Exploring Physiological Correlates of Visual Complexity Adaptation: Insights from EDA, ECG, and EEG Data for Adaptation Evaluation in VR Adaptive Systems

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ABSTRACT

Physiologically-adaptive Virtual Reality can drive interactions and adjust virtual content to better fit users' needs and support specific goals. However, the complexity of psychophysiological inference hinders efficient adaptation as the relationship between cognitive and physiological features rarely show one-to-one correspondence. Therefore, it is necessary to employ multimodal approaches to evaluate the effect of adaptations. In this work, we analyzed a multimodal dataset (EEG, ECG, and EDA) acquired during interaction with a VR-adaptive system that employed EDA as input for adaptation of secondary task difficulty. We evaluated the effect of dynamic adjustments on different physiological features and their correlation. Our results show that when the adaptive system increased the secondary task difficulty, theta, beta, and phasic EDA features increased. Moreover, we found a high correlation between theta, alpha, and beta oscillations during difficulty adjustments. Our results show how specific EEG and EDA features can be employed for evaluating VR adaptive systems.

CCS CONCEPTS

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

KEYWORDS

Physiological Computing, Virtual Reality, Adaptive Systems

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1 INTRODUCTION

Physiological computing is an emerging field investigating how physiological correlates of human affective and cognitive states can be used as an input in adaptive systems to achieve specific goals [24]. Virtual Reality (VR), in particular, is a fertile ground for such physiologically-adaptive systems as it allows for online manipulation and adaptation of visualizations, virtual content, and interactions [14] that would otherwise be impossible in physical reality. Adaptive VR systems can optimize a set of behavioral, physiological, and subjective measures by dynamically adjusting the system's current task parameters to improve performance and support users to maximize their amount of productive work or task engagement. Physiologically-adaptive systems are now deployed in various VR scenarios such as social VR, exergaming, and cognitive training. Chiossi et al. [12] adapted the visual complexity of the secondary task in the form of virtual agents based on electrodermal activity (EDA). Campbell and Fraser [9] made use of variations in heart rate (HR) for adapting the physical load of a VR exergame [9], while Dey et al. [20] adjusted the amount and properties of distractors in a visual search task based electroencephalographic (EEG) alpha oscillations.

Central and peripheral physiological measures showed to be able to quantify and predict workload [10, 58] across various VR applications, such as learning [16], balance training [21] or executive tasks [48]. HR increased with mental workload [6] and EDA discriminated across workload levels [42] and showed better test-retest reliability than other physiological measures [44]. Furthermore, different EEG features behave differently upon the involvement of specific attentional processes, i.e., external or internal attention [17, 40] or working memory [45], which might be differentially allocated in complex tasks with different degrees of workload [1, 15]. Based on the adaptive alpha response to task demands, a decrease/increase in alpha oscillations has been associated with cortical excitation/inhibition in WM [8, 35] and visual detection tasks [23]. Moreover, an increase in frontal-midline theta EEG oscillations was reported when cognitive demands for updating, organizing and retrieving information were recruited [33, 55]. Finally, beta oscillations have been shown to discriminate between different task complexity levels [11, 25] and correlate with physiological arousal [32, 43]. However, there is no universal physiological measure or method to index mental workload, as different physiological measures have been shown to discriminate between different features of task load [10]. Certain measures are more sensitive to task demands, and others are more sensitive to task complexity.

Those challenges are shared with the ones of physiological computing [24], such as psychophysiological inference, i.e., mapping a physiological signal to a specific cognitive state of the user. Therefore, combining different physiological measurements can allow for a hybrid online evaluation of the adaptive system. Essentially, a

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second signal would be used to evaluate the success of the adaptation, instead of just measuring the final effect of an unsuccessful adaptation, i.e., a decrease in task performance. This solution has been proposed to increase the reliability, proficiency, and utility of Brain-Computer Interface (BCI) systems, otherwise known as multimodal or hybrid BCIs [2, 30]. A first attempt was performed by Labonte-Lemoyne et al. [38], which employed automatic facial expression analysis as a second signal to evaluate dynamic difficulty adjustments of a Tetris based on alpha and theta EEG oscillations. However, they reported that the hybrid adaptive system did not improve the participants' experience as the hybrid system showed more negative affect than the control condition.

Therefore, more work is needed to link behavioral performance, workload, and physiological measures to investigate how to align them for user's personalization and adaptation effectively [53]. This is specifically relevant for adaptive systems, as multimodal input has been relatively overlooked [14] or mainly focused on alternative channels for adaptation, i.e., speech and gesture recognition [34]. Thus, the goal of this work is to investigate which are the relationships between a range of measures, extracted from physiological signals such as EDA, ECG, and EEG, and evaluate the effect of VR system adaptation on such measures. This is especially relevant considering that different physiological signals might need different time windows to react to adaptations, and therefore some might be more suitable for faster paces of adaptations, while other might need slower paces [28, 57]. To achieve this, we analyzed a dataset encompassing multiple physiological signal recordings and physiological adaptation. Specifically, we chose the dataset of Chiossi et al. [12], which featured an adaptation of secondary task difficulty based on EDA feature and co-registration of ECG and EEG data.

