpha/delta, alpha/theta, alpha/beta, alpha/gamma, beta/delta, beta/theta, beta/alpha, beta/gamma, gamma/delta, gamma/theta, gamma/alpha, gamma/beta
	Metrics (skewness and kurtosis computed for each metric)	ES AI VI FAA
	Magnitude square coherence (Computed for each of the 55 pairs)	msc-delta msc__theta msc__alpha msc__beta msc__gamma
	Phase coherence (Computed for each of the 55 pairs)	phc-delta phc-theta phc-alpha phc-beta phc-gamma
	Amplitude modulation rate-of-change (Computed for each of the 55 pairs)	delta-mdelta theta-mdelta theta-mtheta alpha-mdelta alpha-mtheta beta-mdelta beta-mtheta beta-malpha beta-mbeta gamma-mdelta gamma-mtheta gamma-malpha gamma-mbeta gamma-mgamma
EOG	Eye blink and saccades	blink duration, blink count, saccades duration, saccades count
	Time-domain	mean, standard deviation, peak value
	Frequency-domain	mean frequency, median frequency
	Statistical	interquartile range, variance, energy
	Eye movement	total number of Up-Down and Left-Right shifts
ECG	Time-domain	HR, IBI mean, SDNN, RMSSD, NN50, pNN50
	Frequency-domain	LF, HF, ULF, VLF
	Nonlinear-domain	SD1, SD2
ACC	Statistics along x, y, and z axes (computed for acceleration, velocity and displacement)	mean, standard deviation, skewness, kurtosis, energy

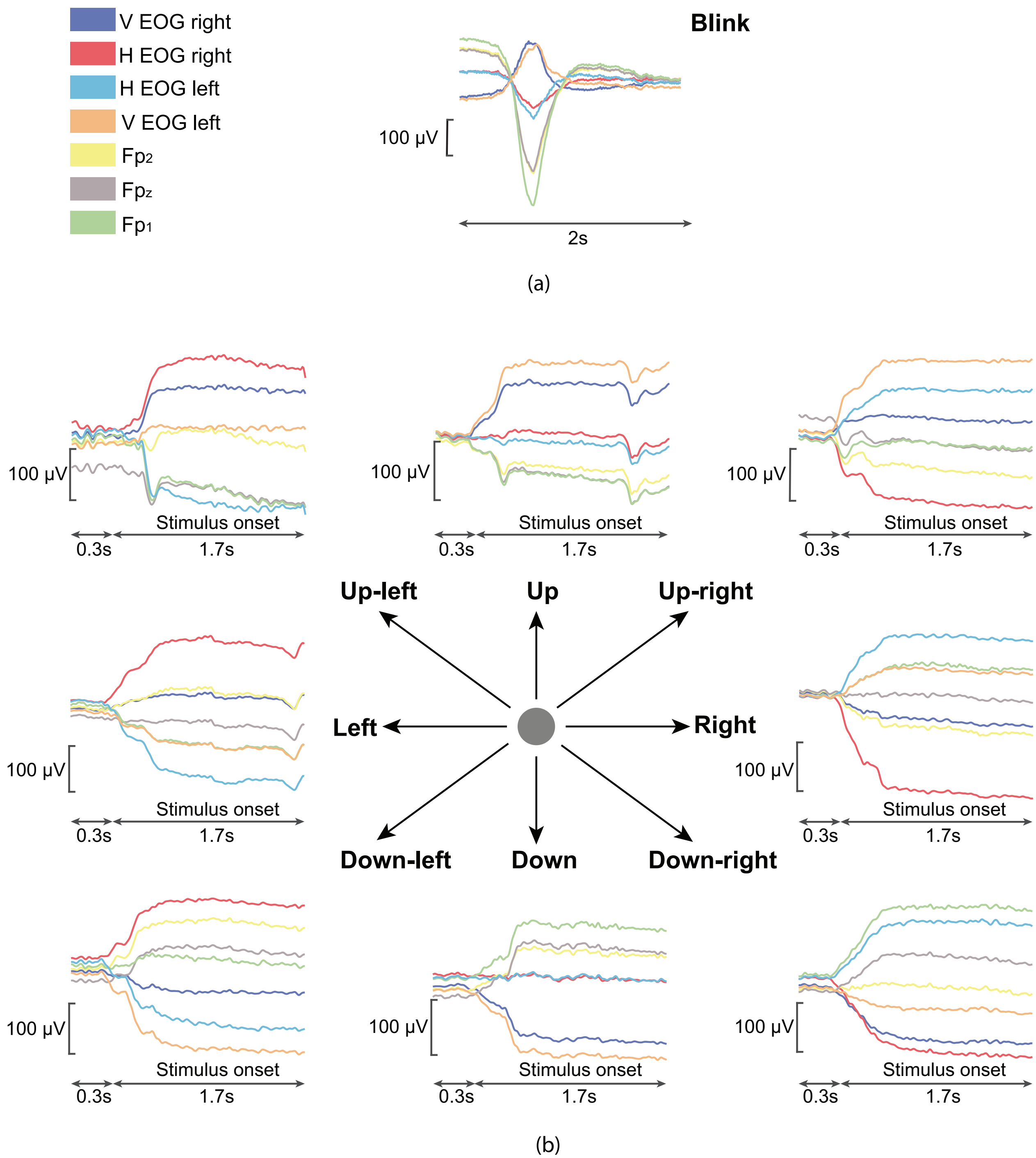


Figure 3.16: Average response for each electrode in the face-piece of the HMD for: (a) blinks; (b) saccades in different directions.

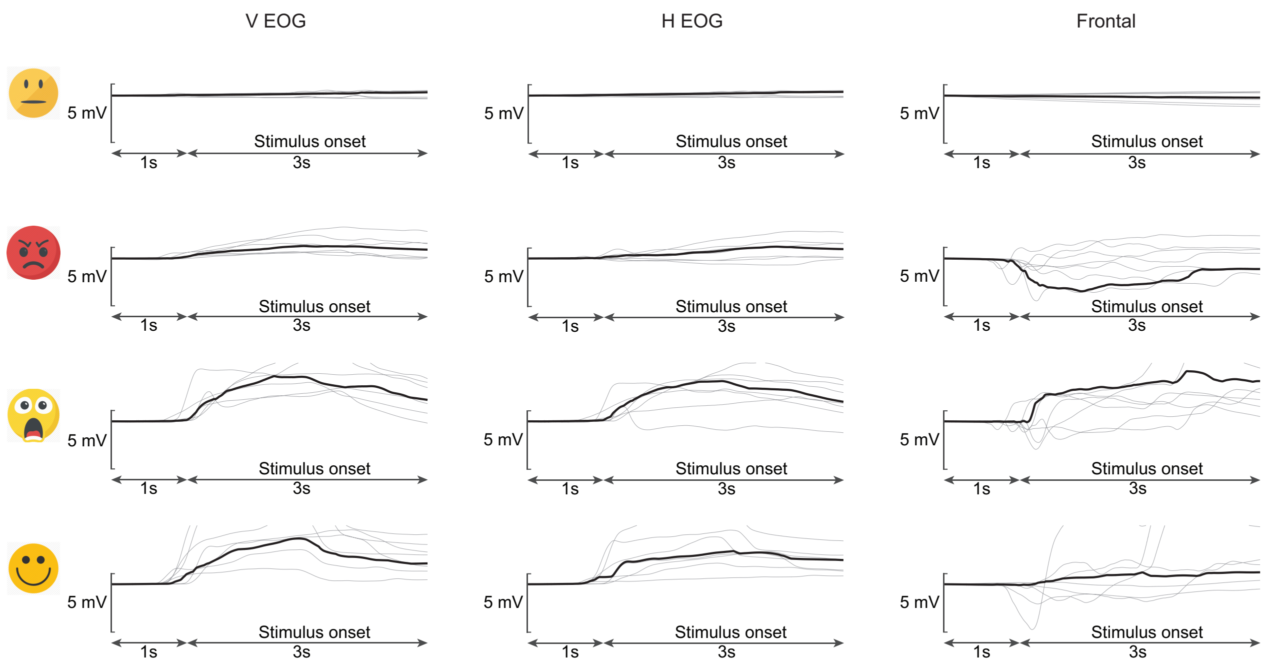


Figure 3.17: Average response for each facial-EMG group of electrodes for different face expressions.

Chapter 4

Eye gaze measurement via an instrumented VR headset

4.1 Preamble

This chapter is compiled from material extracted from the article published in the conference *2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC)* [151].

4.2 Introduction

The last few years have seen considerable advances in computer graphics and sensors which have led to the development of more efficient HMD for VR. These advances have opened door to numerous new immersive applications, ranging from entertainment to training, health monitoring, and rehabilitation, to name a few. One of the most important factors for the success of VR immersive applications is the capability of simulating the sense of presence and the perception of immersion in VR. To this end, eye-tracking has emerged as an interesting modality that allows for virtual environments to adapt to a user's gaze, much like humans do in person-to-person interaction [160, 161, 162].

More specifically, eye tracking in VR has gained traction as it enables virtual applications to measure eye position and eye movement to better understand when people interact with objects or environments, as well as what objects have the most effect on user behavior, decision-making and emotions. Combined with VR, eye tracking can help create more immersive VR experiences by making interactions more natural. The majority of recent HMD eye trackers rely on infrared cameras (e.g., Tobii VR), though a few solutions have emerged based on EOG.

EOG is an inexpensive electrophysiological method for measuring the corneo-retinal standing potential via pairs of electrodes that are placed either above and below the eye and/or to the left and right of the eye. Saccades are one of the popular eye movement types that can be detected through EOG signals. They are rapid (up to 700 degrees/second), simultaneous movements of both eyes as they fixate in the same direction. After the onset of the stimulus, it takes about 200 ms for eye movement to target the stimulus. Duration of the saccade is typically between 30 and 120 ms. To better visualize the concept of a saccadic eye movement, please refer to Figure 4.1, which illustrates the rapid shift in gaze direction during a saccade. EOG-based measurement of saccades can be very useful, as they allow not only for eye movement classification [163, 164, 165, 166, 167], but also as correlates of sense of presence in immersive virtual environment [59], emotion detection, and blink rate measurement, which have been shown useful in predicting cybersickness [149]. Recently, commercial systems have started relying on electrodes embedded directly on the foam of the VR headset for facial biometrics and user affective state monitoring (e.g., EMTEQ and Mind Maze). Such systems, however, are still very expensive and out of reach for the popular VR user. Here, we explore the low-cost, "do-it-yourself" (DIY) alternative based on the openBCI framework and described in the previous Chapter.

One key factor to achieve satisfying classification performance for EOG-based eye tracking lies in the feature extraction step. In the literature, statistical features (i.e., "functionals") extracted from the ExG time series have been proposed [168]. Alternate feature extraction methods that have shown to be popular include continuous wavelet transform [169], peak amplitude detection [170], power spectral density [166], and EOG signal slope measurement [165]. In this chapter, we will rely on two popular feature extraction methods: time series functionals [171] and EOG signal slope measurement [165]. Two conventional classifiers are explored, namely a feedforward artificial neural network (multilayer perceptron - MLP) and a support vector machine (SVM) classifier. A new hierarchical classification tree method is also proposed. To gauge the performance of the developed

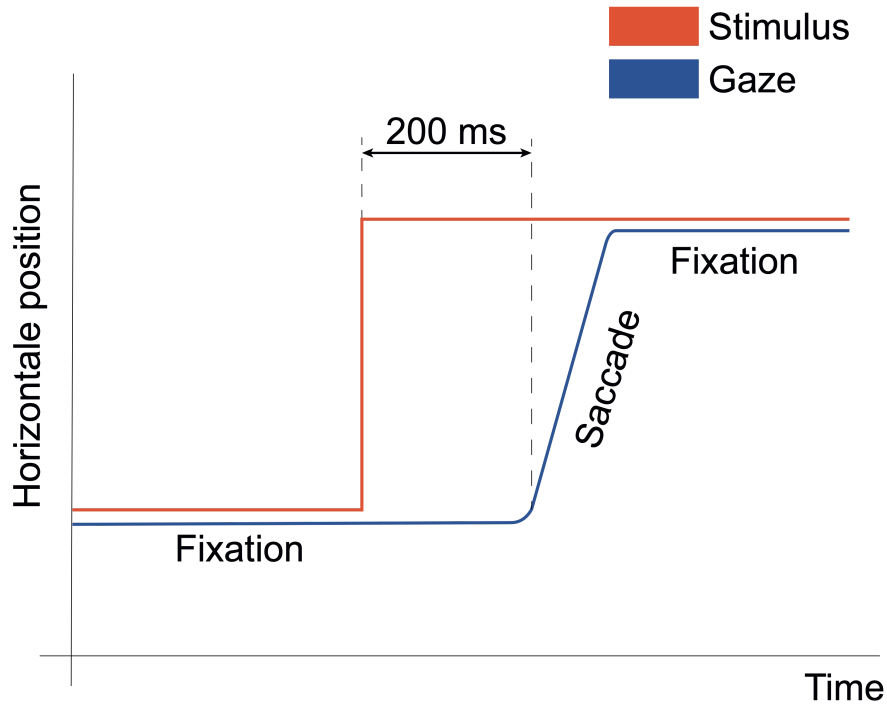


Figure 4.1: Horizontal movement of the eyes where they appear to make a fixation-saccade-fixation sequence. The red curve represents the stimulus, while the blue curve corresponds to the eye gaze tracking the stimulus.

solution, a test aimed at measuring 10 degree saccadic eye movements over a circumference was performed with four subjects during the COVID-19 global pandemic.

4.3 Materials and methods

In this section we describe the experimental data collection protocol, the pre-processing, the ExG features extraction methods, the two machine learning algorithms used, and the hierarchical classification methodology.

4.3.1 Sensor-equipped VR headset

Here, we focus only on the part of the face piece of the VR headset that is equipped with seven sensors and is described in detail in Chapter 3. In particular, the Oculus Rift (Development Kit 2) was used. We proposed to acquire seven ExG signals from flat Ag/AgCl dry (flat) electrodes placed near Fp1, Fpz and Fp2 locations, as well as two vertical and two horizontal electrodes (H

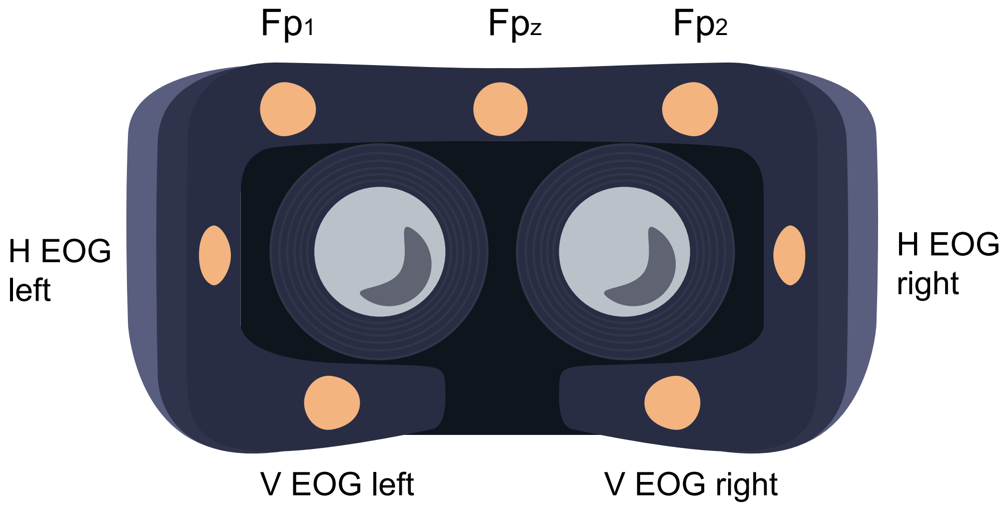


Figure 4.2: Proposed 7-ExG electrode configuration embedded into the foam of the VR headset

EOG right, H EOG left, V EOG right, and V EOG left), all embedded directly into the foam of the VR headset, as shown in Figure 4.2. Signals were acquired at a sampling rate of 250 Hz. Lastly, two standard Ag/AgCl disposable sticker electrodes were used as references on each mastoid. Data was streamed wirelessly using open source MuLES software [172].

4.3.2 Experimental protocol and data acquisition

In our experiment, the VR application was developed with Python 3 and Unity3D. The ExG data was recorded from four participants (3 male and 1 female) who consented to participate in the study. During the experiment, each participant was asked to visually focus on a target that moved from the center of the FOV to one of 36 positions on the screen for a duration of 1.6 seconds. The 36 positions corresponded to 10 degree angles spread evenly over a circle, as shown in Figure 4.3. Each participant repeated the experiment six times. Moreover, to avoid blink and facial muscular artifacts, each time the target moved back to the center of the FOV, the participants had a break of a few seconds to let them rest and blink a few times before the target moved again.

4.3.3 Pre-processing, feature extraction, and feature selection

Signals were first band-pass filtered between 25 and 125 Hz and then zero-mean normalized. Data was then epoched with intervals of 1.6 seconds, thus corresponding to the saccade duration. After epoching, different features were extracted, as detailed next.

