Excite-O-Meter: Software Framework to Integrate Heart Activity in Virtual Reality

Luis Quintero*
Department of Computer and Systems Sciences, Stockholm University

John E. Muñoz†
Department of Systems Design Engineering, University of Waterloo

Jeroen de Mooij‡
Applied Media Development, The 1st Floor

Michael Gaebler§
Max Planck Institute for Human Cognitive and Brain Sciences

Abstract

Bodily signals can complement subjective and behavioral measures to analyze human factors, such as user engagement or stress, when interacting with virtual reality (VR) environments. Enabling widespread use of (also the real-time analysis) of bodily signals in VR applications could be a powerful method to design more user-centric, personalized VR experiences. However, technical and scientific challenges (e.g., cost of research-grade sensing devices, required coding skills, expert knowledge needed to interpret the data) complicate the integration of bodily data in existing interactive applications. This paper presents the design, development, and evaluation of an open-source software framework named `Excite-O-Meter`. It allows existing VR applications to integrate, record, analyze, and visualize bodily signals from wearable sensors, with the example of cardiac activity (heart rate and its variability) from the chest strap Polar H10. Survey responses from 58 potential users determined the design requirements for the framework. Two tests evaluated the framework and setup in terms of data acquisition/analysis and data quality. Finally, we present an example experiment that shows how our tool can be an easy-to-use and scientifically validated tool for researchers, hobbyists, or game designers to integrate bodily signals in VR applications.

Keywords: Bodily Signals, Heart Activity, Software, Architecture, Experiment, Virtual Reality, Open Source.

Index Terms: Human-centered computing—Interactive systems and tools—; Human-centered computing—Virtual reality—;—— Computer systems organization—Real-time system architecture—

1 Introduction

Virtual Reality (VR) technology provides a safe platform to simulate situations that might be unfeasible or expensive to create in real-life. Researchers have extensively used VR to understand how humans perceive and experience both physical and virtual environments [22]. Neuroscientists and psychologists have developed tools and established psychological and physiological principles that uncover the relationships between stimuli and human perception [25, 63]. It has been shown that human perception of the world is not only determined by features of physical objects; but internal physiological aspects, such as bodily processes or emotions, can also influence our perception of the world [55]. For example, perceiving a stimulus as threatening and experiencing fear is associated with an increased heart rate (HR), dilated pupils, and sweaty hands. Thus, the coupling of the central and the autonomic nervous system influences our perception and interaction with a virtual environment [12, 29, 58].

*e-mail: luis-eduardo@dsv.su.se
†e-mail: john.munoz.hci@uwaterloo.ca
‡e-mail: jeroen@the1stfloor.net
§e-mail: gaebler@cbs.mpg.de

Bodily data could be a valuable input for understanding how users perceive and interact with virtual experiences. As shown in multiple serious games [40] and clinical applications [27], including physiological signals might represent a new era of VR, where more effective interactions maximize the targeted individual user's gains (e.g., engagement, productivity, learning). Although this integration presents advantages and positive impact, the creation of personalized and adaptive VR involves modelling the behavior of each user, who has unique psychological characteristics (e.g., interests and expectations) and complex physiological dynamics [28, 64].

Two technological advances of the last decade could support the widespread creation of systems that combine both bodily data and VR environments. First, the advent of affordable wearable sensors can gather reliable physiological data, like smartwatches or chest straps commonly used for exercising [47]. The development of novel headsets with embedded physiological sensors is also a trending field with high potential [2]. Second, the availability of game engines, like Unity [61], has enabled easy creation of interactive 3D scenarios capable of interfacing with external devices.

Although there are affordable and accessible technologies, the integration of bodily signals in VR still undergoes scientific and technical challenges [32]. From the scientific side, the extraction of meaningful features requires domain experts and researchers that understand the underlying body processes, i.e., principles of psychophysiology [6]. Moreover, experimenters need synchronized data that let them study causality between visual stimuli and physiological responses, mainly because every physiological phenomenon has a different response time [6]. From the technical standpoint, the main stages of real-time data analysis (acquisition, feature extraction, and visualization [38]) are inherently compatible with the game engines for simulations in robotics or computer vision. However, these platforms are not fully adapted to conduct the real-time analysis on data incoming from external physiological sensors [35].

In this paper, we present the design, development, and evaluation of the `Excite-O-Meter`. An open-source software framework that allows developers, researchers, and hobbyists to integrate bodily signals in custom VR applications in Unity game engine [61]. The design requirements were created from potential users that answered an online survey. This first version of the tool integrates heart activity from the commercial electrocardiography (ECG) chest strap Polar H10 [50], provides real-time analysis of heart rate and its variability (HRV) features, and offers easy online/offline signal visualization. The tool lets non-experts integrate heart data in VR environments or facilitates scientific studies with psychophysiological research questions. The architecture can extend more physiological sensors in the future. Two technical experiments validate the reliability of the data acquisition/analysis and the current hardware setup (i.e., the use of the Polar H10 with VR). A final evaluation exemplifies how this tool can be used in scientific experiments to propose a physiology-based metric to estimate "excitement level".

We present related work in section 2. Design process and system architecture of the `Excite-O-Meter` are outlined in sections 3 and 4. The evaluation is outlined in section 5, a feasibility test in section 6, closing with discussion and conclusion in section 7.

978-1-6654-0158-6/21/$31.00 ©2021 IEEE
DOI 10.1109/ISMAR52148.2021.00052

2 Related Work

2.1 Physiology-based adaptive systems

Frameworks like the `Excite-O-Meter` have been of interest in fields such as affective computing or biocybernetic adaptation. The main goal is to design systems that adjust their functionalities to match the skills, emotions, or expectations of a user [11]. Several research projects have attempted to infer psychological states from the interaction of a user with a system and the monitoring of their body reactions [35,40,46,53]. Additionally, physiology and VR have been part of scientific experimentation to design adaptive systems. For example, bodily signals have been used to infer relaxation levels during HRV biofeedback [4], recognize emotions [19], estimate engagement in pilot training [1], classify mental workload in train traffic control [17], understand readiness level in firearms training [44], or excitement during VR experiences [21]. Nevertheless, the readiness of tools is still limited although the importance of integrating body signals in VR content is generally acknowledged [32].

2.2 Tools to integrate bodily signals in VR

Some commercial and free options have been proposed to add bodily signals into interactive and immersive virtual environments. The hardware industry has pioneered some commercial options; for example, Emteq[1], LooxidLabs[2], NextMind[3], and Neurable[4]. These companies provide custom VR headsets that include physiological sensors to enrich the interaction. The main obstacles of these solutions are that they are proprietary, require specific VR equipment, and the software provided for the analysis of physiological signals is restricted to each hardware manufacturer. On the other hand, some open-source tools have been designed by academic initiatives but all have shortcomings, and some require codings skills that restrict its utility in some possible users. For example, visual perception experiments in VR can be conducted with PsychXR [8] but it requires the use of Python to configure the experiments, or Unity-compatible tools that unlock analysis of human behavior with UXF [5] are not compatible with external wearable sensors, HRV integration with PARE-VR [51] does not provide heart rate features, or the BL-engine [41] and PhysioVR [43] used to create physiologically adaptive games do not incorporate dedicated interfaces for synchronized experimentation and post-session analyses.

2.3 Heart Rate Variability in Virtual Environments

HRV is a measure calculated from raw cardiovascular data (e.g., ECG, PPG). The starting point to conduct HRV analysis involves the extraction of the highest peaks of the signal (e.g., R peaks in the ECG) and the calculation of the time between consecutive regular peaks, leading to a time-series called R-to-R intervals (RRi) [10]. Two main branches of HRV analysis include time and frequency domains. Popular time-based features like the standard deviation of the RRi (SDNN) and the root mean square value of the successive RRi differences (RMSSD). Some metrics in frequency domain cover the absolute power of the different frequency bands (very low, low, and high) and ratios between those absolute values [56].