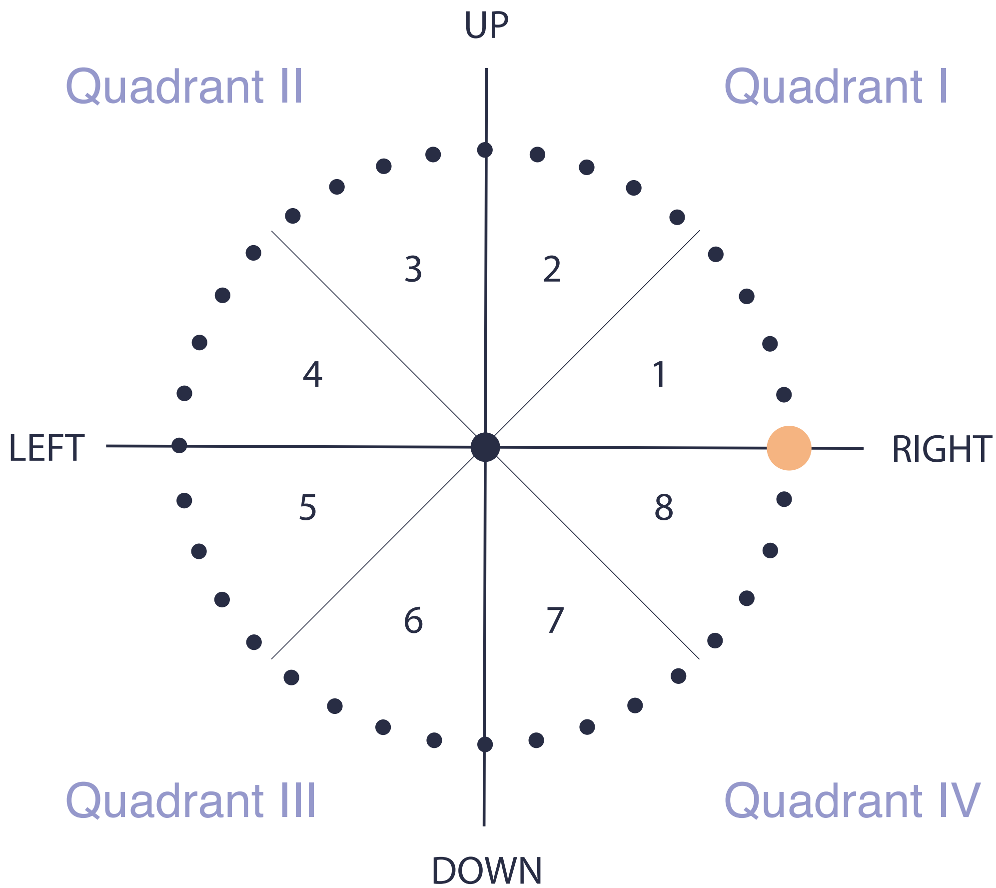


Figure 4.3: Eye gaze experiment

4.3.3.1 Time-series features extraction

Here, the highly comparative time-series analysis (HCTSA) toolbox [171] was used to extract 7664 statistical features from the ExG epochs. To remove redundant or non-discriminatory features, the minimum redundancy maximum relevance (mRMR) feature selection algorithm was used for feature ranking [173]. The mRMR algorithm is a feature selection method that aims to select features that are highly relevant to the target variable while maintaining low redundancy among themselves. By striking a balance between maximum relevance and minimum redundancy, the algorithm identifies a set of features that contribute valuable information for classification or prediction tasks without including redundant or irrelevant features that could hinder performance. In our case, the top-7 features selected, one for each channel, were then explored for the task at hand. This number of features was chosen to correspond to the number of slope-based features described next, thus making the comparison between features more fair.

4.3.3.2 Slope-based feature extraction

Figure 4.4 depicts the average representation of the seven recorded ExG signals when participants were looking up, down, left and right. As can be seen, the patterns across the seven signals varies for the different eye movements, especially in regards to the direction of change (or slope) of each signal. For example, for the up and down directions, the vertical (V EOG right and V EOG left) and frontal EEG channels (Fp1, Fp2, and Fpz) show opposite slope signs for the different directions. Similarly, for the left and right directions, all signals (with the exception of Fpz) showed varying slope signs for the different directions. These patterns correspond with those previously reported in the literature [322].

As such, slope-based features are also explored, as motivated by [165]. The slope feature from each ExG signal can be expressed as:

$$M = \frac{VAV - PAV}{VAP - PAP},$$

where M is the slope, VAV is a minimum valley amplitude value, PAV is a maximum peak amplitude value, VAP is the position where the minimum valley amplitude value is located, and PAP is the position where the maximum peak amplitude value is located. In total, one feature per channel is computed, per trial, thus totalling seven features.

4.3.4 Hierarchical classification methodology

We propose a hierarchical classification methodology in which classification is performed in four steps, as shown in Fig. 4.5. The first three levels correspond to a series of binary classification tasks, whereas the last level corresponds to either a 4- or 5-class task. The first level aims at discriminating if the user was looking at the upper or lower quadrants. The second level, in turn, discriminates from the right or left directions, thus combined provide details about which of the four quadrants the person was looking at (see Fig. 4.3 for a visual of the four quadrants). Once a quadrant has been defined, the third level classifies the upper or lower half of such quadrant, thus one of the eight regions depicted by Fig. 4.3. Lastly, the fourth level aims to classify eye saccade direction to the nearest 10 degrees.

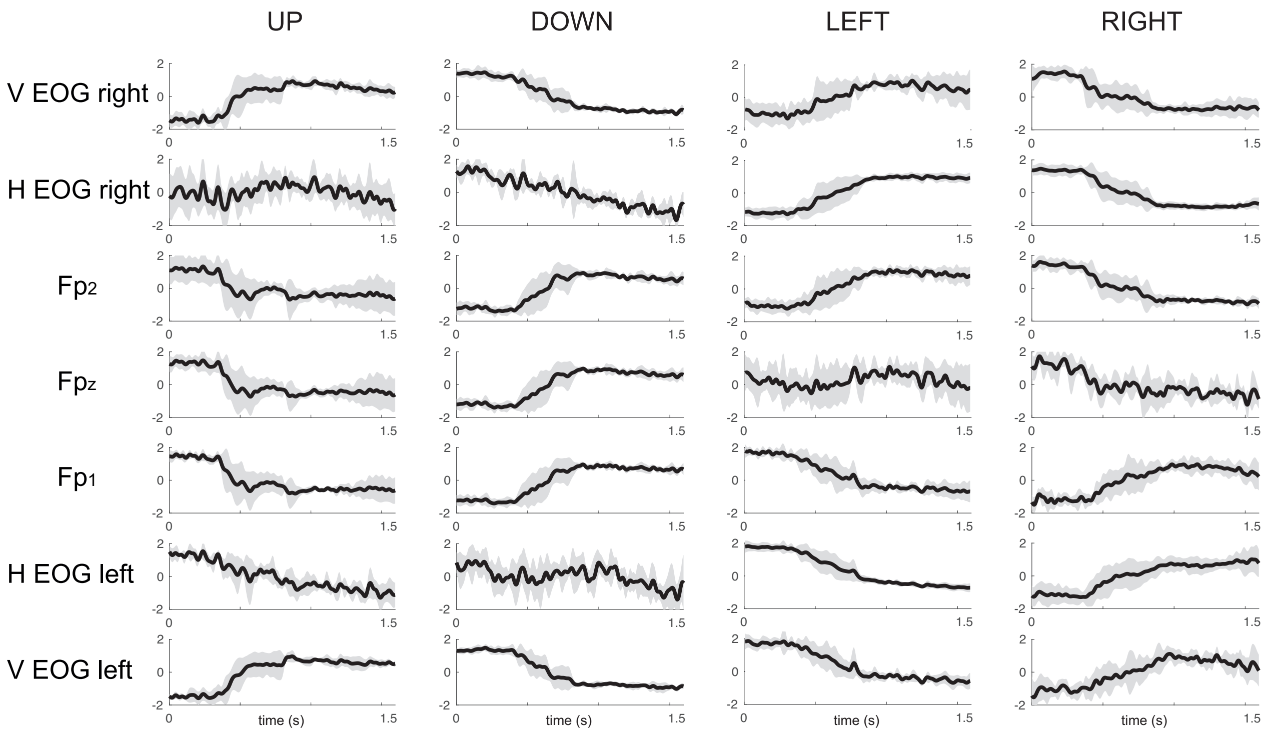


Figure 4.4: Representative ExG signals for four different eye movement directions.

4.3.5 Classifiers and test setup

Two different classifiers were tested for each of the 2-, 4-, and 5-class tasks described above. Here, SVM [174] and MLP [175] classifiers were explored. The Classification Learner toolbox from MATLAB [323] was used to train the SVM and a linear kernel with default hyperparameters were used. For the MLP, in turn, the Deep Learning toolbox in MATLAB was used. The network was trained using the scaled conjugate gradient method [324]. The hidden layer was empirically fixed to 10 hidden nodes. Four-fold cross-validation was performed where 75% of the data was used for training and 25% was left for testing.

4.4 Results and discussion

4.4.1 Feature importance

As mentioned previously, for the proposed hierarchical classification approach, the top-7 features for each of the 14 classifiers were selected from the 7664 statistical features using the mRMR feature

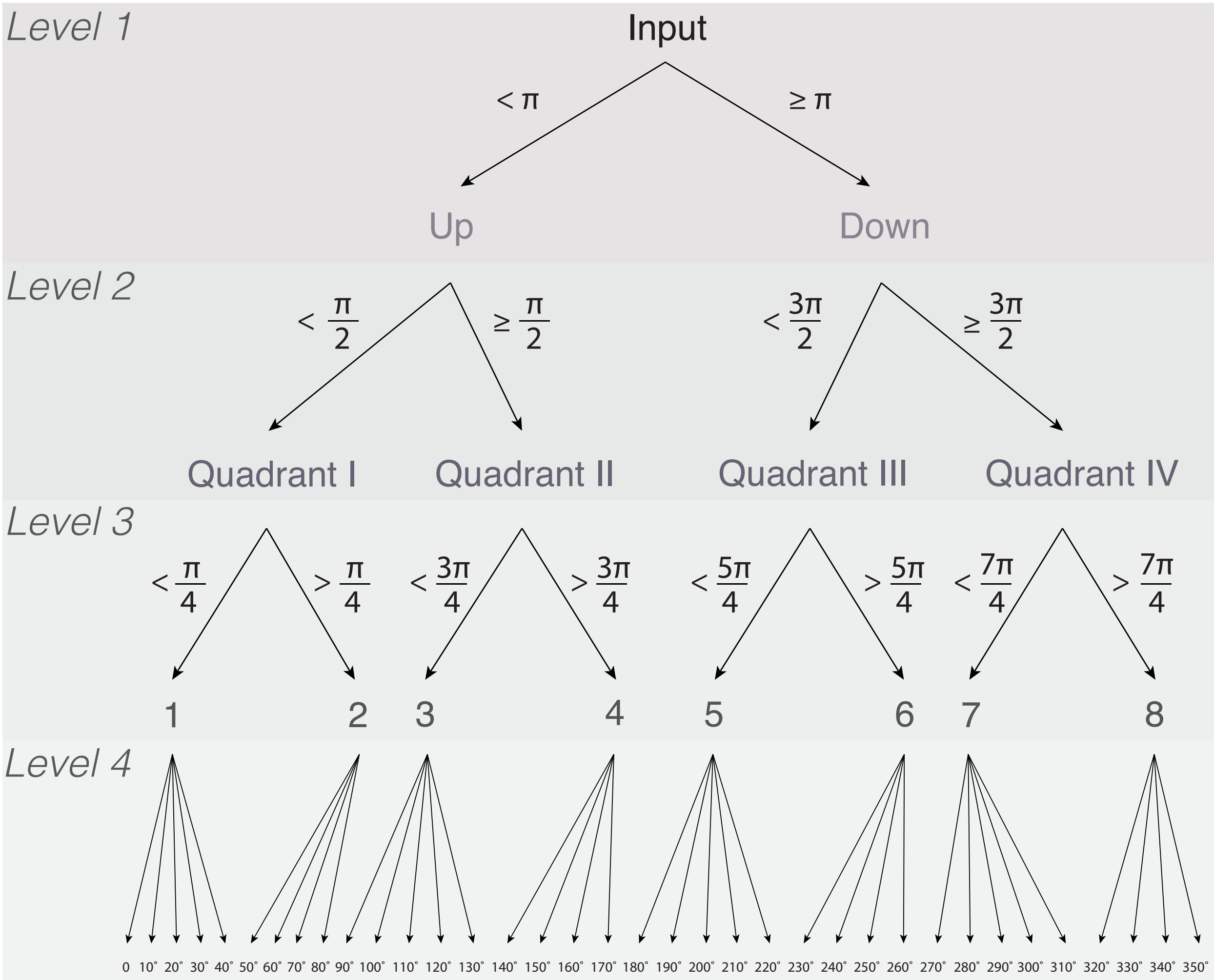


Figure 4.5: Proposed hierarchical classification methodology.

selection algorithm. Figure 4.6 shows the relative importance of the top-20 features that were selected most often. The interested reader is referred to [171] for a complete detail of what each feature represents. The top-3 most important features are the statistics on local segments, the normalized non-linear autocorrelation, and the time series properties variation, being present in 12, 11, and 7 of the 14 classifiers, respectively. The statistics on local segments showed to always be important for the H EOG left and V EOG left channels. It is based on sliding windows along the time series, measuring some quantities, such as the mean, the standard deviation, or the entropy, in each window, and outputting some summary of this set of local estimates of those quantities. The normalized non-linear autocorrelation features showed to be the most relevant for the V EOG right, Fp1, Fp2, and Fpz channels. This quantity is often used as a nonlinearity statistic in surrogate data [176]. The time series properties variation, in turn, always showed importance for the Fp1, Fp2,

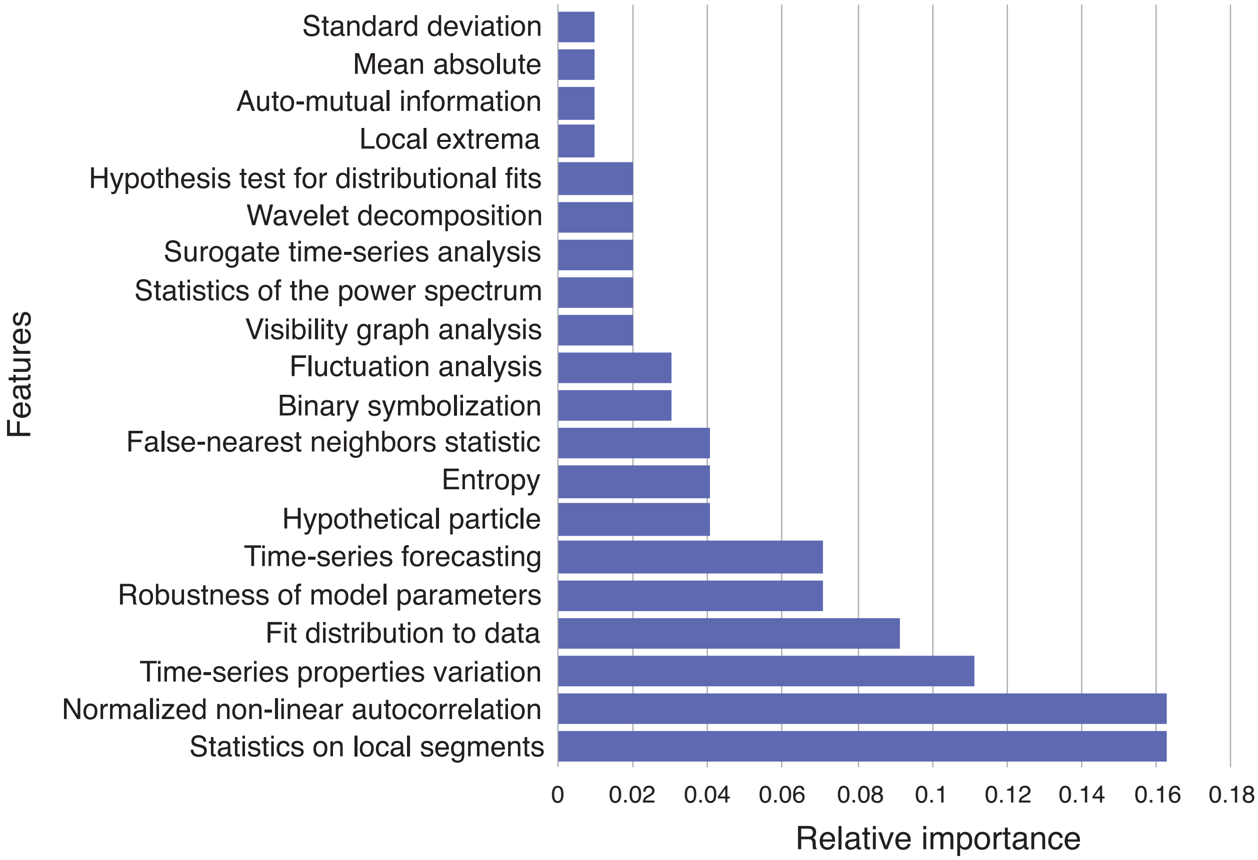


Figure 4.6: Feature importance evaluation.

ans Fpz channels. It applies a given pre-processing transformation to the time series (polynomial, or sinusoidal detrending) and returns statistics on how various time-series properties change as a result.

4.4.2 Classification accuracy

In this study, we compared the proposed hierarchical classification approach to a non-hierarchical method. Table 4.1 presents the average classification accuracy and standard deviation obtained across each cross-validation trial for all participants. In the Table, for the hierarchical approach, levels 1, 2, 3, and 4 correspond to the compounded accuracy of the classifiers at each of the four levels. Results are presented for each feature type separately, as well as combined via feature fusion. In the non-hierarchical approach, in turn, results presented for levels 1-4, correspond, respectively to 2-, 4-, 8-, and 36-class tasks using either an SVM or an MLP classifier. In order to compare the final 36-class accuracy, level 4 results are to be used. Lastly, mindful that in VR applications

Features	Level	SVM Hierarchical	SVM Non-hierarchical	MLP Hierarchical	MLP Non-hierarchical
HCTSA-mRMR	1	93.63 ± 3.7	93.63 ± 3.7	92.59 ± 4.3	92.94 ± 4.7
	2	90.62 ± 4.8	87.38 ± 4.8	88.77 ± 5.6	84.14 ± 7.9
	3	83.22 ± 7.5	76.62 ± 7.5	79.86 ± 7.8	71.64 ± 7.2
	4	31.13 ± 5.6	26.62 ± 5.6	24.88 ± 8.3	21.76 ± 6.0
	4*	69.45 ± 5.5	67.48 ± 8.2	62.15 ± 7.6	55.90 ± 11.8
Slopes	1	92.48 ± 2.7	92.48 ± 2.7	85.19 ± 8.3	85.65 ± 7.8
	2	87.50 ± 5.0	86.46 ± 6.6	75.58 ± 12.6	76.04 ± 15.0
	3	78.94 ± 7.2	78.59 ± 7.8	65.62 ± 10.8	59.84 ± 14.9
	4	43.17 ± 7.7	42.13 ± 9.2	24.54 ± 9.1	12.73 ± 8.6
	4*	74.07 ± 8.3	70.55 ± 3.5	53.13 ± 9.9	44.91 ± 18.4
Fusion	1	94.10 ± 3.4	94.10 ± 3.4	93.87 ± 3.4	92.13 ± 5.6
	2	91.32 ± 3.7	88.89 ± 7.4	90.97 ± 4.6	85.88 ± 8.6
	3	83.56 ± 4.3	81.25 ± 6.9	82.52 ± 7.9	75.46 ± 7.3
	4	40.51 ± 6.5	43.52 ± 8.1	29.52 ± 6.3	25.69 ± 7.2
	4*	76.51 ± 9.5	72.87 ± 8.4	63.54 ± 7.7	62.27 ± 10.1

Table 4.1: Performance comparison of accuracy (across validation trials and subjects) for three different feature sets and two classification algorithms under the proposed hierarchical and non-hierarchical classification approaches.

being off by 10 degrees may not pose a serious threat for eye gaze monitoring, we further explore a scenario in which errors that are off by just 10 degrees are not counted as errors. In Table 4.1, this is listed as "Level 4*".

As can be seen, the SVM classifier always outperformed the MLP for all feature types and classifier levels. In general, the slope-based features almost always outperformed the top-HCTSA ones. Moreover, in the hierarchical approach, the errors from previous levels were propagated down, though the final accuracy remained higher than the conventional 36-class approaches (i.e., non-hierarchical). Feature fusion showed to improve classification accuracy, thus suggesting feature complementarity.

After an in-depth investigation of the errors, it was found that the majority of the errors made were with 1-step neighbouring classes. For VR applications, an error in eye gaze detection of less than 10 degrees may not be crucial. As an alternative approach, we considered the scenario where such errors were not encounted. As can be seen from the Table 4.1 under rows labeled "Level 4*", accuracy levels increased substantially for all feature types and classifiers. The hierarchical method with SVM classifiers and the fused feature set showed to be the best approach, achieving an accuracy of 76.51%. Lastly, the low standard deviation values reported in the Table suggest that the proposed method is fairly insensitive to data partitioning and to inter-subject variability. This is an important factor for practical applications.

4.5 Conclusion

In this chapter, we presented a hierarchical classification approach to accurately classify the saccadic eye movements into 36 directions using a low cost solution based on embedding 7 ExG sensors directly into the faceplate of a virtual reality headset. We explored two different feature types (individually and fused) and two conventional classifiers (SVM and MLP). It was found that with as low as seven ExG electrodes, seven features, and a series of simple linear SVM classifiers, 76.51% accuracy could be achieved on the 36-class classification problem. These findings are encouraging and suggest that accurate saccadic eye movements can be tracked in a low-cost manner and with negligible computational requirements, two important factors for real-world applications. In Chapter 6, we will further explore the use of these features for time perception classification. By examining the relationship between saccadic eye movements and time perception, we aim to uncover additional insights into the human cognitive process and the impact of virtual reality on our perception of time.

Chapter 5

Highly-ecological validation of the headset: Monitoring HIFs from gamers

5.1 Preamble

This Chapter is compiled from material extracted from the manuscript published in the journal *Frontiers in Virtual Reality* [203].

5.2 Introduction

Recent reports have shown that the VR sector grew nearly 30% since January 2021, suggesting that the sector growth was not affected by the worldwide COVID-19 pandemic[1]. The Meta (formerly Oculus) Quest 2 portable VR headset, for example, now accounts for nearly half of the headsets used on the Steam VR platform[2]. The total number of monthly connected VR headsets has increased by 29.5% since January 2021. Gaming, however, is just one of the possible domains in which VR is expected to make an impact. Applications in rehabilitation, education, training, and exercise are

[1] https://store.steampowered.com/hwsurvey/Steam-Hardware-Software-Survey-Welcome-to-Steam
[2] https://www.statista.com/statistics/265018/proportion-of-directx-versions-on-the-platform-steam/

also emerging [325, 326]. Ultimately, the success of immersive applications are known to rely on the user experience they provide and not necessarily on the technology they use [5]. As virtual reality and the metaverse are projected to burgeon in the coming years, being able to objectively quantify user experience in immersive settings is crucial. To this end, automated measurement of HIFs, such as sense of presence/immersion, attention, stress, engagement, and fun factors, has become an extremely important factor [7].

Traditionally, subjective methods have been utilized, which rely on post-experience questionnaires, such as the Presence Questionnaire to evaluate the sense of presence [26]. Subjective tests, however, can be highly biased, lack temporal resolution, and are performed after the immersive application is finished, thus relying on gamer memory to recall events. Monitoring HIFs in real-time, in turn, requires objective methods and physiological signals have proven to be particularly effective [202]. For instance, stress and engagement levels, emotions, sense of presence and immersion, and overall experience have been monitored from EEG, ECG, and EOG [197]. As psychophysiological signals are known to be sensitive to movement artifacts, studies have been typically conducted in controlled laboratory settings with significant experimenter intervention to ensure high-quality signal recordings. Findings from these studies, however, may not transfer to everyday settings, such as gamers' homes, and thus may have limited practical use. Additionally, the recent COVID-19 pandemic and its worldwide lockdowns along with social distancing directives have made measuring gamer experience in controlled settings extremely challenging. As such, alternative solutions to enable "in the wild" experiments are still drastically needed.

To overcome this issue, here we describe a system and protocol to collect multimodal physiological signals from the "plug-and-play" instrumented HMD system described in Chapter 3 that was delivered to participants' homes together with a gaming laptop and a biosignal data streaming laptop. The headset was equipped with 16 ExG biosensors, including EEG, ECG, and EOG. A portable, wireless bioamplifier was used to collect, stream, and store the signals in real-time. An in-house developed signal quality and analysis software was integrated into the HMD to ensure high-quality signals were collected. Proper device cleaning and sanitation, as well as hardware quarantining, were performed to minimize the spread of COVID-19, following protocols in place at the authors' institution. We build on the work of [177] and propose the extraction of several HIF-related measures from the ExG signals and correlate them to experience ratings reported by the gamers. Overall, with this study we aim to answer two main research questions (RQs): (1) Can

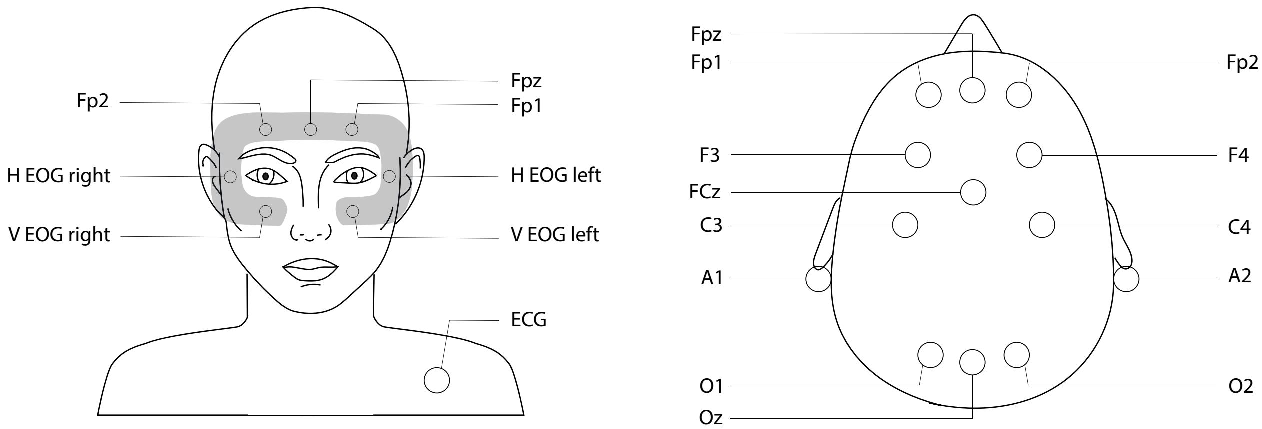


Figure 5.1: Locations of the 16-ExG electrodes placed directly onto a VR headset. The left figure shows sensors placed on the faceplate of the headset and the right figure those placed on the headset straps. Placement of electrodes follow the 10-10 international system [2]. EEG electrodes notation: Fp - Frontopolar; Fpz - Midline Frontopolar; F - Frontal; FCz - Midline Frontocentral; C - Central; O - Occipital; OZ - Midline Occipital.

the proposed instrumented HMD be used in highly ecological settings with minimal experimenter intervention? and (2) Can the measured physiological signals be used as correlates of gamer HIFs?

5.3 Materials and method

In this section, we detail the experimental protocol followed, including remote data collection, signal pre-processing, analysis, and the measurement of HIF metrics.

5.3.1 Instrumented VR headset

Section 3.3.5 details the HTC VIVE Pro Eye VR headset's integration. We propose to acquire 11 EEG signals located in three areas: frontal (Fp1, Fpz and Fp2), central (F3, F4, FCz, C3 and C4), and occipital (O1, Oz and O2), as shown in Figure 5.1. The EOG signals were derived from the EEG electrodes on the frontal area, as well as two vertical and two horizontal electrodes (H EOG right, H EOG left, V EOG right, and V EOG left), all embedded directly into the foam of the VR headset, as shown in Figure 5.1 (left).

Three different types of electrodes were used: flexible, flat, and disposable, depending on their location in the instrumented HMD. Ag/AgCl dry electrodes (CGX Systems, USA) were used for EEG measurement in locations with the presence of hair. Flat Ag/AgCl dry electrodes (Thought

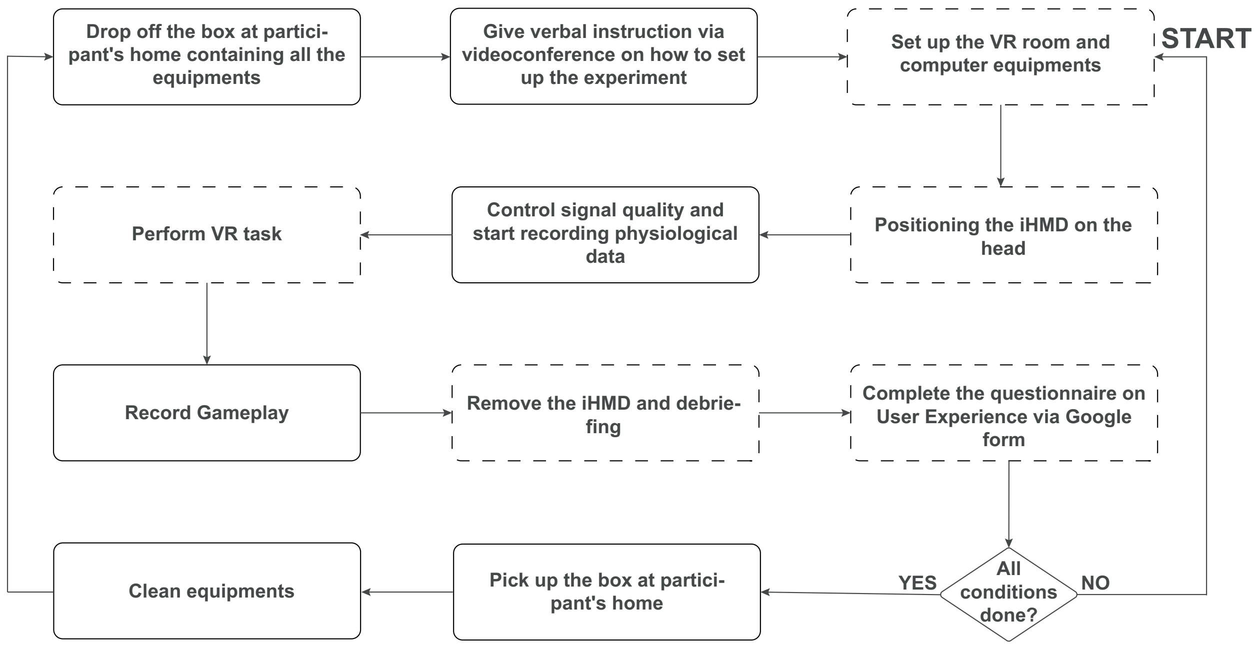


Figure 5.2: Flowchart of the experimental procedure. The solid rectangles correspond to the experimenter tasks and the dashed rectangles to participant tasks.

Technology Ltd., Canada) were used in places where contact with the bare skin is needed (i.e., around the face-piece to record EOG, and frontal EEG). Lastly, one disposable electrode (Thought Technology Ltd., Canada) was placed on the user's collarbone for ECG recording. The collarbone electrode has been shown to acquire reliable ECG signals without adding discomfort to the user, relative to chest-placed electrodes. All signals were acquired at a sampling rate of 125 Hz. Lastly, two earclip electrodes were used as references on each lobe. Data was streamed wirelessly using the standalone OpenBCI GUI to a nearby laptop.

5.3.2 Experimental procedure

The entire experimental procedure is detailed in Figure 5.2, where solid rectangles correspond to experimenter tasks and dashed rectangles to participant tasks. Eight participants consented to take part in this experiment (5 male and 3 female, 28.9 +/- 2.9 years of age) that received Ethics approval from the INRS Ethics Committee. Participants consisted of consenting adults with normal hearing, normal or corrected-to-normal vision, and without any known issues with virtual reality, such as severe cybersickness. Participants had no previous experience with playing the game Half-Life: Alyx. As can be seen, first a box was placed in front of the participant's home at a mutually-

Figure 5.3: On the left: entire equipment drop off at participant's home including 2 laptops, base stations, controllers and the instrumented HMD; on the right: 16 ExG sensor-equipped VR headset.

agreed time including two laptops, two controllers, two base stations, and the instrumented HMD (see items displayed in Figure 5.3). The MSI GT62VR 6RE Dominator Pro laptop was used to display the VR content and an ASUS k550 was used to record the streamed biosignal data. Next, gameplay and real-time signal quality monitoring were achieved through the "Teamviewer" platform and a dedicated videoconference session via in-house developed quality monitoring tools. Moreover, instructions on how to set up the gaming environment, how to wear the HMD, as well as how to play the game (Half-life: Alyx) were given via a videoconference call.

For proper tracking of the HMD and controllers, participants had to mount the base stations diagonally at opposite corners of their gaming room. Each base station has a 150-degree horizontal field of view and a 110-degree vertical field of view. Half-Life: Alyx is one of the most immersive VR first-person shooter games developed by Valve where players are immersed into deep environmental interactions, puzzle solving, world exploration, and visceral combat. During the action parts, players need to get supplies, use interfaces, throw objects, and engage in combat. In the experiment, participants went through two conditions, which we term (1) baseline and (2) exploration/fight. The baseline corresponds to the first two chapters of the game (about 30 minutes of gameplay) where the player discovers the game storyline, learns how to navigate by flicking the analog stick, and how to manipulate physical objects throughout the world using the "gravity gloves", including realistically reloading weapons.