The access to simple sensing devices has popularized the integration of heart signals into interactive applications. Including a growing interest in HRV features as descriptors of stress, engagement, and significant imbalances within the autonomous nervous system [10]. For instance, heart rate values have been utilized to assess perceived overall experience in collaborative VR environments [9], HRV metrics have also been included in VR biofeedback games to encourage players to manage their stress levels [33], or to promote breathing strategies that help preserve attentional resources [4].

Moreover, HRV analysis has also been widely used to explain players' behavioral responses when interacting with games and VR applications, complementing the conventional methods to capture perceived user experiences [14]. In non-VR settings, the real-time analysis of HRV is a critical approach to determine psychological aspects of a person, such as pain [23], mental workload [18], or stress [15, 36]. However, measurement of heart activity in VR systems often poses challenges (e.g., due to wired connections and data synchronization) that interfere with the natural interaction of the user; an example can be found in a project that estimated stress for VR pain management using HRV biofeedback [7].

The architecture of the `Excite-O-Meter` aims to facilitate the integration of bodily signals within controlled and immersive VR-based scenarios. The tool was designed to fill many of the before-mentioned gaps and provide user-friendly physiological (e.g., heart activity) information embedded into VR applications.

[1]https://www.emteqlabs.com/
[2]https://looxidlabs.com//
[3]https://www.next-mind.com/
[4]https://www.neurable.com/

3 Designing the `Excite-O-Meter`

3.1 Online Survey

In order to specify the design requirements of the `Excite-O-Meter`, a survey[5] was conducted online (using LimeSurvey running on institutional servers) from April 24, 2020 to May 14, 2020. No person-identifiable information (e.g., no demographics or IPs) were collected. Users were recruited through mailing lists, VR forums (Unity, reddit), and social media (twitter). Questions were presented after a short description of the `Excite-O-Meter` , which mentioned the integration of "heart rate data", described three example use cases (developers, market and UX researchers, clinicians), and included a simplified sketch of the system architecture.

3.2 Requirements

The survey was conducted and completed by 58 potential users who described themselves as "researcher" (n=49), "Unity developer" (n=21; mostly beginner or intermediate level), "marketing/product tester" (n=4), "clinical practitioner" (n=2). Multiple options could be selected in the responses. Results showed the interest of the `Excite-O-Meter` as a tool for "experimental design" (n=35), "clinical applications" (n=28), "cognitive enhancement" (n=16), "training" (n=15), "games" (n=21), "360 video/cinematography" (n=5). The highest-ranked features were the possibility to observe the user's physiology in real-time (n=48), ability to make VR applications react to user physiology (n=37), and analyze user's reactions offline (after use) (n=37). Respondents insights were used to determine the following design approaches and system requirements:

- **(R1)** Be compatible with the game engine Unity so that it is accessible to a broad community of VR researchers and developers.
- **(R2)** Be easy to include in VR projects with minimal coding.
- **(R3)** Support communication with a portable and accurate wearable sensor for collecting heart activity signals.
- **(R4)** Facilitate scalable integration of additional modalities in the future (e.g., sensors, physiological signals, features).
- **(R5)** Provide scientifically validated physiological metrics (extracted from HR and HRV), which estimate users' level of excitement, arousal, or general physiological reactivity.
- **(R6)** Include data visualization to facilitate interpretation of bodily signals, both in online and offline modes.

[5]Full survey on: `https://cutt.ly/Excite-O-Meter_survey`

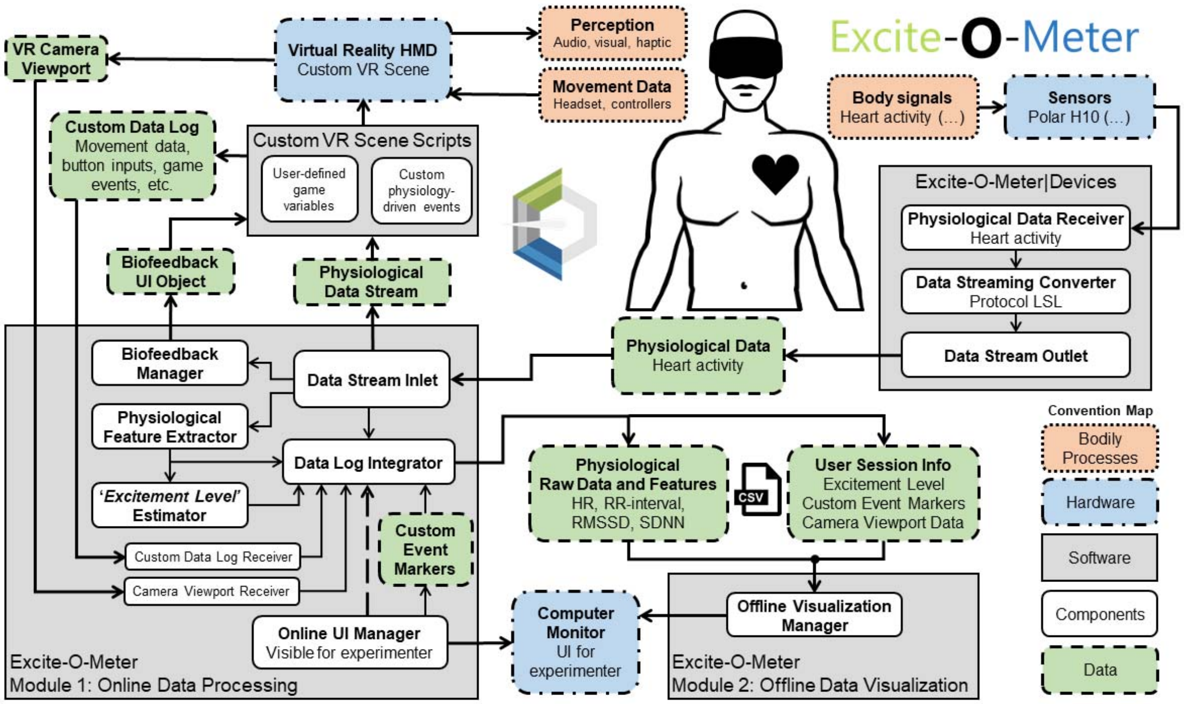

Figure 1: System architecture of the `Excite-O-Meter` . The data flow starts with the body signals collected by the sensors and converted by the `Excite-O-Meter|Devices` application into compatible physiological data. Then, the two modules for *Online Data Processing* and *Offline Data Visualization* are embedded in the game engine to enable the core functionalities of the framework. On the other end, any *Custom VR Scene* can leverage physiological data to trigger user-defined events or generate logs of new variables.

3.3 Design references

Primary analysis was conducted along three lines to define the design of the `Excite-O-Meter` regarding visual interface and features:

a. Available tools: A qualitative analysis was carried out about key features of existing solutions that integrate physiological signals, particularly HRV, for user experience research. Namely, the interfaces of the applications iMotions [20], OpenSignals [3], KubiosHRV [26], EliteHRV [16] and PhysioLab [42]. The features were described and discussed between scientists and developers, which resulted in defining elements like having grouped icons instead of texts, color coding for signals, expandable elements, and modifiable time window.

b. Visualization concepts: An examination of visualization techniques for physiological (particularly cardiovascular) metrics was performed to create a pool of options that facilitate understanding of data displayed in the `Excite-O-Meter` , especially the time-series plots. Multiple options were discussed from scientific papers about visualization of cardiovascular reactivity [60] from the tools aforementioned and ideas devised by the team.

c. Low fidelity prototypes: A wireframe prototype was used to define the visual elements for the real-time and offline data analysis. This sketch was developed to start exploring the final solution's modularity directly in Unity. Visual layouts were iteratively created and discussed among designers, developers, and scientists.