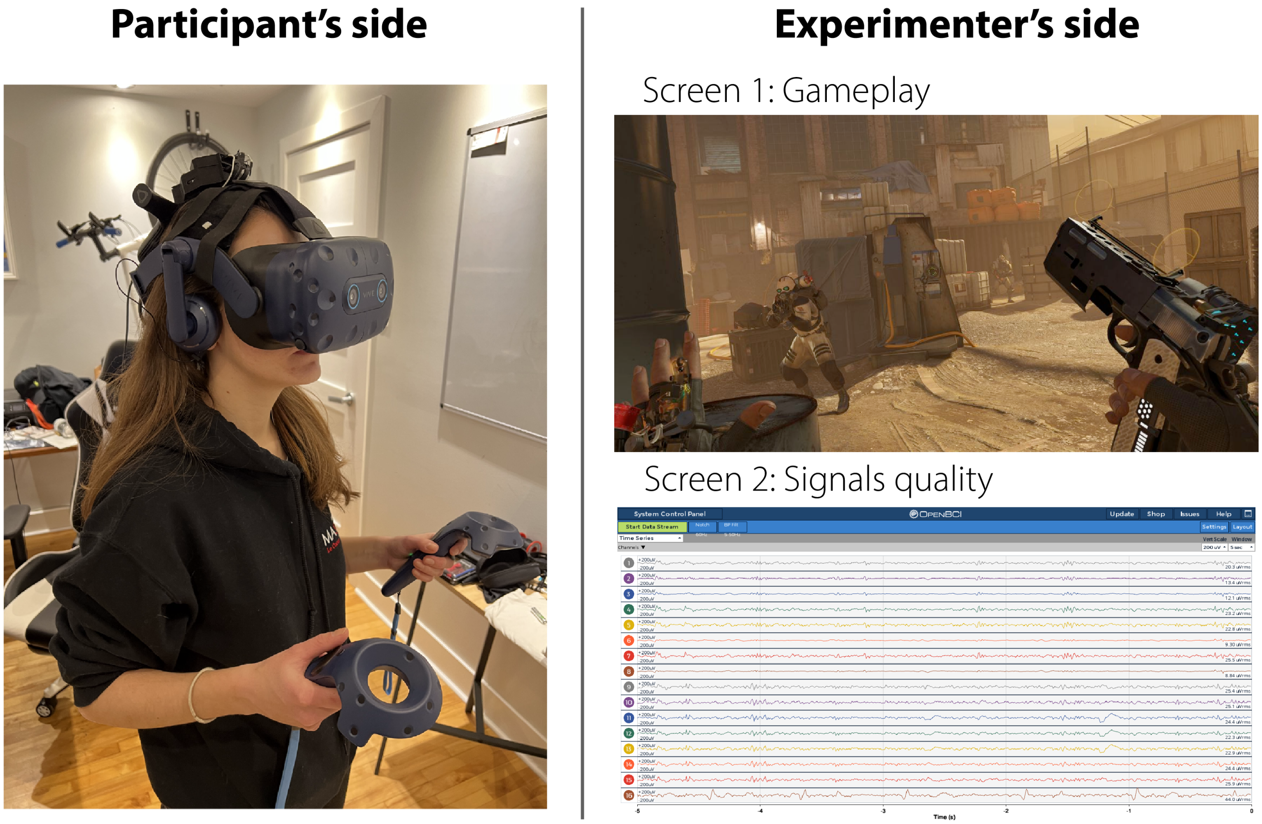


Figure 5.4: Representative view of one session of the experiment from the perspective of the participant (left) and the experimenter (right).

After concluding the two chapters, participants filled out an online unified user experience questionnaire (more details in the next Section). Next, participants would continue with subsequent chapters of the game, which we term 'exploration/fight' as the player is confronted with puzzle-solving and fighting challenge phases to advance through the game (about 1 hour of gameplay). The top-right plot of Figure 5.4 shows a representative exploration/fight scene where the player must confront soldiers and defeat them. The player can hide behind surrounding structures, if possible, to avoid getting shot at and attacked once the soldiers reload. At the end of this second session, participants filled again the unified user experience questionnaire. Participants were free to play the baseline and exploration/fight conditions at different times of the day or even different days to minimize visual fatigue and maintain spatial awareness of the room around them.

Figure 5.4 shows a representative view of the experiment conducted from the participant's (left) and the experimenter's (right) perspectives. Lastly, once the two sessions were completed, participants were asked to put all the hardware back inside the box. Once the box was collected by the experimenter, the cleaning and disinfecting phase would start. Proper device cleaning and

Figure 5.5: An illustration showing the HMD system positioned inside a Cleanbox UV-C chamber.

sanitation were performed to minimize the spread of COVID-19, following protocols in place at the authors' institution. All VR equipment, the electrodes, and the two laptops were thoroughly disinfected with alcoholic wipes. The instrumented HMD was disinfected using a Cleanbox UV-C chamber built specially for VR headsets (Cleanbox Technology, USA), as shown in the Figure 5.5 depicting the system within the Cleanbox. Upon sanitation, the HMD stayed in quarantine in the chamber for 24 hours and outside the chamber for another 24h. After 48h of quarantine, all the material was ready to be boxed up again and delivered to the next participant. No cases of COVID-19 were reported during this study.

5.3.3 Subjective user experience assessment

In order to measure the impact of immersive media-related HIFs on gamer's user experience, we utilized the unified questionnaire proposed by [178]. The questionnaire combines 87 different items, compiled from 10 different scales measuring the gamer's sense of presence, engagement, immersion, flow, usability, skill, emotion, cybersickness, judgment, and technology adoption, as well as three open-ended questions aimed at gathering candid gamer feedback about their experiences. Scale construction was based on nine other existing questionnaires. The 87 items used a 10-point Likert scale with the lower value indicating a ‘strongly disagree’ response. The complete questionnaire can be found in Appendix A for further reference.

5.3.4 Pre-processing and biosignal feature extraction

5.3.4.1 Signal pre-processing

In this study, the total 1.5 hours of data collected per subject was divided into 5-minute window. Signal pre-processing was performed using MATLAB; the EEGLab toolbox [327] was used for EEG analysis. In particular, EEG signals were first band-pass filtered between 0.5 and 45 Hz and then zero-mean normalized. Motion artifacts were removed using the ASR method detailed in Section 3.4.1.4. Before the beginning of each game session, it is important to note that the initial loading time of the game was utilized as a reference point for calibrating the ASR algorithm for each participant. Lastly, each 5-minute window was further segmented into 2-second epochs with a 50% overlap for features extraction.

5.3.4.2 EEG features

We focused on measuring user experience by examining several EEG metrics described in Section 3.4.2.1, specifically: the engagement score (ES), arousal and valence indices (AI and VI), and frontal alpha asymmetry (FAA). To compute these metrics, we segmented the EEG signals into 2-second windows with a 50% overlap, using a Hamming window. Additionally, skewness and kurtosis measures were extracted from each EEG metric as supplementary features. Finally, we measured the EEG subband frequency powers for each electrode and calculated their corresponding ratios. In total, we extracted 32 features from the EEG data.

5.3.4.3 EOG features

The frequency range of EOG signal is 0.1 to 50 Hz and the amplitude lies between 100-3500 μV [147]. From the EOG signals, we extracted eye blink and saccade rate measures and their durations presented in Section 3.4.2.2. EOG signals (Fp1, Fp2, Fpz, H EOG right, H EOG left, V EOG right, and V EOG left) were therefore band-pass filtered in this frequency range and then zero-mean normalized. The ASR algorithm was also applied to remove head motion-related artifacts while keeping the eye blinks and eye movements intact. In total, we extracted 4 features from the EOG data.

5.3.4.4 ECG features

For ECG signal processing, we extracted the 15 features related to HR and HRV presented in Section 3.4.2.3. These traditional HRV-based measures have been used to assess user experience, especially when experiencing emotional or physical stress, where an increase in HR can be observed [69, 70]. Moreover, changes in HR and HRV have been reported with varying game difficulty levels [328]. These features were calculated within 2-second windows with a 50% overlap to capture the dynamic changes in HR and HRV during gameplay.

5.3.5 Statistical tests

First, to validate the experimental protocol, we compare the baseline and exploration/fight conditions using a t-test on each question of the 10 scales of the subjective questionnaire with a significance level of 95%. Next, to help answer RQ1, a t-test is conducted on each physiological metric (significance level of 95%) over the two conditions. The degree of freedom of the test, the estimated population standard deviation, and confidence intervals are reported. Lastly, to help answer RQ2, we use Pearson correlation between the measured physiological signals and the subjective ratings to explore which metrics best correlate with each HIF.

5.4 Experimental results

Table 5.1 reports the 21 subjective questions, out of the 87 available, that showed a significant difference between the baseline and exploration conditions across all subjects. As can be seen, eight of the 10 different scales showed a significant difference, with only the ‘usability’ and ‘technology adoption’ scales not showing any significant difference. In general, the exploration/fight scenes showed an increased sense of presence, flow, immersion, and emotions, but somewhat higher cybersickness symptoms. These results help answer RQ1.

Scales	Items	Questions	Ratings: Mean ± std	
			Baseline	Fight
Emotion	Q2	*"I did not get tense in the virtual environment"*	5.75 ± 2.6	4.13 ± 1.0
	Q13	*"I enjoyed the challenge of learning the virtual reality interaction devices"*	6.63 ± 2.5	8.38 ± 1.3
	Q14	*"The virtual environment did not scare me since I fully understand it"*	8.13 ± 1.1	6.38 ± 2.0
Cybersickness	Q21	*"I did not suffer from fullness of the head during my interaction with the virtual environment"*	3.13 ± 2.8	1.75 ± 0.7
	Q23	*"I did not suffer from vertigo during my interaction with the virtual environment"*	2.38 ± 1.8	1.63 ± 0.5
Engagement	Q27	*"I was involved in the virtual environment experience"*	9.25 ± 0.7	9.63 ± 0.7
Presence	Q28	*"The virtual environment was responsive to actions that I initiated"*	9.13 ± 0.8	9.88 ± 0.4
	Q29	*"My interactions with the virtual environment seemed natural"*	7.38 ± 2.3	8.50 ± 1.2
	Q33	*"I could examine objects from multiple viewpoints"*	8.00 ± 1.5	9.13 ± 0.8
Flow	Q43	*"Time seemed to flow differently than usual"*	4.75 ± 3.0	7.50 ± 2.3
	Q48	*"I felt I was experiencing an exciting moment"*	8.50 ± 0.9	8.75 ± 1.2
	Q50	*"When I mention the experience in the virtual environment, I feel emotions I would like to share"*	7.38 ± 0.5	8.88 ± 1.1
Immersion	Q52	*"I become so involved in the virtual environment that I was not aware of things happening around me"*	8.38 ± 1.6	9.25 ± 1.2
	Q53	*"I identified to the character I played in the virtual environment"*	7.38 ± 1.5	8.25 ± 0.9
	Q54	*"I become so involved in the virtual environment that it is if I was inside the game rather than manipulating a controller and watching a screen"*	7.13 ± 1.6	8.25 ± 1.7
	Q56	*"I did not get scared by something happening in the virtual environment"*	4.50 ± 3.3	1.75 ± 2.1
	Q57	*"I become so involved in the virtual environment that I lose all track of time"*	7.38 ± 2.3	8.13 ± 0.9
Skill	Q61	*"I felt confident selecting objects in the virtual environment"*	7.13 ± 1.6	8.38 ± 1.5
	Q62	*"I felt confident moving the cross hair around the virtual environment"*	7.13 ± 1.2	8.13 ± 1.1
Technology Adoption	Q71	*"The interaction devices would make work more interesting"*	7.13 ± 1.4	8.25 ± 0.9
	Q72	*"I would like working with the interaction devices"*	6.38 ± 3.0	8.38 ± 1.3

Table 5.1: Summary of the 21 scales that showed significant differences between baseline and exploration/fight conditions across all subjects.

Next, we explore the changes seen in the measured physiological signals between the two conditions. Table 5.2 shows the difference between the average metric in the exploration/fight condition to the average metric over the baseline condition, represented by a Δ symbol, for each of the eight

	Subjects								
$\Delta Metrics$	**S1**	**S2**	**S3**	**S4**	**S5**	**S6**	**S7**	**S8**	**Mean**
ΔHR	14.5	16.9	10.6	5.1	14.0	12.1	5.4	6.3	11.9
ΔBL	-1.5	2.9	-0.6	10.7	5.0	-0.2	3.6	2.2	2.8
ΔSAC	33.9	19.6	25.9	5.5	23.0	23.1	20.9	29.2	22.6
ΔES	-2.6	1.4	2.2	3.6	0.3	0.9	-2.7	0.8	1.1
ΔAI	-1.6	3.8	0.1	1.9	5.6	-5.6	0.7	1.2	1.2
ΔVI	-4.8	6.9	-5.0	-0.6	-13.1	-4.7	-5.0	-1.4	-3.5
ΔFAA	-2.4	-1.9	0.2	0.5	0.2	-0.4	-0.7	5.5	0.1

Table 5.2: Difference between the average metrics in the exploration/fight condition to the average metrics over the baseline condition for each subject and averaged over all subjects. Units: HR – beats per min; BL – blinks per minute; SAC – saccades per minute.

	Mean ± Std						
Metrics	**B**	**E/F**	**P-value**	**t-statistic**	**df**	**sd**	**95 % CI**
HR	85.1±6.5	97±8.0	0.0308	2.4006	14	11.25	[-25.5900; -1.4400]
BL	13.8±5.8	16.6±7.2	0.2267	1.2645	14	4.03	[-6.8680; 1.7732]
SAC	113.7±24.3	136.3±34.3	0.0818	1.8748	14	37.47	[-75.3157; 5.0585]
ES	56.6±9.8	57.7±10.1	0.4345	0.8046	14	2.65	[-1.7736; 3.9031]
AI	20.7±15.5	21.9±15.8	0.1527	1.5122	14	5.70	[-1.8054; 10.4371]
VI	52.4±10.6	48.9±15.7	0.6699	0.4354	14	11.82	[-10.1039; 15.2509]
FAA	-0.5±2.1	-0.4±1.6	0.8744	0.1610	14	1.62	[-1.8777; 1.6155]

Table 5.3: Statistics of the difference between conditions for each computed metric averaged across all subjects. Units: HR – beats per min; BL – blinks per minute; SAC – saccades per minute.)

subjects, as well as the average across subjects. As can be seen, there is an increase in HR of approximately 12 beats per minute in the fighting condition, as well as an increase of 23 saccades per minute. To test the significance of these changes, Table 5.3 further presents the results of the statistical test. As can be seen, heart rate showed a significant difference whereas the changes in saccades were mildly significant.

In order to study the temporal evolution of each physiological metric, Figure 5.6 depicts the averages of the metrics presented as a function of time across all participants during baseline and exploration/fight conditions (black and grey curves, respectively). As can be seen, the heart rate remained consistently higher in the fight condition, as expected, as this is a more stressful condition. The saccades per minute metric was also consistently higher in the exploration condition. This is also expected as the gamer is trying to escape from being shot, and thus needs to survey the scene more intensely. The "humps" seen in the SAC plots are likely indicative of the brief period when

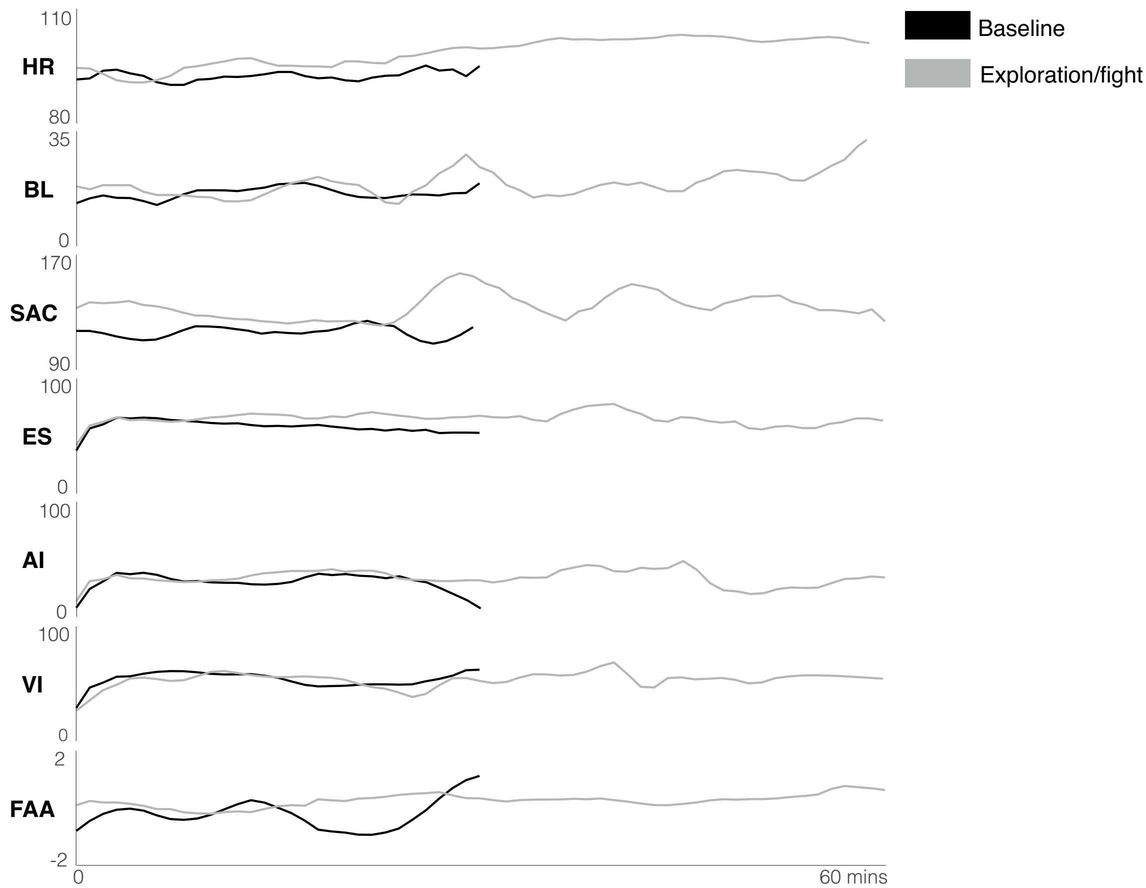


Figure 5.6: Instrumental measures over time in baseline (black) and exploration/fight (grey) conditions for all participants.

the gamers moved to subsequent chapters. The engagement index, in turn, decreased with time in the baseline condition, likely indicating that gamers became bored after roughly 15 minutes. In the fighting condition, on the other hand, engagement levels remained consistent throughout the experience. The arousal index suggests that towards the end of each session, arousal levels decreased in both conditions. With such temporal information available, thresholds could be set such that adaptive games could be developed (e.g., if ES drops below a certain value, increase the number of attacks or puzzles that need to be solved).

Lastly, Figure 5.7 shows the Pearson correlations achieved between all physiological measures and the 21 subjective scales from Table 5.1 with values concatenated for both conditions. The correlations are color-coded based on the strength of the correlations, ranging from strong (e.g., greater than 0.7), to moderate (between 0.3 and 0.7) to low (below 0.3). As can be seen, several HR and HRV measures showed strong correlations with several scales, in particular for flow and immersion. EEG alpha and beta band features showed a strong correlation with emotional states

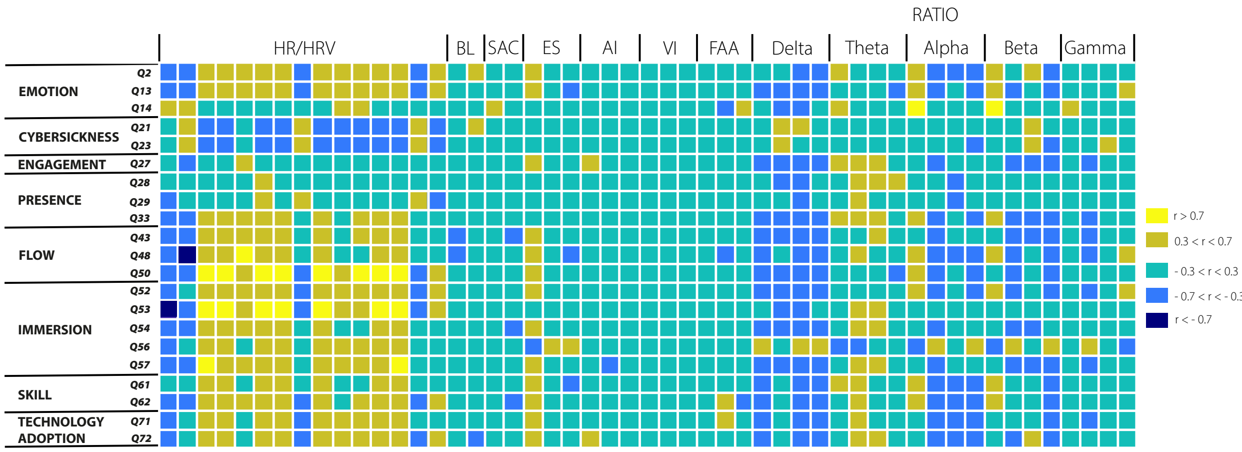


Figure 5.7: List of metrics that showed correlation with each subjective rating.

and moderate correlations with several other scales; the same was true for the delta band features. The engagement score showed a moderate correlation with engagement ratings and EOG-based measures showed moderate correlations with emotion and cybersickness ratings. Overall, almost all HIFs showed moderate to strong correlations with at least one physiological signal, thus helping answer RQ2.

5.5 Discussion

5.5.1 Answering RQ#1: Can the proposed instrumented HMD be used in highly ecological settings with minimal experimenter intervention?

Results reported herein suggest that, yes, the instrumented HMD can be used reliably in gamer homes with minimal experimenter intervention. The changes seen not only in the subjective ratings reported across experimental conditions but also with the physiological signal measures (in both time-averaged and real-time changes) suggest that the headset can be correctly deployed and interfaced with commercial games and used by the average gamer at the comfort of their own homes. The subsections to follow discuss the reported subjective measures and computed physiological metrics in more detail.

5.5.1.1 Capturing (expected) subjective insights

As can be seen in Table 5.1, the scales emotion, cybersickness, engagement, presence, immersion, skill, and technology adoption showed significant differences between the two conditions. For each question, except Q2 (emotion), Q21 and Q23 (cybersickness), and Q56 (immersion), the average scores were higher in the exploration/fight condition relative to the baseline. Note, however, that these four questions were asked in a negative manner; for example, Q56 mentioned "*I did not get scared by something happening in the virtual environment*." As such, a lower value indicates that the gamers were more scared in the exploration/fight condition.

In fact, since this condition includes fight and puzzle-solving challenges, the exploration/fight condition is likely to induce higher stress and concentration levels for the gamer, thus increasing such states. Increases in their perception of skill, for example, could also be due to the fact that the exploration/fight condition came second, thus the gamers had obtained some experience in navigating and interacting with the objects. Moreover, as the fight conditions were more challenging, participants also reported becoming more involved, excited, and engaged during this phase, hence explaining the increases in emotion, engagement, presence, flow, and immersion subscales. However, in most cases, participants complained of visual fatigue after 15-20 minutes of playing. Only one participant reported cybersickness with little nausea when using VR for a while. After 50 minutes of play, some participants experienced physical and mental fatigue, thus explaining the lower ratings in the exploration/fight in cybersickness. The changes observed were expected (e.g., higher stress levels in the fight conditions) and indicate that the commercial game and HMD were correctly deployed and gamers, who had no previous experience with Half-Life: Alyx, were able to successfully perform the experiment from the comfort of their own homes with minimal experimenter intervention.

5.5.1.2 Measuring aggregate physiological changes and insights

While the subjective changes reported above suggest that the gamers were able to correctly deploy the game from home, changes in the measured physiological signals will indicate if the instrumented HMD was correctly placed and that the signal processing pipelines were accurate and ensured high-quality signals were collected with minimal experimenter intervention. To obtain an overall snapshot of the changes seen in the physiological measures, Table 5.2 shows that for ECG the ΔHR (in bpm) is positive for all participants, as well as an average values across all participants of 85.1 bpm and 97 bpm in baseline and exploration/fight conditions (according to Table 5.3), respectively. This is expected, as in the first condition, the gamers explore the virtual environment and are not facing any stressful scenes, while in the second condition, they are confronted to a period of stress while fighting sequences.

Moreover, as can be seen from the metrics extracted from the EOG signals, the number of eye blinks/min (ΔBL), for 6 of the 8 participants, as well as the number of saccades/min ΔSAC, for all participants, increased by 2.8 and 22.6, respectively, for the exploration/fight condition. Indeed, during the combat sequences, participants have to react very quickly and look in several directions, which explains the increase in the number of saccades/min. In addition, visual fatigue is known to increase the number of blinks/min [179]. Several participants reported visual fatigue. Since the exploration/fight condition lasted twice as long as the baseline condition, this could explain the increased number of blinks for many participants.

Next, we examine the EEG signals and note that for six of the eight participants, a slightly higher positive ΔES during the exploration/combat condition could be seen, suggesting greater engagement. According to the valence and arousal results, all participants showed low values for the arousal index (with averages of 20.7 and 21.9 on a 0–100 scale for the baseline and exploration/fight condition, respectively), and moderate values for the valence index (with average of 52.4 and 21.9 on a 0–100 scale for the baseline and exploration/fight condition, respectively), suggesting an overall positive emotion eliciting joy and happiness with a greater interest in the second condition. However, we observed similar effects as [139], where the valence index decreased during death events, except for participant S2. In fact, participants face death situations several times during the exploration/fight condition, hence explaining the decrease in valence index for several of the participants, as well as on average. Lastly, from the FAA metric, we can observe that most of the participants exhibited a negative ΔFAA, hence corroborating the increased levels of fear.

Lastly, from Table 5.3, HR showed to be significantly different between the two conditions across all subjects. Moreover, the t-statistic value indicates that the observed difference is more than twice the variability of the data, thus suggesting a potentially useful metric to objectively characterize gamer experience. Overall, these findings show that the collected physiological metrics followed expected behaviors, thus indicating that high-quality signals were indeed measured from the gamer's homes and did not require lengthy preparation sessions in controlled laboratory settings.

5.5.1.3 Measuring real-time physiological changes and insights

While measuring aggregate measures of physiological signals can be useful and suggest the measurement of high-quality data, aggregate measures may not be as useful for real-time tracking of gamer behavior, which would ultimately be needed for adaptive gaming at home. To this end, real-time measurement and monitoring of physiological measures are needed, as enabled by the developed HMD. As shown in Figure 5.6, HR increased over time, especially for the fight condition. In fact, movements related to interaction in the game, increased temperature and sweating, as well as higher stress levels in the fighting scenes are all factors that can lead to increases in heart rate over time. For the blinks, it can be observed that it increases with time for both conditions, but more substantially for the longer exploration condition. This corroborates the use of blink rate as a potential indicator of visual fatigue, which could be useful for QoE assessment.

For the engagement score, as mentioned above, the decrease over time for the baseline condition could be indicative of boredom, whereas in the fighting condition, it remains fairly consistent. Indeed, in the exploration/fight condition, the player is constantly solicited, whether to fight or to solve puzzles. On the other hand, in the baseline condition, not much happens and players could potentially become bored. We observe the same trends in the arousal index where in the baseline condition, the drops towards the end could be indicative of boredom. In the exploration/fight condition, on the other hand, this dropped happened only after 45 minutes of gameplay. This drop in arousal could be indicative of fatigue, as this coincided with an increase in blink rate as well around the same time.

Combined, the temporal information available from multiple physiological signal modalities could be used to infer the gamer's QoE levels in real time. With simple thresholding or more complex machine learning models, real-time game adaptation could eventually be performed, thus maximizing QoE on a per-gamer basis. This capability was enabled with the proposed HMD with minimal experimenter intervention. Overall, these combined insights help validate RQ#1 and show that a biosensor-instrumented headset, coupled with a signal processing pipeline, could be used in highly ecological settings with minimal experimenter intervention.

5.5.2 Answering RQ#2: Can the measured physiological signals be used as correlates of gamer HIFs?

Ultimately, we are interested in using physiological signals to extract measures that correlate with gamer experience HIFs in an objective manner. Here, Pearson correlation was used to help pinpoint which of the explored objective metrics could be used as correlates of immersive gaming HIFs. From Figure 5.7, it can be seen that ECG and EEG signals generated features that showed the most moderate to strong correlations with the majority of the subjective ratings, thus indicating their importance for gamer experience assessment. More specifically, from the ECG signal, HR (in bpm) and several HRV measures, including SDNN, rmsRR, IBImean, LF, HF and total powers, pNN50, SD1, and SD2, showed a strong correlation with most of the subjective flow and immersion ratings. The ratios α/δ and β/δ also showed a strong correlation with the emotion rating. Similar to the studies presented in Section 3.4.2.1 that linked spectral powers to HIFs, we observe a moderate correlation between immersion and θ/α, stress regulation and δ/β, as well as the presence and θ/β. Moreover, ES showed a moderate correlation with engagement, emotion, flow, immersion, skill, and technology adoption ratings. Finally, eye blinks showed a correlation with the cybersickness rating, further confirming its usefulness for visual fatigue monitoring. Overall, several metrics showed strong correlations across all tested human influential factors, thus corroborating the usefulness of the developed HMD to extract correlates of gaming HIFs.

Taken together, the results obtained herein are promising as they (1) were achieved in highly uncontrolled "in-the-wild" scenarios, with minimal experimenter intervention, and (2) resulted in measured physiological measures that could be used for real-time gamer QoE assessment. None of the participants reported any difficulty in setting up the VR room and the instrumented headset. The fact that the system is wireless and portable, and that setup times, including automated data quality analysis, can take less than a minute, makes it ideal for at-home deployment. Ultimately, it is hoped that the work presented here will inspire researchers in various fields to replicate and use this technology to develop next-generation immersive applications.

5.6 Conclusions

In this Chapter, we presented a new protocol for collecting physiological data remotely for home-based VR studies with minimal experimenter intervention. By equipping a plug-and-play VR headset with a number of ExG sensors, combined with a strict sanitization protocol, we were able to collect data from eight participants remotely from their homes during periods of COVID-19 lockdowns. From the collected biosignals data, we extracted several metrics that were found to correlate with several HIFs, including emotional states, engagement, presence, immersion, skills, flow, and technology adoption. In the next Chapter, we will explore the development of a new marker of IMEx, namely, perception of time in VR environments.

Chapter 6

Multimodal quantification of a gamer's perception of time

6.1 Preamble

This chapter is compiled from material extracted from the manuscript under review in the journal *Frontiers in Neuroergonomics* [204].

6.2 Introduction

Researchers and developers have become interested in understanding the psychological and physiological factors that influence the users' immersive quality of experiences, such as the sense of presence, immersion, engagement, and perception of time [202]. While substantial work has been reported on presence, immersion, and engagement (e.g., [8, 275, 276]), very little work has been presented to date on characterizing the user's perception of time and the role it has on overall immersive media quality of experience.

Time perception is a complex cognitive process that allows individuals to estimate the duration and timing of events. It plays a crucial role in several aspects of human life, such as decision-making, memory, and attention [329, 330]. Measuring a user's sense of perception of time in

VR can be challenging due to potential confounds with sense of presence and flow [185]. Existing methods of measuring time perception in VR commonly rely on self-reports and questionnaires, such as the Metacognitive Questionnaire on Time [331]. While these methods have provided valuable insights into the mechanisms of time perception, they have several limitations. For instance, they are prone to response biases and are influenced by various cognitive and contextual factors, such as attention and arousal [332]. Furthermore, these methods may not capture the dynamic nature of time perception as they depend on the individual's ability to accurately perceive and report time. Moreover, questionnaires are often presented post-experiment, thus providing little insight for in-experiment environment adaptation to maximize the user experience.

Recently, there has been a push to use wearables and biosignals to measure, in real-time, cognitive and affective states of users while immersed in VR experiences [333, 206, 203]. For example, EEG signals have been used to study engagement correlates within virtual reality experiences [275, 276]. ECG have been used to uncover the relationship between valence and HRV [71, 72], while the research by [208] has established connections between relaxation, heart rate, and breathing patterns while the user is immersed in a virtual forest. EDA, in turn, has been investigated to gain insights into the user's sense of presence and relaxation in virtual environments [82, 334]. Furthermore, other studies have explored head movements to better comprehend users' reported levels of valence and arousal, as well as emotional states [63, 64]. Eye movement has also been examined to assess factors such as immersion, concentration levels, and cybersickness in VR settings [59, 62].

Despite all of these advances, limited research exists on the use of biosignals to monitor correlates of time perception while the user is immersed in VR. This is precisely the gap that the current research aims to address. In particular, two research questions are addressed: (1) what modalities and features provide the most important cues for time perception modeling and (2) how well can we objectively measure time perception. To achieve this goal, we show the importance of different modalities, including features extracted from EEG, eye gaze patterns derived from EOG signals, heart rate measures computed from ECG, and head movement information extracted from tri-axis accelerometer signals from the headset, for time perception monitoring. This study contributes to the development of new methods to monitor time perception from biosignals, thus opening the door for future adaptive systems that maximize user experience in VR on a per-user basis.

6.3 Time perception research: Background

Previous studies have investigated the connection between the brain and time perception, revealing that the frontal and parietal cortices, basal ganglia, cerebellum, and hippocampus are critical brain regions involved in the perception of time [335]. Specifically, the dorsolateral prefrontal right cortex has been identified as a significant region involved in time perception. EEG has been a common method used to study the neural correlates of temporal processing. It is important to note that time perception involves various psychological constructs, including attention, engagement, arousal, and even the influence of emotional stimuli. Each of these factors can modulate our perception of time in different ways, making time perception a multifaceted and dynamic process [336, 337]. This complexity is reflected in the diverse range of methods and measures used to study time perception, as we will discuss in the following sections.

The work of [338] examined semantic processing of time using EEG and found that the right parietal electrodes showed an event-related potential (ERP) response specific to the perception of event duration, with stronger alpha/beta band desynchronization. The work of [339] investigated the mechanisms involved in time perception related to emotional stimuli with equal valence and arousal levels using electrophysiological data. The results show that the ability to estimate time is influenced by various cognitive and emotional factors. Specifically, valence and arousal can modulate time perception, thus altering perceived duration. This highlights the importance of considering these factors when studying time perception, and the need for measures that can capture these dynamics.