4 System Architecture and Modules

The `Excite-O-Meter` has been designed as a modular and flexible tool, enhanced with intuitive visualizations that facilitate the interpretation of useful physiological metrics. The system architecture comprises four main software components, as depicted in Figure 1. The software is open-source and publicly available on `www.exciteometer.eu`.

This tool represents an integrative and unified approach where end-users can easily include bodily signals in existing VR projects developed in Unity (section 4.1). The first stage is the software `Excite-O-Meter|Devices` (section 4.2), which configures the data acquisition from the wearable sensors and is the only softare outside the game engine. Then, the module 1 for online data preprocessing (section 4.3) comprises the framework's core functions. The module 2 named offline data visualization (section 4.4) enables visual post-hoc analyses to compare behavior from multiple users of the VR experience. In this paper, the development and validation of the framework uses one heart rate sensor, but the architecture is scalable and can easily support more physiological sensing modalities in the future.

4.1 Custom VR scene scripts

Researchers, hobbyists, and game designers working with VR technology usually have very different needs when developing their scenarios. Whereas researchers might prioritize reliable data collection and flexibility to control experimental settings, other users might prefer a straightforward integration of bodily signals. Therefore, the tool seamlessly integrates with existing VR projects for different use cases. It is packaged as a Unity plugin, in line with requirement **(R1)**. The software contains all programming scripts, visual assets, and external libraries needed to enable physiology-based capabilities just by dragging and dropping objects to an existing scene, as in requirement **(R2)**. Personalized functionalities are feasible from any *custom VR scene script* (top-left in Figure 1) to access raw physiological data, utilize a biofeedback panel, or log more system variables with a single line of code. Hence, scientists could quickly create experimental sessions from existing VR environments, and non-academic users could smoothly explore how their own heart activity reacts in real-time to the virtual experience under construction.

4.2 Excite-O-Meter|Devices

A critical technical challenge concerns the integration of data from external sensors to the game engines commonly used to build VR applications. Including physiological data from commercial wearable sensors usually requires considerable efforts in engineering and programming. The Excite-O-Meter|Devices is a standalone software client that solves this problem. The software accesses the services of Bluetooth Low Energy devices, requests the physiological data, and forwards it to VR applications developed in Unity.

To meet requirement **(R3)**, the commercial heart activity sensor (chest strap) Polar H10 was selected as data input for the Excite-O-Meter . This sensor enables real-time HRV analysis by providing raw ECG, HR, RRi with precision of milliseconds [50]. Besides, it is relatively low-cost (about €80) compared to other ECG devices with similar precision [48].

The Excite-O-Meter|Devices (top-right in Figure 1) acts as a bridge between the sensors and the Unity game engine. Its main role is to convert raw physiological data into a continuous data stream to be processed in the rest of the framework. The selected communication protocol is Lab Streaming Layer (LSL) [24], a middleware that allows networking, time-synchronization, and (near-) real-time access to time-series data. LSL is a standardized, cross-platform library already adopted in a wide range of hardware to record physiological data. The existing compatibility streamlines the scalability of the Excite-O-Meter to more sensors without affecting the data structure, as required in **(R4)**.

Two different software clients of Excite-O-Meter|Devices were developed to access the data from the Polar H10. An Android application for mobile devices (e.g., smartphones or tablets) is based on the software development kit (SDK) of the sensor's manufacturer [49]. Another option is a Windows Universal Windows Platform (UWP) application that runs on computers (e.g., PCs or laptops). The desktop application can simultaneously stream raw ECG, HR, and RRi data; but due to network restrictions needs to be executed in a computer different from the one used to run the VR environment.

4.3 Online data processing

The *Online Data Processing* module (bottom-left in Figure 1) integrates the main functionalities of the Excite-O-Meter into custom VR applications. Each component is described next:

4.3.1 Feature extraction

The component *Data Stream Inlet* receives physiological data and enables all the online functionalities. Raw physiological data is shared with custom VR scenes through script functions. Also, the *Biofeedback Manager* provides a UI object to let VR users see their own physiological signals. The *Physiological Feature Extractor* processes data samples and calculates relevant physiological metrics.

There are a large number of features that can be extracted from heart activity [56]. The tool includes two features from heart activity that are useful for both experts knowing the underlying scientific details and non-expert users, fulfilling requirement **(R5)**. Namely, the Standard Deviation of the RR intervals (SDNN) and the Root-Mean-Squared of Successive Differences (RMSSD), both measured in milliseconds (ms). SDNN collects information from the sympathetic (fight and flight) and parasympathetic (rest and digest) nervous system. It has been used as the "gold standard" for cardiac risk stratification when recorded in long (24h) periods [56]. A preliminary study with ten subjects reported that SDNN values decrease during feelings of excitement when used in VR [21]. RMSSD is a cardiac variable that reflects beat-to-beat variance in HR, used to describe the changes produced in HRV due to the vagus nerve (a fundamental component of the parasympathetic nervous system) [56].

These physiological features are calculated directly in the Unity game engine from the data streamed by the software clients. The *Physiological Feature Extractor* uses predefined default parameters to govern this process. It determines if a feature is calculated every particular time (time-based) or after a specific number of received samples (sample-based), time-based window length, sample-based buffer size, and window overlapping percentage. A json configuration file is included if the users want to adapt the default setup to a different real-time signal processing pipeline. The programming structure for real-time feature calculation allows for the addition of more metrics from raw physiological data without difficulty.

Figure 2: Annotation system for sessions. The image exemplifies a situation where an experimenter writes that a participant suffered motion sickness around 30 seconds after the start of the session.

4.3.2 Online UI manager

When the Excite-O-Meter is included in any VR application, the experimenter can activate a UI that is only visible on the computer screen (not the VR headset). This interface can monitor the physiological signals and control the recording sessions. The Figure 3 (left) outlines the *Online UI Manager*. The button at the top, label number (1), allows switching before online and offline modes. Panel number (2) shows the instant value and time-series visualization of the last 20 raw physiological data samples received via LSL. The visual warning labeled (3) will appear in case of sensor connectivity issues.

External experimenters also have the option to control the start/end of data logging from the desktop computer (thick dashed line from *Online UI Manager* in Figure 1). For example, scientists can record separate sessions for every participant of the VR experiment, by writing a unique identifier in box number (4). The offline data visualization module retrieves these sessions from logged files for specific analyses (details about data log in section 4.3.3).

The annotation system through *Custom Event Markers* is an essential feature to register special events, which is critical when studying behavioral responses to stimuli with VR experiments. From the panel (5), the user can mark specific events and save them for further analysis (Figure 2). For instance, an experimenter could register glitches in the VR application, qualitative behaviors of participants, or think-aloud responses for usability research. All markers contain a synchronized timestamp helpful to compare contextual information with the evoked physiological responses, as shown in box number (6). Programmers can use activate all functions from scripts in case the online UI interferes with existing objects in the VR scene. Finally, label (7) shows the UI object containing the *Biofeedback Manager*. It can be added to any custom VR environment (in the image, a simple scene with blue cubes) to let the VR user see in real-time their HR and RRi signals.