In the work of [340], in turn, the effects of oral bromazepam (a drug used for short-term treatment of anxiety by generating calming effects) on time perception were explored. The study monitored the EEG alpha asymmetry in electrodes associated with the frontal and motor cortex. The study found that bromazepam modulated the EEG alpha asymmetry in cortical areas during time judgment, with greater left hemispheric dominance during a time perception task. Moreover, the study of [341] explored the use of EEG absolute power and coherence as neural correlates of time perception. They found that participants who overestimated time exhibited lower activity in the beta band (18–30 Hz) at several electrode sites. The study suggested that although beta amplitude in central regions is important for timing mechanisms, its role may be more complex than previously thought.

Lastly, the work by [342] investigated correlates of time perception and reported on the importance of beta and theta frequency subbands.

Moreover, eye movements have become a valuable tool to investigate temporal processing and its relation to attention and eye gaze dynamics. Recent studies, for example, have highlighted the close link between eye movement and time perception, revealing that time compression could be due to the lack of catch-up saccades [180]. Other works have linked saccade and microsaccade misperceptions [343], as well as their role in visual attention and, consequently, on time perception [344]. Finally, it has been reported that when short intervals between two successive perisaccadic visual stimuli are underestimated, a compression of time is perceived [181]. These findings emphasize the importance of eye movements in understanding temporal processing, its connection to visual perception, and how our perception of time is influenced not only by our cognitive and emotional state but also by our visual attention and gaze dynamics.

Physiological measures, such as HRV and skin conductance, have also been used to explore the mechanisms underlying time perception. A study found that low-frequency components of HRV were associated with less accurate time perception, suggesting that the autonomic nervous system function may play a crucial role in temporal processing [345]. Another study showed that increased HRV was linked to higher temporal accuracy [346]. Additionally, changes in the sympathetic nervous system (SNS) activity have been found to affect time perception, with research showing that increased SNS activity, indicated by elevated heart rate and frequency of phasic skin conductance response, was linked to the perception of time-passing more quickly [347]. These findings highlight the importance of physiological measures in understanding the complex interaction between the body and time perception.

As can be seen, while numerous studies exist exploring the use of psychophysiological measures to characterize the perception of time, their measurement in virtual reality has remained a relatively unexplored area of research. Perception of time in VR has relied mostly on participant-provided ratings of judgement of time, usually provided post-experiment [348]. Being able to track time perception in real time could be extremely useful for immersive experiences. While time compression has been linked with high levels of engagement and attentional resources [186], time elongation could also be linked to boredom [349]. As such, time perception monitoring could be extremely useful for

Figure 6.1: On the left: 16 ExG biosensor-instrumented VR headset used to collect data. On the right: participant's view of a scene played in the VR game Half-Life: Alyx.

user experience assessment. In the next section, the materials and method used to achieve this goal are described.

6.4 Materials and method

In this section, we detail the experimental protocol followed, including the dataset used in Chapter 5, signal pre-processing, feature extraction and selection methods, and the regression method used.

6.4.1 Experimental procedure and time perception ratings

The dataset used in this study has been described in detail in Chapter 5. Here, we combine both tasks (baseline and exploration/fight conditions) and explore the use of the biosignals in monitoring the two ratings provided to two questions related to time perception: Q1 - *"Time seemed to flow differently than usual"* and Q2 - *"I lost the sense of time"*.

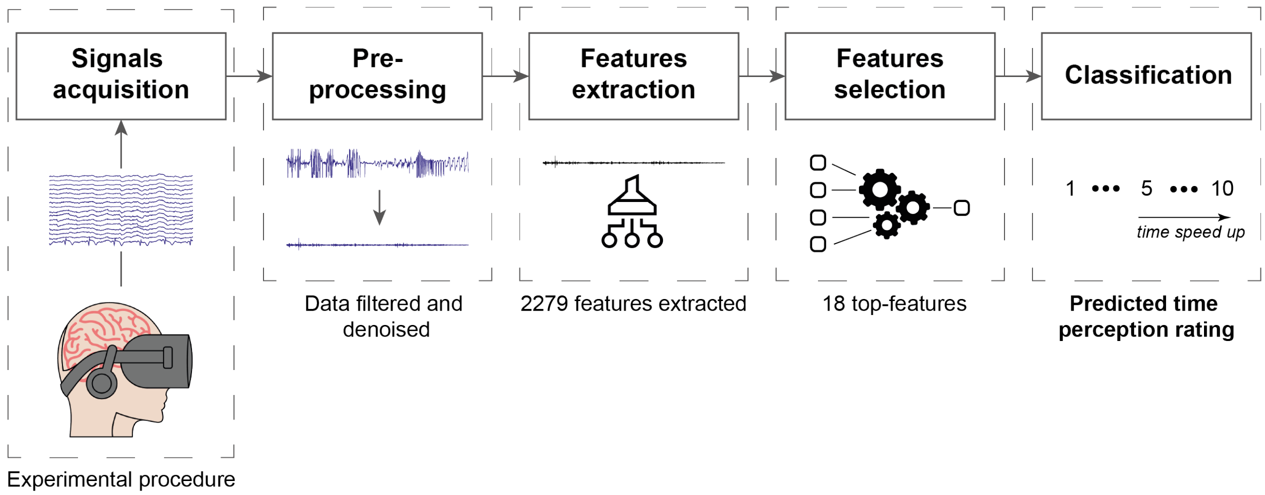


Figure 6.2: Processing pipeline to predict time perception ratings from biosignals.

6.4.2 Feature extraction

To answer the first research question of this chapter, we extracted several features from the EEG, EOG, ECG, and accelerometer data. These features were selected based on their potential relevance to time perception and cognitive processing in VR. For a comprehensive understanding of our methodology, including feature extraction and subsequent steps, please refer to the processing pipeline illustrated in Figure 6.2. In the following sections, we will provide a description of the different features we utilized and how they were extracted from the physiological signals.

6.4.2.1 EEG features

In this study, the total 1.5 hours of data collected per subject was divided into 5-minute window. As detailed in Section 3.4.2.1, we pre-processed EEG signals for feature extraction and computed EEG band ratio for the five frequency bands, resulting in 20 features. Indeed, previous research has shown that certain EEG band ratios, such as delta-beta coupled oscillations, play a crucial role in temporal processing [350]. These features provided valuable information on the power distribution of different frequency bands in the EEG signals, which are known to be associated with various cognitive and emotional states.

In addition to the EEG band ratio features, we extracted four indexes to further explore the participants' mental states during the task (presented in Sectfion 3.4.2.1), namely engagement, arousal, valence, and frontal alpha asymmetry, resulting in a total of 12 additional features for EEG modality. These measures have been shown to be related to cognitive and emotional processes that are involved in time perception, such as attention, motivation, and affective valence [351, 352, 146]

Subsequently, we extracted the 550 PMSC features and the 1540 PMSC-AM features, as described in Section 3.4.2.1. These features have proven to be useful in predicting arousal and valence by [144]. Given the established relationship between arousal and valence and time perception [145, 146], here we explore the potential use of these features as correlates of time perception.

6.4.2.2 EOG features

In this study, we extracted the 4 EOG features presented in Section 3.4.2.2: blink duration, blink count, saccade duration, and saccade count. These metrics have been shown to have a correlation with time perception [180, 181]. Next, we extracted time-domain and frequency-domain additional features from the EOG signals using the signal processing toolbox in MATLAB. The time-domain features include measures such as mean, standard deviation, skewness, and kurtosis, while the frequency-domain measures include mean frequency, median frequency, peak amplitude, and frequency location of the peak amplitude. These features provide information on the distribution of power across different frequency bands in the EOG signals and can reveal patterns related to eye movement. We also calculated statistical features such as interquartile range, variance, and energy. These features were calculated within 5-minute windows. In total, we extracted 31 additional features from the EOG signals, providing valuable information on eye movements during gameplay.

In addition to the aforementioned EOG features, we also extracted eye movement features related to the number of times eye movements shifted from the upper to the lower quadrant, as well as from the left to the right quadrant in the field of view of the VR headset, as introduced in Section 3.4.2.2. To this end, we employed a Support Vector Machine (SVM) classifiers. These classifiers were trained across 36 distinct points within the visual field, each separated by an angle of 10 degrees. For each 500 ms window within the seven EOG signals recorded by the instrumented headset from electrode locations Fp1, Fpz, Fp2, horizontal EOG right, horizontal EOG left, vertical EOG right, and vertical EOG left, we calculated the signal slope and input it into the SVM classifiers. These classifiers were designed to discern between up-down and left-right eye movements. The output of the classifier provided the eye's direction, and we subsequently calculated the number of gaze shifts between the quadrants of interest. These shifts were then incorporated as two additional features within our EOG feature set, bringing the overall count to 37 eye movement features for our analysis.

6.4.2.3 ECG features

As previously discussed in Section 3.4.2.3, we extracted 15 ECG features related to HR and HRV. These features encompass time-domain, frequency-domain, and nonlinear methods, providing a comprehensive understanding of HR and HRV during VR gameplay sessions. For a detailed description of the extracted ECG features, please refer to the mentioned section.

6.4.2.4 Accelerometer features

Features from the accelerometer data can offer insights into head motion and orientation during the VR experience. Given the potential influence of bodily movements on temporal perception and the difference in head movements based on arousal and valence states, we extracted 117 features, including statistical measures for acceleration, velocity, and displacement along the x, y, and z axes. For more information on the accelerometer feature extraction, please refer to Section 3.4.2.4.

6.4.3 Feature selection

Feature selection is an important step in classification tasks that involves the removal of irrelevant or redundant features, thus providing dimensionality reduction prior to classification. In our study, feature selection is particularly important given the amount of data collected. We performed a two-step process for feature selection using built-in functions in Matlab: first, we applied the Spearman correlation coefficient to identify features with a medium to high correlation with the ratings from Q1 and Q2; second, we applied the minimum redundancy maximum relevance (mRMR) algorithm to these selected features. The Spearman correlation coefficient measures the strength and direction of the relationship between the physiological features extracted and the ratings of the two questions on time perception. Specifically, we performed a Spearman correlation between all the 2279 features extracted from each 5-minute window of the entire dataset, which includes all recordings from all participants, and the ratings of the two questions Q1 and Q2. To align the number of ratings with the number of 5-minute window, we replicated the same rating for each window within a single recording. This approach allowed us to assess the relationship between each feature and the time perception ratings across all 5-minute windows and all participants. Spearman correlation is a non-parametric measure that assesses the monotonic relationship between two variables [182]; hence, does not assume linearity, making it suitable for our analysis. Only features with a Spearman correlation coefficient greater than 0.3 or less than -0.3 were retained, indicating a medium to high correlation.

Next, we applied the mRMR algorithm [183] on the physiological features that showed significant Spearman correlations with the ratings from Q1 and Q2. This selection method has been show to be very useful for biosignal data [144, 112, 353]. We used 5-fold cross-validation in our analysis. In this process, the dataset was divided into five subsets. For each fold, 80% of the data was used to calculate the mRMR, and the top features were recorded. This process was repeated five times, each time with a different subset held out. At the end, we compare the features that were consistently present across the five folds and use these as candidate features for time perception monitoring. With this analysis, a total of 18 top-features were found to be present in at least two of the five folds.

6.4.4 Regression, testing setup, and figures-of-merit

With the top-18 ranked features found, we employed a Gaussian process regressor (GPR) with a rational quadratic kernel to predict the two time perception ratings [184]. To find the optimal number of features to use, top-ranked features were added one by one and three figures-of-merit were used, namely root mean square error (RMSE), mean absolute error (MAE), and the R-squared (R^2). Both RMSE and MAE provide insights into to overall error distribution of the predictor, with RMSE providing greater emphasis to larger errors. In both cases, lower values are better. The R-squared measure, in turn, measures the goodness of fit of the data to the regression model; higher values are desired. These three figures-of-merit are widely used in regression to assess the performance of the model.

For the analysis, a bootstrap testing methodology was followed where the data was randomly partitioned into 80% for training and 20% for testing and this partitioning was repeated 100 times. Lastly, to gauge if the obtained results were significantly better than chance, a "random regressor" was used. With this regressor, the same bootstrap testing setup was used, but instead of training

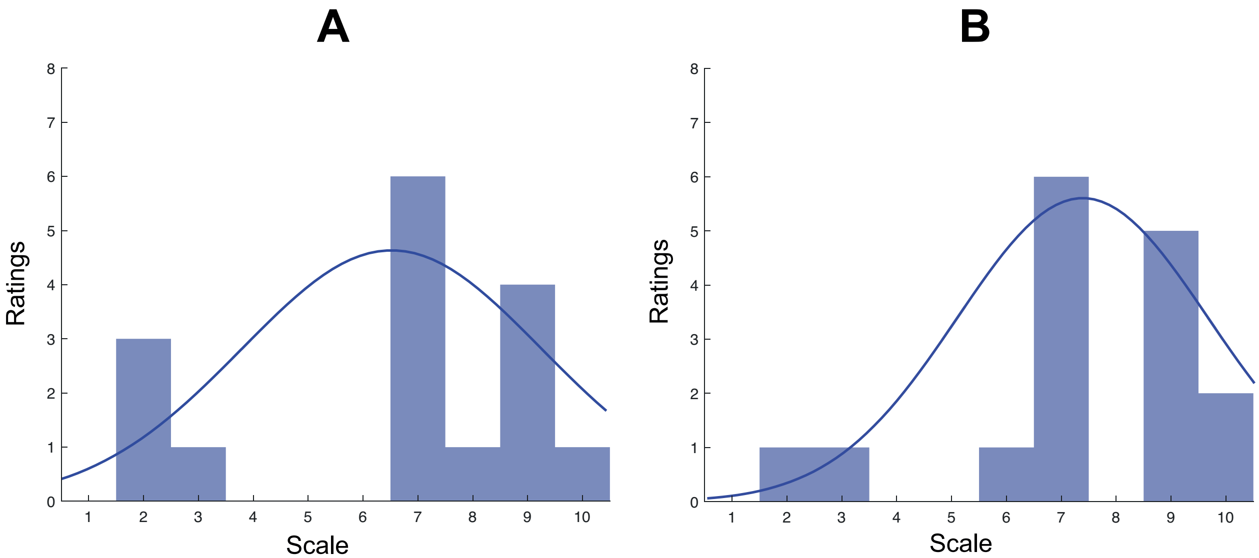


Figure 6.3: (A) Distribution of Q1 ratings across both testing conditions; (B) Distribution of Q2 ratings across both testing conditions.

the regressor with the true ratings reported by the participants, random ratings between 1 and 10 were assigned. To test for significance, a Kruskal-Wallis test was used [354] for each of the metrics (RMSE, MAE, and R^2). The Kruskal-Wallis test is a non-parametric statistical test that assesses whether samples originate from the same distribution. It is used to compare the means of two or more independent samples and is particularly useful when dealing with non-normally distributed data.

6.5 Experimental results

Figures 6.3 A and B display the distribution of the Q1 and Q2 ratings, respectively. For Q1, the ratings ranged from 2 to 10, with the majority being in the range of 7 to 9. The mean rating for Q1 was 6.40 (SD = 2.78). Similar findings were seen for Q2, where an average rating of 7.37 (SD = 2.27) was seen.

A total of 2279 features were extracted from the EEG, EOG, ECG, and accelerometer signals. After passing through the two feature ranking steps mentioned in Section 6.4.3, 18 top features were found for each of the two time perception ratings. Figures 6.4 A and B display the selected features for Q1 and Q2, respectively, arranged in ascending order of importance given by the mRMR selection algorithm. As can be seen, for both Q1 (*"Time seemed to flow differently than usual"*)

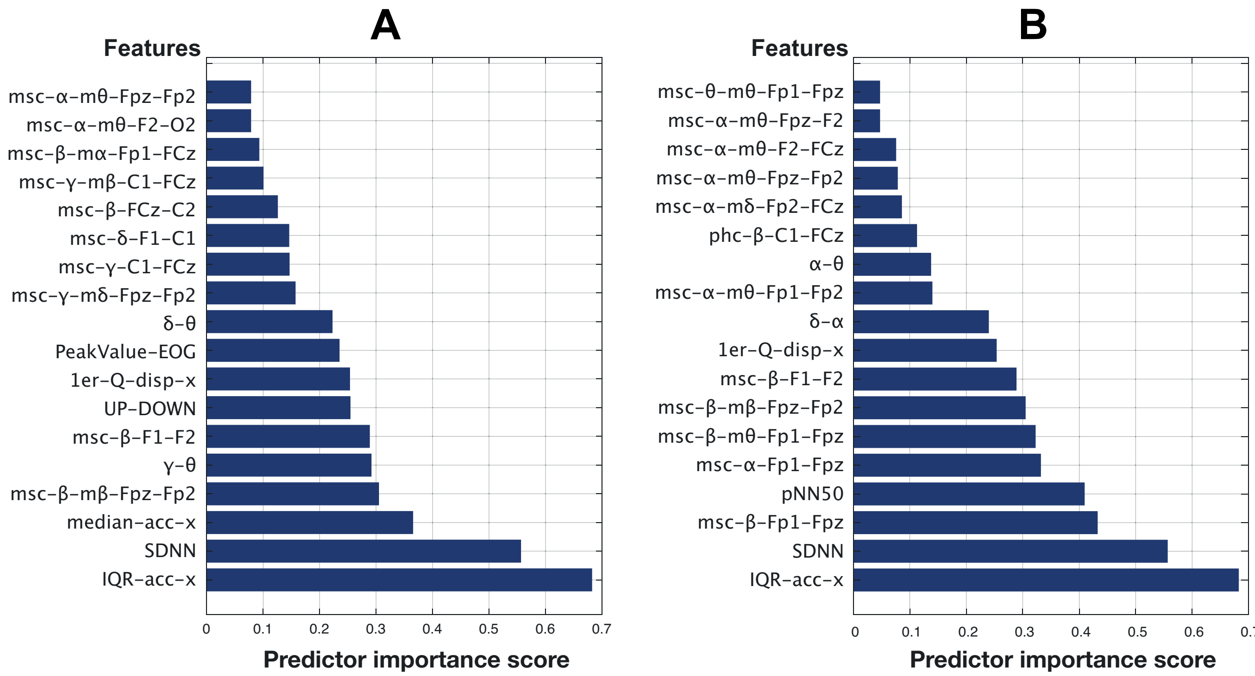


Figure 6.4: (A) Top features ranked for Q1; (B) Top features ranked for Q2.

and Q2 (*"I lost the sense of time"*), head movement and HRV-related measures corresponded to the top-two most important features. The majority of the other top features are related to EEG measures of coherence between different electrode sites. For Q1, two EOG measures stood out, one of them corresponding to a number of shifts from the top-bottom quadrants based on outputs from the EOG-based classifier described by [151].