4.3.3 Data log integration

The data logging system is a structured, automatic, and simplified way to collect participants' data when running experiments with the tool. After each session in VR, the Excite-O-Meter generates a subfolder inside the folder LogFiles_ExciteOMeter with the date, time, and identifier input from panel (5). The start/end log are handled by the *Online UI Manager*. Each session contains multiple .csv files containing the time-series data, including raw physiological data (HR, RRi), extracted features (SDNN, RMSSD), the "excitement level" estimated at the end of the session, and the *Custom Event Markers* input by the experimenter. Then, the *Camera Viewport Receiver* creates screenshots, by default every 15-sec, of the specific view of the VR users; this images are useful to associate

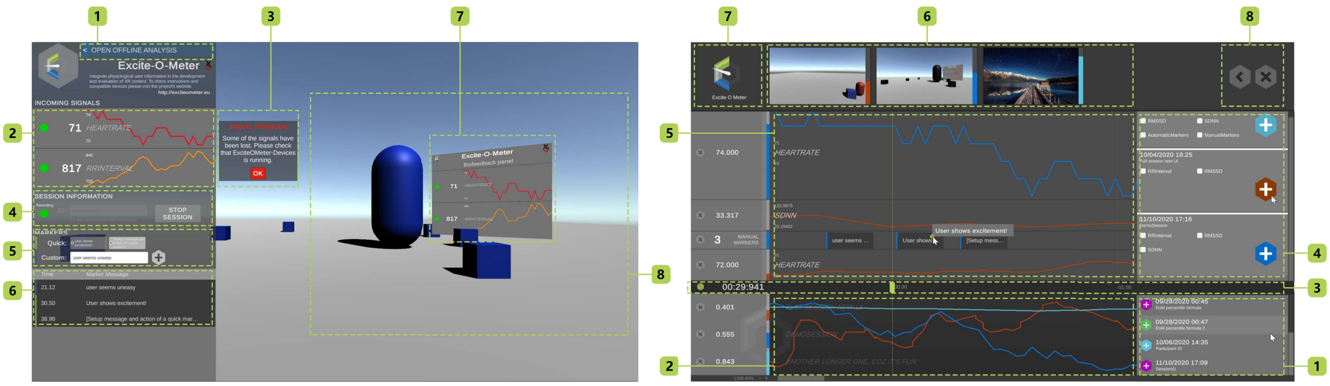

Figure 3: `Excite-O-Meter` user interface. Left: Online data processing module. Right: Offline data visualization module.

visual stimuli that triggered a body reaction. Finally, the *Custom Data Log Receiver* lets developers log user-defined variables, which are not visible in the *Offline Visualization Manager* but are crucial for offline analysis with external software tools (e.g., R, Python).

4.4 Offline data visualization

Together with the online data processing module, the integration of an *Offline Data Visualization* tool completes the requirement **(R6)**. This module augments any Unity VR application with a dashboard for post-hoc visualization of the recorded sessions. The dashboard is compiled in the same executable as the original VR application, without requiring coding, and accessible with a single click. The *Offline Visualization Manager* handles all the functionalities to load the logged files from the disk and to control the dashboard's UI that the experimenter can manipulate in the desktop screen.

The figure 3 (right) depicts the user interface of the data visualization dashboard. First, from the region labeled as (1) in the image, a user can choose one to three sessions available from the list; each session is identified with a different color. When a session is loaded, the estimated "excitement level" will appear as a time series at the bottom of the screen, labeled as (2). The horizontal timeline bar, label number (3), and the buttons at the bottom can be used to navigate the session, change the zoom, or select a specific timestamp. The panel number (4) can be used to select the specific variables to visualize among the raw physiological data (HR, RRi), extracted features (SDNN, RMSSD), or custom event markers. The session data appears in the region (5). The top panel with the label (6) displays the camera viewport; this image corresponds to what the user was observing at the chosen timestamp. The `Excite-O-Meter` visualizer, label (7), serves to indicate the "excitement level" of the VR scene at a specific timestamp. It is calculated as the average excitement among all the users that are loaded in the dashboard. Finally, the buttons in the top-right corner, label (8), are used to exit the application or to return to the custom VR scene to continue recording more sessions.

5 System Evaluation

The evaluation included two validation tests aiming to assess the technical adequacy of the `Excite-O-Meter` .

1. **Reliability of data acquisition:** Does the integration of real-time physiological analysis in the Unity game engine induce data loss or errors in the real-time calculation of HRV features?
2. **Validity of the setup and sensor:** Can the wearable sensor Polar H10 provide valid cardiac information compared to a research-grade ECG system?

5.1 Test 1: Reliability of data acquisition

This technical test assessed whether the integration of physiological data into the game engine would produce data loss and wrong feature calculation. Generally, rendering virtual environments puts high computational demands on the game engine, which has to process large amount of data. By embedding real-time data acquisition from external sensors, additional demands are induced and might lead to a drop in the number of recorded samples. During the test, our software framework was included in an empty Unity scene and compared with an external data receiver to compare if the game engine can capture physiological data reliably.

Materials: A 1-lead ECG with the Polar H10 chest strap [50] was the device used to measure cardiac activity. Then, two applications were used to collect physiological data from the heart sensor simultaneously: i) The application LabRecorder [24], which was assumed as ground truth because it is a standalone desktop application included by default to log incoming data with LSL; moreover, it does not run 3D elements that might affect performance. ii) The `Excite-O-Meter|Devices` streamed data to an empty virtual scene augmented with the `Excite-O-Meter` and was compiled as a standalone desktop application using Unity 2019.4.1f1. Both applications were executed on a laptop with Intel Core i7-6700HQ CPU, with 8GB RAM and Nvidia GeForce GTX 960M running Windows 10.

Experimental procedure: Data was recorded from one co-author during a 5-min session wearing the heart sensor. The first minute was sitting in a resting state, then two minutes doing jumping-jacks to increase heart activity, and the last two minutes sitting. The LabRecorder was started first and stopped last to guarantee that it contained all samples logged by the `Excite-O-Meter` . The cardiac activity signals sent from the sensor were: Heart rate at 1Hz, RRi between 1Hz-2Hz, and raw ECG at 130Hz. The different levels of physical activity and signal frequency allowed to check the effects of user movement and data frequency on the acquisition performance.

Data analysis: Data logs from LabRecorder were manually aligned with the timestamps recorded by the `Excite-O-Meter` so that both contained data in the same time window. Mean squared error (MSE) was used to quantify the difference between the collected time series. First, the timestamps and signal values between both data loggers. The HRV features were also (RMSSD, SDNN) calculated both in real-time by the `Excite-O-Meter` and offline with a data analysis library. This analysis was performed with Python [62](version 3.7.6), using the library pyxdf to load logs from LabRecorder, and the neurophysiological toolbox NeuroKit2 [34] as ground truth for HRV features.

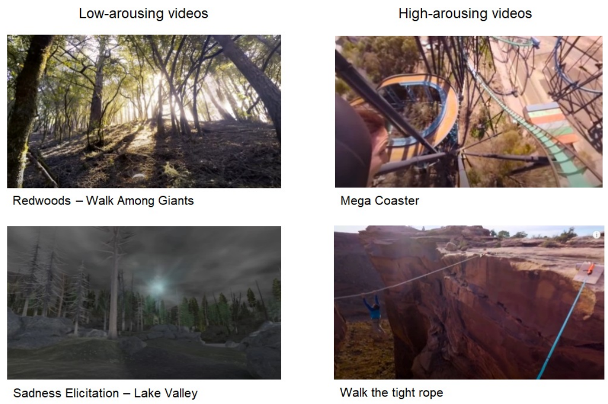

Figure 4: Screenshots of the 360° videos used in the experiment. Normative values defined in reference [31].

Results from test 1

Regarding loss of data packages. The number of data samples was exactly the same both in the application with the `Excite-O-Meter` and in the official standalone recorder provided by the LSL. Hence, no data loss was detected when integrating real-time acquisition of physiological data into the Unity game engine.

Table 1: Mean Square Error between data acquired with `Excite-O-Meter` and ground-truth systems

	Recorded samples	MSE (value)	MSE (timestamps)
ECG	38056	0	3.9×10^{-6}
HR	301	0	2.5×10^{-4}
RRi	439	9×10^{-8}	2.5×10^{-4}
SDNN	31	4.35	-
RMSSD	31	0.099	-

When analyzing the extracted features in real-time versus offline feature extraction, outliers were found in the ECG signal in both data receivers. The data outliers, which were caused outside the `Excite-O-Meter` (presumably caused by saturation in communication channel of the sensor), were corrected by applying filtering that skips calculations on signal values higher than 1×10^7. For this reason, raw ECG is not considered a fully compatible physiological source yet, and only HR and RRi are used as data inputs.