Table 6.1 reports the impact that including these top features one-by-one has on regressor accuracy. The goal of this analysis is to explore the optimal number of features for time perception monitoring. As can be seen from the Table, there is an elbow point for Q1 at 7 features and at 8 features for Q2. In fact, for Q2, the accuracy achieved with just 2 features was very close to that achieved with 8. For Q1, the top-7 features included: IQR-acc-x, SDNN, median-acc-x, msc-beta-mbeta-Fpz-Fp2, gamma-theta ratio, msc-beta-F1-F2, and UP-DOWN. For Q2, the top 8 features correspond to IQR-acc-x, SDNN, pNN50, msc-beta-Fp1-Fpz, msc-alpha-Fp1-Fpz, msc-beta-mtheta-Fp1-Fpz, msc-beta-mbeta-Fpz-Fp2, msc-beta-F1-F2.

Figures 6.5 A and B display the scatterplots, including confidence intervals, of predicted versus true subjective ratings for Q1 and Q2, respectively, using the top-7 and top-8 features mentioned above for one of the bootstrap runs. The reference, perfect-correlation line is included for compar-

	Q1			Q2		
Nb of features	**RMSE**	**MAE**	R^2	**RMSE**	**MAE**	R^2
1	1.82	1.36	0.60	1.39	0.97	0.64
2	1.55	1.19	0.71	1.13	0.77	0.76
3	1.56	1.22	0.71	1.45	1.02	0.60
4	1.43	1.11	0.75	1.45	0.92	0.60
5	1.33	1.01	0.79	1.40	0.95	0.63
6	1.07	0.85	0.86	1.30	0.93	0.68
7	0.95	0.76	0.89	1.37	0.92	0.64
8	1.09	0.86	0.86	1.13	0.76	0.76
9	1.12	0.88	0.85	1.14	0.78	0.75
10	1.03	0.80	0.87	1.15	0.80	0.75
11	1.20	0.95	0.82	1.52	0.92	0.56
12	1.30	1.02	0.80	1.50	0.89	0.57
13	1.33	1.04	0.79	1.51	0.89	0.57
14	1.42	1.10	0.75	1.53	0.91	0.55
15	1.65	1.22	0.67	1.61	1.03	0.51
16	1.57	1.20	0.70	1.60	1.01	0.51
17	1.53	1.16	0.72	1.63	1.01	0.50
18	1.56	1.18	0.71	1.68	1.04	0.46

Table 6.1: Figures-of-merit as a function of number of features used to train the regressor for Q1 and Q2 ratings.

isons. For Q1, a significant correlation of 0.95 can be seen between predicted and true ratings. For Q2, in turn, a significant correlation of 0.90 is observed. To test if these results are significantly better than chance, the prediction task is repeated 100 times using a bootstrap method. Figures 6.6 A and B show the boxplots of the figures-of-merit achieved with the chance regressor and the proposed regressors for 100 bootstrap runs. As can be seen, the error based measures from the chance regressor result in similar trends and are almost three times as higher as the proposed method. Lastly, the Kruskal-Wallis test was performed over the entire 100 bootstrap trials and showed a significant difference (p-value = 10^{-34}) for all three figures-of-merit.

6.6 Discussion

6.6.1 Time perception ratings

Our findings suggest that the majority of the participants experienced altered time perception during the experiment, with the majority strongly agreeing that time seemed to flow differently

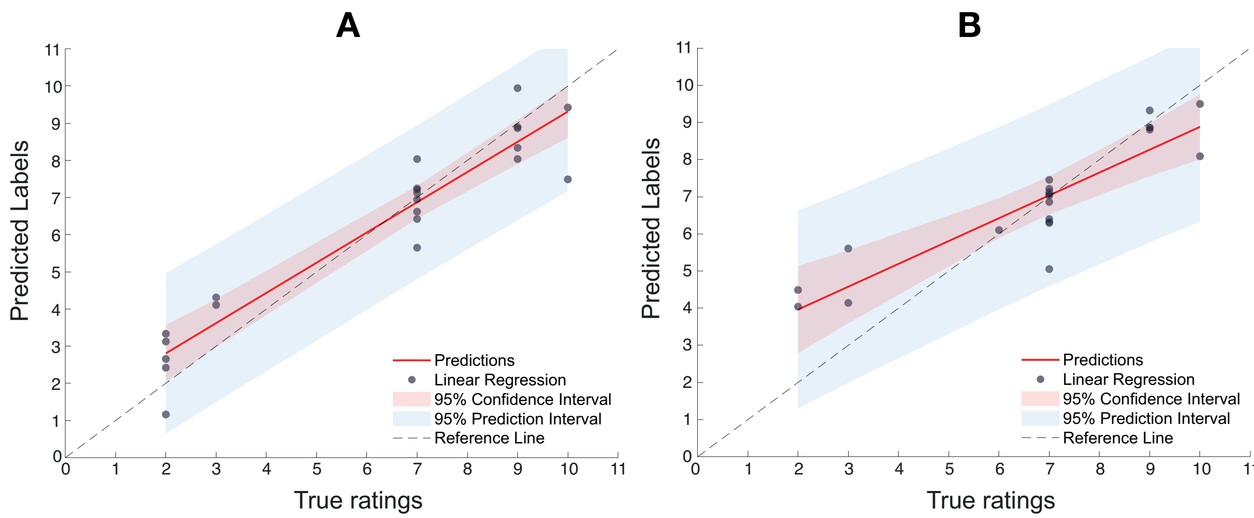


Figure 6.5: (A) Scatterplot of predicted vs. true ratings for Q1 (number of features = 7); (B) Scatterplot of predicted vs. true ratings for Q2 (number of features = 8).

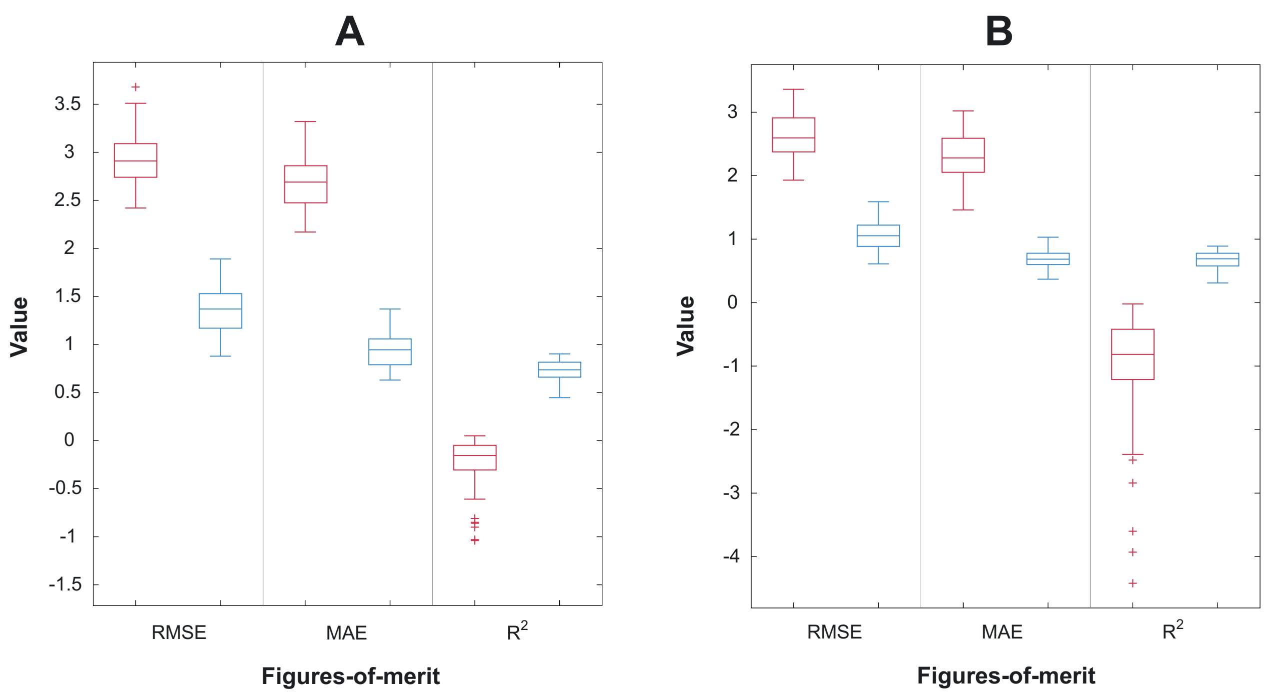


Figure 6.6: (A) Performance comparison of 100 random bootstrap trials for the random (red) and proposed (blue) regressors for Q1; (B) Performance comparison of 100 random bootstrap trials for the random (red) and proposed (blue) regressors for Q2.

than usual for them and that they lost the sense of time while in gameplay. This is consistent with previous research on time perception in VR, which has demonstrated that the sense of time passing can be significantly influenced by the level of immersion and engagement with the virtual environment [185, 186]. The VR environment used in our study was a highly-rated videogame known for its immersive qualities. This emphasizes the importance of examining the relationship between immersion and time perception in VR settings.

To empirically investigate this relationship, we conducted a correlation analysis between the Q1 ratings and the ratings from the seven items in the immersion scale. A significant correlation of 0.81 was found between the Q1 ratings and the ratings from the seven items in the immersion scale, particularly with the item - *"I felt physically fit in the virtual environment"*. This strong correlation suggests that the more participants felt physically fit and comfortable in the virtual environment, the more they experienced altered time perception. This provides empirical support for the link between immersion and time perception, reinforcing the idea that immersion can significantly influence how individuals perceive time in VR. Interestingly, lower values were observed during the puzzle-solving tasks, as shown in Figure 6.3, which were rated by the participants as being less engaging than the shooting tasks. This further corroborates the link between engagement, immersion, and altered time perception in VR. The immersive qualities of the VR environment, combined with the engaging nature of the tasks, appear to have a significant impact on participants' perception of time.

6.6.2 Feature importance

The identified features provide valuable insights into the neural, physiological, and behavioral correlates of time perception in VR. The prominence of head movement and HRV-related measures among the top features for both Q1 and Q2 underscores the integral role of physical engagement and physiological responses in shaping time perception in VR. The acceleration of head movements along the x-axis may be indicative of embodiment while in gameplay, as one often moves their head sideways to move away from shots fired by the enemy. Indeed, levels of embodiment have been linked to altered perceptions of time [355, 356, 357]. In a similar vein, the Up-Down shifts feature, present in Q1, suggests that the players are continuously scanning the scene and engaged. This is expected for fully immersed gamers, as players need to get supplies, which could be on the ground, pick up objects and throw them, and engage in combat with enemies appearing, for example, on floors below you, as shown in Figure 1. In contrast, less immersive screen-based first-person shooter games have shown eye gaze patterns to be mostly in the centre of the screen, where the aiming reticle is usually placed [358, 359]. SDNN, in turn, characterizes the heart rate variability of the players and has been linked to emotional states [187], stress [188, 189], and mental load [190], which in turn, have also been shown to modulate the perception of time. This suggests that physiological responses, as indicated by HRV measures, could also significantly influence time perception in VR.

For the top EEG measures, two out of three top measures corresponded to coherence measures in the beta frequency band. The electrodes showing the strongest involvement were located over the pre-frontal cortex areas. The pre-frontal cortex has been linked with temporal processing with activation in the right pre-frontal cortex has been reported during time perception tasks [360]. The inter-hemispheric PMSC measure msc-beta-F1-F2 may be quantifying this activation. Moreover, beta-band activation has also been linked with perception of time across multiple studies (e.g., [341, 361]). The work by [362] also showed that beta band activity around the Fpz region could be linked to task complexity, which in turn, was shown to also modulate time perception. In a similar vein, the work by [363] showed that transcranial alternating current stimulation over the fronto-central cortex at beta frequency could shift the perception of time to make stimuli seem longer in duration. Such properties could be captured by the PMSC-AM feature msc-beta-mbeta-Fpz-Fp2. Lastly, cortical gamma-theta coupling has been linked to mental workload [364, 365], whereas theta-gamma coupling to working memory [366, 367], which itself has been shown to modulate perception of time [368]. As the puzzle-solving tasks often require the use of short-term working memory, this feature is likely quantifying this aspect.

For Q2, four of the top 8 features (i.e., IQR-acc-x, SDNN, msc-beta-F1-F2, and msc-beta-mbeta-Fpz-Fp2) overlap with those seen with Q1, suggesting their importance for time perception monitoring and the need for a multimodal system to combine information from EEG, ECG and head movements. The other four provide alternate views of HRV and EEG modulations. For example, pNN50 has been shown to be an HRV correlate of focus [191]. High levels of focus and attention have been shown to be a driving factor for losing sense of time in VR [192]. In turn, inter-hemispheric differences in alpha band have also been linked to time perception [369, 370]. Lastly, several previous works have linked the theta-beta ratio to attentional control [371, 372, 373, 374]. While the ratio is usually computed using frequency bands computed over a certain analysis window, the PMSC-AM feature msc-beta-mtheta-Fp1-Fpz computes the temporal dynamics of this ratio over the window, thus may capture temporal attention changes more reliably. As with focus, high attention levels have been linked to losing sense of time in VR [192].

6.6.3 Monitoring time perception

The high correlation coefficients observed between the predicted and true subjective ratings for Q1 and Q2, as shown in Figures 6.5 A and B, are not only indicative of the accuracy of the proposed feature selection but also highlight the potential of using such features to effectively characterize time perception in VR. The fact that the error-based measures from the chance regressor were almost three times higher than those from the proposed method underscores the importance of careful feature selection and the use of machine learning techniques in predicting time perception. The significant difference in figures-of-merit between the chance regressor and the proposed regressors, as revealed by the Kruskal-Wallis test, further emphasizes the enhanced performance and effectiveness of the present study. This finding is particularly encouraging as it suggests that the proposed method could be used to enhance the design and evaluation of VR experiences by providing a more nuanced understanding of how users perceive time in VR. Moreover, the overlap of top features between Q1 and Q2 suggests that there are common underlying mechanisms in different aspects of time perception in VR, reinforcing the need for a multimodal system that combines information from EEG, EOG, ECG, and head movements.

6.7 Conclusions

The experiments described herein have shown the importance of a multimodal system to characterize time perception while immersed in VR. To characterize aspects of time flowing differently features from four modalities – EEG, ECG, EOG, and accelerometry – were shown to be crucial, thus signaling the importance of an instrumented headset. The aspect of time flowing differently also showed significant correlations with aspects related to immersion, thus suggesting that the developed instrumented headset could provide useful insights for the overall monitoring of immersive media quality of experience. If interested in monitoring only aspects of the users losing a sense of time while in VR, our results suggest that head movement features and HRV measures can achieve reliable results. Such findings could potentially be achieved with accelerometer data already present in VR headsets and with a heart rate monitor. The instrumented headset, nonetheless, could provide neural correlates of additional factors related to the overall experience and other aspects of time perception.

In this chapter, we examined time perception in a highly immersive VR environment using a combination of physiological signals, including head movement, heart rate variability, EEG, and EOG measured from sensors embedded directly into the VR headset. Experimental results show that participants experienced a high degree of time distortion when playing the game. Top features were found and used to characterize the gamers' sense of time perception using a simple Gaussian process regressor. An in-depth analysis of these top features was performed. Results showed that the proposed models were able to characterize the gamers' perception of time significantly better than chance. Ultimately, it is hoped that the insights and models shown herein can be used by the community to understand better the relationship between immersion and time perception in virtual environments, thus leading to improve immersive media experiences.