Table 1 shows that the MSE values comparing log files from both recorders were lower than 10^{-3} for most timestamps and physiological signal values. However, the MSE between the real-time and offline calculation of the feature SDNN was higher than the rest. A posterior analysis showed that the difference was caused by the use of a biased estimator of standard deviation (dividing by N-1 instead of N). This difference was corrected to match the real-time analysis in the `Excite-O-Meter` with other existing signal processing packages.

5.2 Test 2: Validity of the setup and sensor

The second test explored the validity of the technical setup by comparing the heart activity gathered from the wearable sensor (Polar H10) and an established research-grade system (Brain Products LiveAmp32) when combined with VR.

Participants: Four healthy participants (two females) completed the experiment. A snowball sampling technique was used to minimize the infection risk and personal contact due to pandemic. A sanitation protocol was also followed to avoid potential risks when using the headset and controllers.

Virtual stimuli: The virtual scenario consisted of 360º videos extracted from a public database[6] [31], which provides normative arousal ratings per video. Four videos were selected, they have comparable length (∼2 min) and maximize the difference on the arousal dimension; see details in Figure 4.

Materials: Two devices collected cardiac activity: i) a 1-lead ECG with the Polar H10 chest strap [50], and ii) a 3-electrode research-grade ECG with the Brain Products LiveAmp32 [13]. The VR application rendered in the headset HTC Vive Pro and it was compiled as standalone using Unity 2019.4.1f1. The experiment ran on a desktop PC with Intel Core i7-3770K CPU, with 16 GB RAM, and Nvidia GeForce GTX 1080 Ti GPU using Windows 10.

Experimental procedure: Upon arrival to the research laboratory, participants were first equipped with the Polar H10 chest strap placed on the sternum and the LiveAmp32 placed in a modified Einthoven arrangement. ECG was continuously sampled throughout the experience at 1000 Hz. After seating themselves on a chair, the HTC Vive headset was placed on their heads. The stimulation consisted of a baseline (30 sec) and the four 360º videos, with four resting periods interspersed between the videos (30 sec each). The experiment took ∼15-min per participant. Participants were instructed to simply watch the videos and freely move their heads. The videos' order was randomized across participants to avoid order effects, and the 30-sec baseline before the first video also served as acclimatization to the VR environment.

Data analysis: Statistical analysis was performed using R (version 3.5.1) [52]. To evaluate the accuracy and validity of the Polar H10 for collecting cardiovascular data in real-time, we compared signals of two sources: i) RRi provided by the Polar H10 (and stored in the logs of the `Excite-O-Meter`), ii) raw ECG data from the LiveAmp32, recorded with the BrainVision Recorder software, and post-processed with Kubios v2.2 [57] to extract the signal peaks and subsequent RRi. The ECG and RRi were visually inspected for artifacts, and the strength of the relationship between signal sources was calculated with Bivariate Pearson's correlation coefficient.

Results from test 2

No artifacts (e.g., movement artifacts, data loss, faulty peaks, extra systoles) were found in the visual inspection of the ECG and RRi data. The RRi collected with the Polar H10 and the BrainProducts LiveAmp were highly correlated for all participants. The weakest correlation was Pearson's r = 0.947, as shown in Figure 5.

This high correlation between signals suggests that the wearable sensor Polar H10 proposed to record cardiac activity (ECG/heartbeats) yields similar precision than the BrainProducts LiveAmp, which can be considered a "gold standard" in research [48]. The differences in the values could be caused by the noise inherent to physiological data collection.

The technical tests confirm the feasibility of real-time data collection. The number of samples between the default LSL receiver and the `Excite-O-Meter` was the same. It shows that embedding data acquisition within the game engine does not affect data transmission or quality (e.g., did not reduce the sampling rate for real-time data analysis). Therefore, physiological data transmission and quality were not affected among applications, and the data received and processed in Unity by the `Excite-O-Meter` is reliable and consistent.

6 Use case: Measuring "Excitement Level"

This section provides an example on how the `Excite-O-Meter` could be used to further explore research questions in behavioral research and psychophysiology. Mainly, supporting scientific experiments involving heart rate signals and VR. Specifically, this use case utilizes the same participants and experimental procedure described in section 5.2 to investigate the question: To what extent does an

[6] https://vhil.stanford.edu/360-video-database/

"excitement level" metric based on heart activity features correspond to normative arousal ratings of VR 360º videos?

6.1 Proposed "excitement level" metric

The psychological state of "excitement", which we aim to infer from physiological reactivity (HR and HRV), conceptually overlaps with other psychological phenomena like 'engagement' or 'emotional arousal' [54]. The `Excite-O-Meter` defines "excitement level" as a general description of autonomic activation [6], a widely studied psychophysiological phenomenon.

In the current architecture, there are two parameters that can lead to the estimation of a metric for "excitement level": RRi, influenced by both sympathetic and parasympathetic activation; and HRV (i.e., variations of the RRi), which mainly reflect parasympathetic activation [56]. To empirically decide for one of the two candidate HRV measures, SDNN and RMSSD were calculated using sliding windows with five RRi per window. The results of this heuristic were highly correlated (e.g., Pearson's r = 0.817), and the RMSSD was used for further analyses, as it captures specifically short-term (e.g., parasympathetically-driven) RRi variations [56].

The process for the calculation of the metric is summarized in Algorithm 1. First, RRi and RMSSD were z-transformed for each participant (i.e., subtracting mean and dividing by the standard deviation). Then, each value was converted into its corresponding percentile over the cumulative density function to scale the values. For both features (RRi and RMSSD), a higher value corresponds to lower cardiac (reactivity, arousal, or "excitement"). Thus, the scores were inverted so that a higher value corresponds to higher cardiovascular (re)activity. The "excitement" score was calculated as the mean of the two standardized scores and can range from 0 (low excitement) to +1 (high excitement).

6.2 Analysis of the proposed metric

The collected heart data is processed to create an estimate for "excitement level" that might discriminate videos with low- and high-arousal normative ratings. A linear mixed-effects model was performed, using the R package lmerTest (version 3.5.1) [52], to test whether the "excitement level" metric differs between both types of stimuli. The test accounts for within-subject variance (repeated testing). The excitement was higher for high-arousal than low-arousal videos in some participants, see Figure 6. ANOVA was applied to

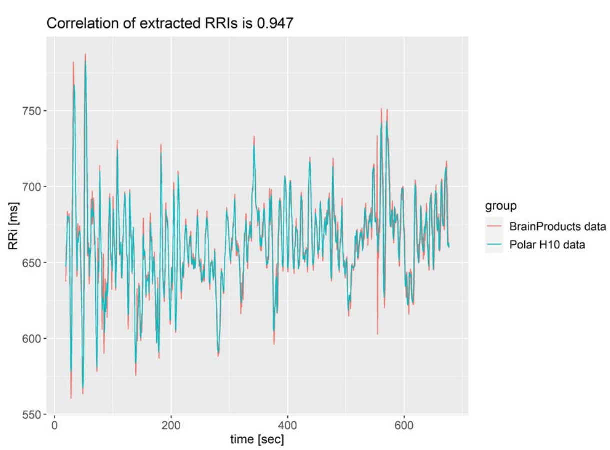

Figure 5: RR intervals (in ms) of one participant. The RR intervals for both devices (Brain Products LiveAmp sensors in red, Polar H10 in blue) were highly correlated, confirming the validity of cardiographic data acquired with the Polar H10.

Algorithm 1: Proposed "excitement level" metric

Data: Data from a session with N values of `RRi` and `RMSSD`
Result: Time-series with `''Excitement level''`
begin
  $RRi_n \leftarrow$ z-scores of RRi
  $RMSSD_n \leftarrow$ z-scores of $RMSSD$
  for $n \leftarrow 1$ **to** N **do**
    `/* Z-score to percentile. */`
    $RRi_p[n] \leftarrow$ CDF of $RRi_n[n]$
    $RMSSD_p[n] \leftarrow$ CDF of $RMSSD_n[n]$
    `/* Excitement level per timestamp */`
    $Excitement[n] = 1 - (RRi_p[n] + RMSSD_p[n])/2$
  end
end

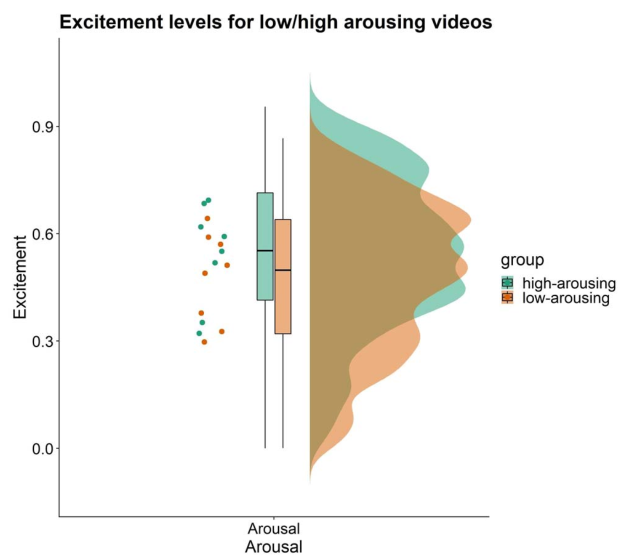

Figure 6: Distribution (density and boxplots) of excitement scores for both videos with lower (orange) and higher (green) normative arousal ratings. Dots represent average excitement scores per participant and video category (low-arousal, high-arousal).

the output of the linear mixed-effects model for easier interpretability of the reported differences. However, the results indicated that values did not differ significantly between low- and high-arousal 360º videos ($F(1,3)=0.339$, $p=0.601$).

6.3 Extending the feasibility study

Note that this example experiment relies on the use of normative ratings from the video database. These ratings can only serve as a proxy for individual subjective arousal, because of large inter-individual variability. Yet, using normative values as reference was chosen because other explicit self-reported ratings can alter the experience itself [59], or cumulative ratings at the end of an experimental session are prone to memory bias [30].

One (longer-term) aim of the `Excite-O-Meter` - and biological psychology in general - is to identify "objective" biological markers of subjective experience. The current metric of "excitement level" will not be able to distinguish between such states with a one- or low-dimensional recording (like cardiac activity). But it would require —if possible at all— additional modalities (e.g., kinematic parameters, brain activation, skin conductance) which can be further included in the current architecture of the system.

In addition, stimuli with interactive immersive experiences (instead of 360º videos) may elicit stronger excitement or overall emotional responses in participants. Also, the granularity of the involved HRV metrics could suggest that our proposed "excitement" metric might detect cardiac reactivity in VR applications in further validation studies. However, more participants are necessary because the small sample size makes it difficult to detect small effects.

The code of the example use-case experiment and the analysis scripts can be requested to further develop the `Excite-O-Meter` and validate the "excitement level" metric.

7 Discussion

In this paper, we have presented the design, development, evaluation, and a possible use case of the software framework. Our tool aims to bridge the technological gap to conduct VR experiments including heart rate signals. The initial survey with potential users steered the design choices and pool of available functionalities. The preliminary empirical evaluations support the technical suitability of the `Excite-O-Meter` as a tool to acquire valid physiological data directly in the game engine. In the use case, we proposed an initial metric for excitement levels from the cardiac activity. We thereby showed how the tool could be integrated into VR user research and for scientific experimentation using immersive technology.

The software framework is a flexible and modular tool that can speed up the process of including bodily signals in VR experiments. The contribution and uniqueness of the `Excite-O-Meter` compared to similar tools is threefold: i) providing compatibility with affordable hardware and software tools to conduct reliable experiments in VR with bodily signals, ii) simplifying the interpretation of complex cardiovascular data (e.g., HRV) by proposing metrics and visualizations of excitement levels for both offline and online analysis and iii) proposing a non-proprietary integrative solution that can be used with any VR content (or desktop games) developed in Unity, accessible to experts and beginners by only dragging and dropping the provided files.

Also, the data visualization module includes time-series plotting that keeps in mind performance, so we are confident that integrating the tool in interactive VR (rather than 360º videos) will not impede the system's performance. Note that data acquisition and real-time feature extraction were not affected when embedded in the Unity game engine for VR development. The current acceptable performance and the integration of the LSL protocol within the software architecture ensure that other hardware tools and sensing modalities can be further integrated with minimal effort. For example, from latest VR hardware with brain activation sensors and kinematic information.

The offline module provides visualization of data for post-hoc analysis. The pilot evaluation showed that our tool provides a stable data acquisition rate when embedded in the game engine. Moreover, the physiological recordings from the wearable device are as valid as research-grade ECG, especially for HRV analysis. A preliminary "excitement level" algorithm that measures psychophysiological reactivity was proposed and integrated within the tool. The feasibility study hinted at increased values for 360° videos with higher normative arousal levels, but this metric requires further study.

Our *future work* includes the extension of the `Excite-O-Meter` with other sensors (e.g., built into future generations of VR headsets) and modalities. Foremost the real-time analysis of kinematic signals (head, body movements), which provide a rich source of data to understand user behaviors at the individual level [37, 39]. In addition, more refined data analysis techniques such as algorithms for supervised and reinforcement learning would open possibilities to use the proposed tool to enhance VR-based training [45]. Ultimately, a fusion of all available modalities is envisaged for a comprehensive and scientifically valid quantification of "excitement level", which might lead to an optimal VR experience.

The *limitations* of the work include the need of evaluating the framework with more physiological sensors compatible with LSL protocol, beyond the use of only cardiac activity. Regarding the preliminary metric of "excitement", a more comprehensive assessment is required for its validation (with higher statistical power once COVID-19 restrictions are over). However, it also is not intended as an exhaustive measure for psychological trials but a simplified and usable metric to display physiological activation information in real-time. Moreover, its calculation requires refinement as the transformation from z-score to percentile may not be helpful. Moreover, although we have simplified the usability of the `Excite-O-Meter` as a Unity package, the integration still requires some experience with the game engine; thus limiting its operability by beginners.

7.1 Conclusion

We presented the `Excite-O-Meter` . A software framework to integrate bodily signals (currently cardiac activity the low-cost Polar H10 chest strap) for developing and evaluating VR applications with Unity. It provides real-time feature extraction, visualization, data logging, and markers of custom events. These features are useful for user-research, scientific experiments, or hobbyists. We suggest the `Excite-O-Meter` and as a validated tool that is better than existing options because is easy-to-use, open-source, and with comprehensive functionalities. Due to its scalable architecture, more sensing modalities beyond cardiac activity (e.g., neurophysiological, kinematic) can be incorporated in the future for enhanced analysis of body reactions. We hope that this tool contributes to promoting the integration of physiological data into VR to create more user-centric experiences.

The `Excite-O-Meter` can be freely accessed on `www.exciteometer.eu` and the instructions to contribute to the open-source project can be accessed on `www.github.com/luiseduve/exciteometer`.

Author Contributions

LQ implemented the applications for data acquisition and communication with Unity, the algorithms for real-time time-series analysis, and wrote the initial draft of the paper. JEM designed the initial architecture of the software, with requirements regarding HRV metrics and user interface, and co-wrote the paper. JdM designed and implemented the offline analysis and time-series visualization in Unity. MG conducted the empirical evaluation, co-wrote the paper, and was the principal investigator. All authors reviewed the manuscript and agreed to the published version.