Chapter 7

Summary, future Research Directions, and conclusions

7.1 Summary

In this doctoral thesis, we have investigated the current challenges associated with the utilization of IMEx and HIFs in VR environments, specifically focusing on assessing and understanding user experiences, physiological responses, and time perception during VR interactions. The challenges encountered include:

- The need for accurate and comprehensive assessment methods that account for the diverse range of HIFs, as well as the rapidly evolving VR technologies and applications,
- The integration of multimodal physiological signal acquisition into VR systems, which is essential for providing real-time feedback and objective outcome measures for various VR-based applications, and
- The identification and understanding of markers for different HIFs based on the collected physiological data, enabling a deeper comprehension of user experiences in VR environments.

To address such challenges, we have investigated: (i) the state of the art in IMEx assessment methods, including their trends, innovations, and limitations, (ii) the development and evaluation of a wireless, biosensor-instrumented head-mounted display that acquires multimodal physiological signals during mobile VR applications, and (iii) the establishment of markers for various HIFs based on the gathered physiological data, resulting in an enhanced understanding of user experiences in VR environments.

In the following subsections, we discuss the contributions of this thesis towards the development of comprehensive and accurate assessment methods for IMEx and HIFs. We have provided a thorough review of existing methods, developed a novel instrumented HMD system for real-time physiological signal acquisition, and explored new protocols for remote data collection during VR experiences. Additionally, we have demonstrated the importance of a multimodal approach to understanding time perception in immersive VR environments and its potential impact on improving the quality of experience for users.

7.1.1 Comprehensive assessment of IMEx and HIFs

This thesis has provided a comprehensive assessment of the current state of IMEx and HIFs by thoroughly reviewing existing methods, identifying their trends, innovations, and limitations. We have presented the background of IMEx assessment with a focus on human influential factors, emphasizing the importance of adopting diverse assessment methods, including subjective, behavioral, and psycho-physiological measures. We have also delved into next-generation applications that incorporate multiple sensory modalities to enhance the realism and immersion of virtual environments. By addressing the limitations and providing insights into potential improvements, this work paves the way for further research and development in the assessment of IMEx and human influential factors in virtual reality environments. Moreover, this comprehensive analysis helps identify areas for future research and contributes to a better understanding of the challenges faced by researchers and practitioners in the field of VR, ultimately enabling the development of more effective tools and methods for IMEx evaluation.

7.1.2 Innovative instrumented HMD system for real-time physiological signal acquisition

A major contribution of this thesis is the development and evaluation of a wireless, biosensor-instrumented HMD that enables the acquisition of multimodal physiological signals during mobile

VR applications. This innovative system allows for real-time feedback, measurement of relevant HIFs, and the creation of objective outcome measures for various VR-based applications. By incorporating multiple physiological signals, including EEG, ECG, EOG, and facial EMG, and enhancing the system's capabilities, we have demonstrated the potential for valuable insights into user experiences in immersive virtual environments. This work sets the stage for future advancements in integrating physiological signal acquisition into VR systems, ultimately improving the overall quality of experience for users. Additionally, our research has contributed to the development of a low-cost solution for tracking saccadic eye movements, which could have significant implications for real-world applications. Furthermore, we have presented a new protocol for collecting physiological data remotely for home-based VR studies with minimal experimenter intervention, ensuring the continuity of research during challenging circumstances such as the COVID-19 pandemic.

7.1.3 Understanding HIFs through multimodal physiological data

This thesis has further contributed to the understanding of human influential factors in VR environments by building markers for different HIFs based on the collected physiological data. By exploring new protocols for remote data collection during VR experiences and investigating the importance of a multimodal approach to understanding time perception, we have demonstrated the potential for a deeper comprehension of user experiences in VR settings. Our findings in this area include the identification of key features from multiple modalities (EEG, ECG, EOG, and accelerometry) that are crucial for characterizing aspects of time flowing differently in immersive VR environments. This work not only highlights the importance of an instrumented headset for monitoring immersive media quality of experience but also suggests alternative approaches for monitoring specific aspects of user experiences using data already present in existing VR headsets. These findings provide valuable information for researchers and practitioners in the field, enabling the development of immersive media experiences that are more engaging, enjoyable, and beneficial for users. Additionally, the insights and models developed in this work contribute to a better understanding of the relationship between immersion and time perception in virtual environments, which could ultimately lead to improved immersive media experiences.

7.2 Future research directions

7.2.1 Incorporation of additional modalities

Future studies could explore the use of additional physiological modalities such as electrodermal activity (EDA) and respiration rate. EDA has been employed in VR research to measure immersive experiences and player arousal states [375, 376]. Arousal is connected to attention, emotional resources, and time perception [377, 378], making EDA a valuable addition to the assessment of user experiences in VR. Recent innovations in VR headset development are already exploring the inclusion of EDA sensors directly on the headset [379]. Respiration rate, conversely, offers valuable insights into a user's stress and relaxation levels during VR experiences. Breathing has been demonstrated as a crucial modality for managing cybersickness symptoms [380] and may play a significant role in adaptive serious games. By monitoring breathing patterns, researchers can identify instances of heightened cognitive load or emotional responses, providing a complementary perspective to other physiological measures. Incorporating these additional modalities and fusing them with existing physiological data could enhance the efficacy of immersive experience assessment methods. By combining multiple modalities, researchers can obtain a more comprehensive understanding of user experiences in VR environments, which in turn can lead to the development of more effective applications and interventions. Additionally, larger sample sizes in future studies would improve the statistical power and strengthen the validity of the results. This would enable a deeper exploration of the relationships between various physiological measures, immersion, presence, and time perception in VR. By accounting for individual differences and uncovering unique patterns in the data, researchers can further refine and customize VR experiences to better cater to users' needs and preferences.

7.2.2 Advanced eye tracking and feature extraction

Further work should focus on more complex eye-tracking tasks, involving a larger number of subjects and the use of advanced machine-learning methods. This could include investigating the role of saccadic eye movements, gaze patterns, and fixation duration in understanding user experiences in immersive VR environments [381]. A deeper understanding of these aspects of visual attention can provide valuable insights into user engagement, cognitive load, and emotional responses during VR experiences. In addition to traditional eye-tracking methods that rely on cameras, future research could explore the estimation of eye position coordinates (x, y) using electrooculography (EOG) signals. This approach offers a low-cost alternative for eye tracking, which can be particularly beneficial for large-scale studies or applications where camera-based eye tracking is not feasible [382]. By leveraging EOG signals, researchers can develop eye-tracking solutions that are more accessible and cost-effective, without compromising the quality of the collected data. Another important aspect to consider in future eye-tracking research is the assessment of visual fatigue during VR experiences. Prolonged exposure to virtual environments can lead to visual discomfort and fatigue, which can negatively impact user experience and immersion [383]. By investigating the relationship between eye-tracking metrics and visual fatigue, researchers can develop guidelines and recommendations for designing VR applications that minimize visual discomfort and promote longer-lasting, more enjoyable experiences. In order to efficiently analyze eye tracking and EOG features, machine learning techniques, such as deep learning and convolutional neural networks, can be employed. These advanced methods can help uncover hidden patterns and relationships in the data, enabling the development of more personalized and adaptive VR experiences tailored to users' individual preferences and needs.

7.2.3 Multisensory integration and analysis

Expanding upon the multisensory capabilities of the VR headset, researchers can investigate how different sensory stimulations, such as olfactory and haptic feedback, impact user experiences. This could involve studying the effects of multisensory stimulations on user relaxation, engagement, and presence in VR environments. The instrumented HMD developed in this thesis has already been employed in several studies investigating the impact of multisensory stimulation in VR [208, 210, 209]. These studies have provided valuable insights into how stimulating different senses can contribute to the overall user experience, by enhancing aspects such as realism, presence, immersion, and emotional responses. In the first study [208], the effects of ultra-realistic multisensory digital nature walks on user relaxation were explored. The findings showed significant improvements in relaxation and various biometric features indicative of stress, anxiety, and relaxation, thus demonstrating the potential of multisensory VR experiences as alternatives to traditional nature walks and the use of wearables for real-time stress monitoring and biofeedback-driven customization. The second study [210] examined the impact of stimulating different senses in a multisensory immersive experience, including the introduction of smells and haptic feedback. The results revealed significant improvements in various aspects of user experience, such as realism, presence, immersion, engagement, flow, and emotion, without negative effects on cybersickness. This suggests the potential of using wearables for real-time objective assessment of multisensory immersive media QoE. In the third study [209], a VR-based multisensory environment was described, with olfactory and haptic feedback added to audiovisual modalities. The study found that the multisensory condition led to increased game scores and differences in physiological signals across numerous modalities, such as mental states, head movements, eye blinks, and heart rate. These objective findings emphasize the potential of real-time biosignal measurements and ExG sensor integration on VR headsets for enabling user-aware game adaptation to maximize QoE. These studies further corroborate the potential of the instrumented HMD in multisensory VR research and highlight the importance of integrating and analyzing data from various sensory modalities to better understand and improve user experiences in VR environments.

Future research could further explore the use of deep neural networks and other advanced machine learning methods to extract more complex features and relationships from the collected data, thereby enhancing the efficacy of multisensory VR applications. Moreover, examining the role of individual differences in sensory processing and perception could provide valuable insights into tailoring multisensory experiences to maximize user enjoyment and satisfaction.

7.2.4 Adaptive content for enhanced user experience

A promising direction for future research is the development of adaptive content in VR environments that maximize user experience based on real-time physiological data. By incorporating end-to-end machine learning algorithms that analyze incoming signals and make decisions accordingly, researchers can create VR environments that adapt to individual user needs. This approach could involve dynamically adjusting the level of immersion, sensory stimulation, or difficulty based on user preferences and physiological responses. For example, the VR environment could respond to a user's stress levels by adjusting the complexity of a task or changing the multisensory scene to enhance relaxation. In serious games, adaptive content could be tailored to provide an optimal challenge level, maintaining user engagement without causing frustration or cognitive overload. Moreover, adaptive content could help mitigate the negative effects of cybersickness by adjusting visual or motion cues based on the user's physiological data, providing a more comfortable experience. Personalized adaptive content could lead to quality of experience-aware applications that offer customized, immersive experiences, enhancing user engagement and enjoyment. By leveraging the capabilities of the developed instrumented HMD and the insights gained from the multisensory research discussed in this thesis, future work can focus on creating sophisticated adaptive content that responds to users' physiological signals in real-time, providing a truly personalized and optimized VR experience.

7.3 Conclusion

The last decade has seen important advances in the development of IMEx/HIFs assessment. This work aimed to address the current challenges associated with these advances, specifically focusing on assessing and understanding user experiences, physiological responses, and time perception during VR interactions. To address these challenges, we conducted a series of studies and made significant contributions towards: (i) the development and evaluation of comprehensive IMEx assessment methods, including a review of existing methods and their limitations, (ii) the creation and evaluation of a wireless, integrated instrumented HMD that acquires multimodal physiological signals during mobile VR applications, and (iii) the identification and understanding of markers for different HIFs based on the collected physiological data, enabling a deeper comprehension of user experiences in VR environments. Ultimately, we hope that the contributions presented in this thesis work will help propel the research in the field of immersive VR experiences and encourage the development of innovative applications that take advantage of advancements in physiological signal acquisition, analysis, and the integration of multisensory information.

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Appendix A

Unified user experience in immersive virtual environment questionnaire

To assess user experience in immersive virtual environments, the questionnaire has been designed by [178] to encompass a wide range of factors. It includes 10 distinct scales that evaluate various aspects of the interaction between the user and the virtual environment. These scales are emotions, cybersickness, engagement, presence, flow, immersion, usability, skill, technology adoption, and judgment.

Table A.1: List of the 87 items used for assessing user experience in immersive virtual environments.

Subscales	Items
	1- I enjoyed being in this virtual environment.
	2- I got tense in the virtual environment.
	3- It was so exciting that I could stay in the virtual environment for hours.
	4- I enjoyed the experience so much that I feel energized.
	5- I felt nervous in the virtual environment.
	6- I got scared that I might do something wrong.
Emotions	7- I worried whether I was able to cope with all the instructions that was given to me.
	8- I felt like distracting myself in order to reduce my anxiety.
	9- I found my mind wandering while I was in the virtual environment.

	10- The interaction devices (HTC Vive headset, controllers) bored me to death. 11- When my actions were going well, it gave me a rush. 12- While using the interaction devices (HTC Vive headset, controllers), I felt like time was dragging. 13- I enjoyed the challenge of learning the virtual reality interaction devices (HTC Vive headset, controllers). 14- The virtual environment scared me since I do not fully understand it. 15- I suffered from fatigue during my interaction with the virtual environment.
Cybersickness	16- I suffered from headache during my interaction with the virtual environment. 17- I suffered from eyestrain during my interaction with the virtual environment. 18- I felt an increase of my salivation during my interaction with the virtual environment. 19- I felt an increase of my sweat during my interaction with the virtual environment. 20- I suffered from nausea during my interaction with the virtual environment. 21- I suffered from "fullness of the head" during my interaction with the virtual environment. 22- I suffered from dizziness with eye open during my interaction with the virtual environment. 23- I suffered from vertigo during my interaction with the virtual environment. 24- I enjoyed dealing with the interaction devices (HTC Vive headset, controllers).
Engagement	25- The visual aspects of the virtual environment involved me. 26- The sense of moving around inside the virtual environment was compelling. 27- I was involved in the virtual environment experience.
	28- The virtual environment was responsive to actions that I initiated. 29- My interactions with the virtual environment seemed natural. 30- The devices (controllers) which controlled my movement in the virtual environment seemed natural. 31- I was able to actively survey the virtual environment using vision. 32- I was able to examine objects closely.

Presence	33- I could examine objects from multiple viewpoints. 34- I felt proficient in moving and interacting with the virtual environment at the end of the experience. 35- The visual display quality distracted me from performing assigned tasks. 36- The devices (controllers) which controlled my movement distracted me from performing assigned tasks. 37- I could concentrate on the assigned tasks rather than on the devices (controllers). 38- I correctly identified sounds produced by the virtual environment. 39- I correctly localized sounds produced by the virtual environment.
Flow	40- I felt I could perfectly control my actions. 41- At each step, I knew what to do. 42- I felt I controlled the situation. 43- Time seemed to flow differently than usual. 44- Time seemed to speed up. 45- I was losing the sense of time. 46- I was not worried about other people s judgment. 47- I was not worried about what other people would think of me. 48- I felt I was experiencing an exciting moment. 49- This experience was giving me a great sense of well-being. 50- When I mention the experience in the virtual environment, I feel emotions I would like to share.
Immersion	51- I felt stimulated by the virtual environment. 52- I become so involved in the virtual environment that I was not aware of things happening around me. 53- I identified to the character I played in the virtual environment. 54- I become so involved in the virtual environment that it is if I was inside the game rather than manipulating a controller and watching a screen. 55- I felt physically fit in the virtual environment. 56- I got scared by something happening in the virtual environment. 57- I become so involved in the virtual environment that I lose all track of time.

Usability	58- I thought the interaction devices (HTC Vive headset, controllers) was easy to use. 59- I thought there was too much inconsistency in the virtual environment. 60- I found the interaction devices (HTC Vive headset, controllers) very cumbersome to use.
Skill	61- I felt confident selecting objects in the virtual environment. 62- I felt confident moving the cross hair around the virtual environment. 63- I felt confident using the controllers to move around the virtual environment. 64- I feel confident understanding the terms/words relating to the interaction devices (HTC Vive headset, controllers). 65- I feel confident learning advanced skills within a specific virtual reality software using the HTC VIVE. 66- I feel confident describing the functions the interaction devices (HTC Vive headset, controllers) of a virtual reality environment.
Technology Adoption	67- If I use again the same virtual environment, my interaction with the environment would be clear and understandable for me. 68- It would be easy for me to become skillful at using the virtual environment. 69- Learning to operate the virtual environment would be easy for me. 70- Using the interaction devices (HTC VIVE, controllers) is a bad idea. 71- The interaction devices (HTC VIVE, controllers) would make work more interesting. 72- I would like working with the interaction devices (HTC VIVE, controllers). 73- I have the resources necessary to use the interaction devices (HTC VIVE, controllers). 74- I have the knowledge necessary to use the interaction devices (HTC VIVE, controllers). 75- The interaction devices (HTC VIVE, controllers) are not compatible with other technologies I use.
	76- Personally, I would say the virtual environment is: impracticale/practical. 77- Personally, I would say the virtual environmnent is: Confusing/Clear. 78- Personally, I would say the virtual environment is: Unruly/Manageable.

	79- I found that this virtual environment was: Typical/Original.
	80- I found that this virtual environment was: Lame/Exciting.
Judgement	81- I found that this virtual environment was: Easy/Challenging.
	82- I found this virtual environment: Amateurish/Professional.
	83- I found this virtual environment: Gaudy/Classy.
	84- I found this virtual environment: Unpresentable/Presentable.
	85- I found that this virtual environment is: Ugly/Beautiful.
	86- I found that this virtual environment is: Disagreeable/Likeable.
	87- I found that this virtual environment is: Discouraging/Motivating.