Acknowledgments

The authors wish to thank Anna Francová and Jessica Gärtner for their support in the empirical evaluation of the physiological metrics; as well as Johanne Tromp, Felix Klotzsche, Mert Akbal, and Alexander Masurovsky for helping in the conceptualization of the project on its first stage (particularly the user survey). This project received funding from the European Union's Horizon 2020 research and innovation programme through the XR4ALL project with grant agreement No 825545.

References

[1] B. Bell, E. Kelsey, B. Nye, and W. W. Bennett. Adapting Instruction by Measuring Engagement with Machine Learning in Virtual Reality Training. In R. A. Sottilare and J. Schwarz, eds., *Adaptive Instructional Systems*, pp. 271–282. Springer International Publishing, Cham, 2020. doi: 10.1007/978-3-030-50788-6_20

[2] G. Bernal, T. Yang, A. Jain, and P. Maes. Physiohmd: a conformable, modular toolkit for collecting physiological data from head-mounted displays. In *Proceedings of the 2018 ACM International Symposium on Wearable Computers*, pp. 160–167, 2018.

[3] BITalino. OpenSignals Overview, 2016.

[4] J. Blum, C. Rockstroh, and A. S. Göritz. Heart rate variability biofeedback based on slow-paced breathing with immersive virtual reality nature scenery. *Frontiers in Psychology*, 10, Sept. 2019. doi: 10.3389/fpsyg.2019.02172
[5] J. Brookes, M. Warburton, M. Alghadier, M. Mon-williams, and F. Mushtaq. Studying human behavior with virtual reality : The Unity Experiment Framework. pp. 455–463, 2020.
[6] J. T. Cacioppo, L. G. Tassinary, and G. Berntson. *Handbook of psychophysiology*. Cambridge university press, 2007.
[7] U. Chauhan, N. Reithinger, and J. R. Mackey. Real-time stress assessment through ppg sensor for vr biofeedback. In *Proceedings of the 20th International Conference on Multimodal Interaction: Adjunct*, ICMI '18. Association for Computing Machinery, New York, NY, USA, 2018. doi: 10.1145/3281151.3281156
[8] M. D. Cutone and L. M. Wilcox. PsychoXR, 2020.
[9] A. Dey, H. Chen, A. Hayati, M. Billinghurst, and R. W. Lindeman. Sharing manipulated heart rate feedback in collaborative virtual environments. In *2019 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*, pp. 248–257, 2019. doi: 10.1109/ISMAR.2019.00022
[10] G. Ernst. *Heart rate variability*. Springer, 2014.
[11] S. H. Fairclough. Physiological computing and intelligent adaptation. In *Emotions and Affect in Human Factors and Human-Computer Interaction*, pp. 539–556. Elsevier, 2017.
[12] S. N. Garfinkel and H. D. Critchley. Threat and the Body: How the Heart Supports Fear Processing. *Trends in Cognitive Sciences*, 20(1):34–46, Jan. 2016. doi: 10.1016/j.tics.2015.10.005
[13] B. P. GmbH. Sensor liveamp 32.
[14] S. Grassini and K. Laumann. Questionnaire measures and physiological correlates of presence: A systematic review. *Frontiers in psychology*, 11:349, 2020.
[15] J. He, K. Li, X. Liao, P. Zhang, and N. Jiang. Real-time detection of acute cognitive stress using a convolutional neural network from electrocardiographic signal. *IEEE Access*, 7:42710–42717, 2019. doi: 10.1109/ACCESS.2019.2907076
[16] T. N. F. . Health. EliteHRV Overview, 2018.
[17] R. H. L. Hillege, J. C. Lo, C. P. Janssen, and N. Romeijn. The Mental Machine: Classifying Mental Workload State from Unobtrusive Heart Rate-Measures Using Machine Learning. In R. A. Sottilare and J. Schwarz, eds., *Adaptive Instructional Systems*, pp. 330–349. Springer International Publishing, Cham, 2020. doi: 10.1007/978-3-030-50788-6_24
[18] A. Hoover, A. Singh, S. Fishel-Brown, and E. Muth. Real-time detection of workload changes using heart rate variability. *Biomedical Signal Processing and Control*, 7(4):333 – 341, 2012. doi: 10.1016/j.bspc.2011.07.004
[19] S. B. i Badia, L. V. Quintero, M. S. Cameirao, A. Chirico, S. Triberti, P. Cipresso, and A. Gaggioli. Toward Emotionally Adaptive Virtual Reality for Mental Health Applications. *IEEE Journal of Biomedical and Health Informatics*, 23(5):1877–1887, 2019. doi: 10.1109/jbhi.2018.2878846
[20] IMotions. iMotions Overview, 2020.
[21] K. Ito, S. Usuda, K. Yasunaga, and M. Ohkura. Evaluation of "feelings of excitement" caused by a vr interactive system with unknown experience using ecg. In W. Chung and C. S. Shin, eds., *Advances in Affective and Pleasurable Design*, pp. 292–302. Springer International Publishing, Cham, 2018.
[22] L. Jamone, E. Ugur, A. Cangelosi, L. Fadiga, A. Bernardino, J. Piater, and J. Santos-Victor. Affordances in psychology, neuroscience, and robotics: A survey. *IEEE Transactions on Cognitive and Developmental Systems*, 10(1):4–25, 2018. doi: 10.1109/TCDS.2016.2594134
[23] M. Jiang, R. Mieronkoski, A. M. Rahmani, N. Hagelberg, S. Salanterä, and P. Liljeberg. Ultra-short-term analysis of heart rate variability for real-time acute pain monitoring with wearable electronics. In *2017 IEEE International Conference on Bioinformatics and Biomedicine (BIBM)*, pp. 1025–1032, 2017. doi: 10.1109/BIBM.2017.8217798
[24] C. Kothe. Lab streaming layer (lsl). https://github.com/sccn/labstreaminglayer.
[25] S. Krohn, J. Tromp, E. M. Quinque, J. Belger, F. Klotzsche, S. Rekers, P. Chojecki, J. de Mooij, M. Akbal, C. McCall, A. Villringer, M. Gaebler, C. Finke, and A. Thöne-Otto. Multidimensional Evaluation of Virtual Reality Paradigms in Clinical Neuropsychology: Application of the VR-Check Framework. *J Med Internet Res*, 22(4):e16724, 2020. doi: 10.2196/16724
[26] Kubios. KubiosHRV Overview, 2018.
[27] A. W. Lam, D. Varona-Marin, Y. Li, M. Fergenbaum, and D. Kulić. Automated Rehabilitation System: Movement Measurement and Feedback for Patients and Physiotherapists in the Rehabilitation Clinic. *Human-Computer Interaction*, 31(3-4):294–334, 2016. doi: 10.1080/07370024.2015.1093419
[28] J. J. LaViola, E. Kruiff, R. P. McMahan, D. A. Bowman, and I. Poupyrev. *3D User Interfaces - Theory and Pratice*. Addison-Wesley, Boston, 2017.
[29] J. LeDoux. The Emotional Brain, Fear, and the Amygdala. *Cellular and Molecular Neurobiology*, p. 12, 2003.
[30] L. J. Levine and M. A. Safer. Sources of bias in memory for emotions. *Current Directions in Psychological Science*, 11(5):169–173, 2002. doi: 10.1111/1467-8721.00193
[31] B. J. Li, J. N. Bailenson, A. Pines, W. J. Greenleaf, and L. M. Williams. A public database of immersive VR videos with corresponding ratings of arousal, valence, and correlations between head movements and self report measures. *Frontiers in Psychology*, 8, Dec. 2017. doi: 10.3389/fpsyg.2017.02116
[32] N. Loewe and M. Nadj. Physio-adaptive systems-a state-of-the-art review and future research directions. In *ECIS*, 2020.
[33] B. M. Maarsingh, J. Bos, C. F. Van Tuijn, and S. B. Renard. Changing stress mindset through stressjam: a virtual reality game using biofeedback. *Games for health journal*, 8(5):326–331, 2019.
[34] D. Makowski, T. Pham, Z. J. Lau, J. C. Brammer, F. Lespinasse, H. Pham, C. Schölzel, and A. S H Chen. Neurokit2: A python toolbox for neurophysiological signal processing, 2020. doi: 10.5281/ZENODO.3597887
[35] J. Marin-Morales, C. Llinares, J. Guixeres, and M. Alcañiz. Emotion Recognition in Immersive Virtual Reality : From Statistics to Affective Computing. *Sensors*, 20(5163), 2020. doi: 10.3390/s20185163
[36] R. Martinez, E. Irigoyen, A. Arruti, J. Martin, and J. Muguerza. A real-time stress classification system based on arousal analysis of the nervous system by an f-state machine. *Computer Methods and Programs in Biomedicine*, 148:81 – 90, 2017. doi: 10.1016/j.cmpb.2017.06.010
[37] M. R. Miller, F. Herrera, H. Jun, J. A. Landay, and J. N. Bailenson. Personal identifiability of user tracking data during observation of 360-degree VR video. *Scientific Reports*, 10(1):17404, 2020. doi: 10.1038/s41598-020-74486-y
[38] Z. Milosevic, W. Chen, A. Berry, and F. A. Rabhi. Chapter 2 - Real-Time Analytics. In R. Buyya, R. N. Calheiros, and A. V. Dastjerdi, eds., *Big Data*, pp. 39–61. Morgan Kaufmann, 2016. doi: 10.1016/B978-0-12-805394-2.00002-7
[39] A. G. Moore, R. P. McMahan, H. Dong, and N. Ruozzi. Extracting Velocity-Based User-Tracking Features to Predict Learning Gains in a Virtual Reality Training Application. *Proceedings - 2020 IEEE International Symposium on Mixed and Augmented Reality, ISMAR 2020*, pp. 694–703, 2020. doi: 10.1109/ISMAR50242.2020.00099
[40] B. Mostefai, A. Balla, and P. Trigano. A generic and efficient emotion-driven approach toward personalized assessment and adaptation in serious games. *Cognitive Systems Research*, 56:82–106, 2019. doi: 10.1016/j.cogsys.2019.03.006
[41] J. Muñoz, E. Rubio, M. Cameirao, and S. Bermúdez. The biocybernetic loop engine: an integrated tool for creating physiologically adaptive videogames. In *Proceedings of the 4th International Conference on Physiological Computing Systems*, pp. 45–54, 2017.
[42] J. E. Muñoz, E. R. Gouveia, M. S. Cameirão, and S. B. i Badia. PhysioLab - a multivariate physiological computing toolbox for ECG, EMG and EDA signals: a case of study of cardiorespiratory fitness assessment in the elderly population. *Multimedia Tools and Applications*, 77(9):11521–11546, 2017. doi: 10.1007/s11042-017-5069-z
[43] J. E. Muñoz, T. Paulino, H. Vasanth, and K. Baras. PhysioVR : A Novel Mobile Virtual Reality Framework for Physiological Computing. In *International Conferences on e-Health Networking, Applications and Services (Healthcom)*. IEEE, 2016. doi: 10.1109/HealthCom.2016

.7749512

[44] J. E. Muñoz, L. Quintero, C. L. Stephens, and A. T. Pope. A Psychophysiological Model of Firearms Training in Police Officers : A Virtual Reality Experiment for Biocybernetic Adaptation. *Frontiers in Psychology*, 11(April):1–14, 2020. doi: 10.3389/fpsyg.2020.00683

[45] R. Nishihara, P. Moritz, S. Wang, A. Tumanov, W. Paul, J. Schleier-Smith, R. Liaw, M. Niknami, M. I. Jordan, and I. Stoica. Real-Time Machine Learning. In *Proceedings of the 16th Workshop on Hot Topics in Operating Systems*, pp. 106–110. ACM, New York, NY, USA, may 2017. doi: 10.1145/3102980.3102998

[46] D. Novak, M. Mihelj, and M. Munih. A survey of methods for data fusion and system adaptation using autonomic nervous system responses in physiological computing q. *Interacting with Computers*, 24:154–172, 2012. doi: 10.1016/j.intcom.2012.04.003

[47] J. M. Peake, G. Kerr, and J. P. Sullivan. A Critical Review of Consumer Wearables , Mobile Applications , and Equipment for Providing Biofeedback , Monitoring Stress , and Sleep in Physically Active Populations. *Frontiers in Physiology*, 9(June):1–19, 2018. doi: 10.3389/fphys.2018.00743

[48] D. J. Plews, B. Scott, M. Altini, M. Wood, A. E. Kilding, and P. B. Laursen. Comparison of heart-rate-variability recording with smartphone photoplethysmography, polar h7 chest strap, and electrocardiography. *International journal of sports physiology and performance*, 12(10):1324–1328, 2017.

[49] Polar. Polar h10 - software development kit.

[50] Polar. Polar h10 - user manual.

[51] L. Quintero, P. Papapetrou, and J. E. Munoz. Open-Source Physiological Computing Framework using Heart Rate Variability in Mobile Virtual Reality Applications. In *2019 IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR)*. IEEE, 2019. doi: 10.1109/aivr46125.2019.00027

[52] R Core Team. R: A language and environment for statistical computing, 2020.

[53] B. Rush, L. A. Celi, and D. J. Stone. Applying machine learning to continuously monitored physiological data. *Journal of Clinical Monitoring and Computing*, 33(5):887–893, 2019. doi: 10.1007/s10877-018-0219-z

[54] J. A. Russell. A circumplex model of affect. *Journal of personality and social psychology*, 39(6):1161, 1980.

[55] A. K. Seth. Interoceptive inference, emotion, and the embodied self. *Trends in Cognitive Sciences*, 17(11):565–573, Nov. 2013. doi: 10.1016/j.tics.2013.09.007

[56] F. Shaffer and J. P. Ginsberg. An overview of heart rate variability metrics and norms. *Frontiers in Public Health*, 5:258, 2017. doi: 10.3389/fpubh.2017.00258

[57] M. P. Tarvainen, J.-P. Niskanen, J. A. Lipponen, P. O. Ranta-Aho, and P. A. Karjalainen. Kubios HRV–heart rate variability analysis software. *Computer methods and programs in biomedicine*, 113(1):210–220, 2014. doi: 10.1016/j.cmpb.2013.07.024

[58] J. F. Thayer, F. Åhs, M. Fredrikson, J. J. Sollers, and T. D. Wager. A meta-analysis of heart rate variability and neuroimaging studies: Implications for heart rate variability as a marker of stress and health. *Neuroscience & Biobehavioral Reviews*, 36(2):747–756, 2012. doi: 10.1016/j.neubiorev.2011.11.009

[59] J. B. Torre and M. D. Lieberman. Putting feelings into words: Affect labeling as implicit emotion regulation. *Emotion Review*, 10(2):116–124, 2018. doi: 10.1177/1754073917742706

[60] M. Umair, N. Chalabianloo, C. Sas, and C. Ersoy. A comparison of wearable heart rate sensors for hrv biofeedback in the wild: An ethnographic study. Mar. 2020. 25th annual international CyberPsychology, CyberTherapy and Social Networking Conference, CYPSY25.

[61] Unity Technologies. Unity.

[62] G. Van Rossum and F. L. Drake. *Python 3 Reference Manual*. CreateSpace, Scotts Valley, CA, 2009.

[63] M. Vasser and J. Aru. Guidelines for Immersive Virtual Reality in Psychological Research. *Current Opinion in Psychology*, p. S2352250X20300683, May 2020. doi: 10.1016/j.copsyc.2020.04.010

[64] M. Zahabi and A. M. Abdul Razak. Adaptive virtual reality-based training: a systematic literature review and framework. *Virtual Reality*, 2020. doi: 10.1007/s10055-020-00434-w