In this work, we shifted our focus from evaluating the adaptive system to a detailed analysis of the relationship between the various physiological measures, and the effect of VR system adaptation on them. By measuring the impact of these changes over different physiological measures, we intend to evaluate the user's reaction to the adaptation in real-time. Based on the logic of the physiologically-adaptive VR system and previous work, we hypothesize that:

- **H1** When the adaptive system adjust for increased secondary task difficulty, this should result in increased workload, resulting in increased participant's physiological arousal. We hypothesis that to an increase in secondary task difficulty should correspond an increase in physiological correlates of arousal, i.e., beta oscillations, skin conductance level (SCL) and average amplitude of non-specific skin conductance responses (nsSCRs).
- **H2** An increased secondary task difficulty could increase the working memory load of N-Back task, as indexed by increased theta oscillations [55].
- **H3** An increased secondary task difficulty could increase the visual load in the visual detection task, resulting in increased external attention and therefore decreased occipital alpha oscillations [40].
- **H4** As Heart Rate (HR) and Heart Rate Variability (HRV) increase are related to increasing task [18] and visual attention demands [5], we might expect increased HR and HRV when the system adjusted for increased secondary difficulty.

2 DATASET PROCESSING

We utilized the dataset [13] from Chiossi et al. [12] containing behavioral, physiological (EEG, ECG, and EDA), and subjective data. We refer to their paper for a detailed description of the task implementation and data collection. The dataset included 18 participants ($M_{range} = 23 - 31$; $M_{age} = 27.9$, $SD_{age} = 2.9$; $male = 9$, $female = 9$), but only 15 are included as three participants were removed due to technical issues. They recorded behavioral and physiological (ECG, EDA, and EEG) during the task. They recorded EDA (at 250Hz) via the GSR module by BrainProducts GmbH, Germany and ECG (at 130 Hz) via a Polar H10 chest strap (Polar, Finland). EEG data recording was performed at 250 Hz with a 7-channel dry electrode cap embedded into the HTC VIVE headset from Wearable Sensing (DSI-VR 300, San Diego, CA, USA) using the electrode positions: FCz, Pz, P3, P4, PO7, PO8, Oz of the 10-20 system.

2.1 EDA Data

We processed EDA data via the Neurokit toolbox [41]. Preprocessing pipeline for EDA data encompassed first via a third-order Butterworth filter with a 3Hz high-pass cutoff. Then, we applied a nonnegative deconvolution analysis [4] to extract tonic and phasic components. Specifically, we computed the average amplitude of Non-Specific Skin Conductance Responses (nsSCRs) and the average tonic Skin Conductance Level (SCL). We identified nsSCRs peaks using a $.05\mu S$ threshold value, upon guidelines cf. [26].

2.2 ECG Data

We evaluated ECG activity in the time domain, focusing on HR and HR. As for EDA data, we used the Neurokit Python Toolbox [41]. We first filtered the ECG signal by the Finite Impulse Response (FIR) band-pass filter (3–45 Hz, 3rd order), and then segmented by Hamilton's method [31] to identify the QRS complexes and extract mean Heart Rate (HR) and Heart Rate Variability (HRV), defined as the root mean square of the successive differences (RMSSD).

2.3 EEG Data

We processed the EEG raw data via the MNE Toolbox [29]. EEG data were recorded with a sampling frequency of 250 Hz from dry electrodes placed on Fz, P3, Pz,P4, PO7, Oz, PO8 locations (10/20 system), with reference set at linked earlobes. We notch-filtered the signal at the power frequency of 50 Hz and then band-passed between 1 and 70 Hz to remove high and low-frequency drifts. We then performed a visual inspection to identify and exclude corrupted channels. Finally, we referenced the data to the common average reference (CAR). Next, we computed an independent component analysis (ICA) using MNE [3] to identify and correct artefactual components automatically with the ICLabel plugin [39, 50]. We then analyzed the preprocessed EEG data in three frequency bands: Theta (4–8 Hz), Alpha (8–12 Hz), and Beta (12-30 Hz), using Welch's method [60]. We computed alpha oscillation for posterior sites, i.e., PO8, PO7, and Oz electrodes and extracted Theta and Beta oscillations from midline sites, i.e. Fz and Pz. Then, we log transformed them to achieve normal distributions [52]. Moreover, we computed the ratio of midline theta activity's absolute power to posterior alpha activity's absolute power as an implicit measure of workload [7, 27].

2.4 Experimental Task

Participants started the experiment upon informed consent signing. The experiment required participants to be engaged in a dual-task paradigm, encompassing a VR N-Back task (N=1) (primary) and a visual detection (VD) task (secondary), where they had to select Non-Playable Characters (NPCs) without a ticket. NPCs entered and walked past the participants' surroundings with or without a ticket. Participants had to select NPCs without a ticket and click on them with the trigger of the HTC VIVE controller. Specifically, participants experienced six conditions; five non-adaptive conditions had fixed Stream of 7, 22, 37, 52, or 67 NPCs per minute entering the scene and one adaptive condition. In the adaptive condition, the Stream was adapted based on user's arousal as measured using EDA. In more detail, Chiossi et al. [12] acquired a baseline EDA baseline recording and computed the baseline EDA tonic component. Then, in the adaptive condition, they adapted the secondary task difficulty based on the variation of the tonic EDA component every 20 seconds. Therefore, secondary task difficulty adjustments were performed in the 20s-window by either (I) adding 4 NPCs to the scene, i.e., increasing the visual complexity of the VD task, if they detected that the participants showed a decreased EDA tonic component as compared to the baseline or (II) removing 2 NPCs from the scene, i.e., decreasing the visual complexity of the VD task, if the online EDA tonic component was increased when compared to the baseline, reflecting a state of higher arousal.

2.5 Data Analysis

Our analyses examined physiological indicators of cognitive workload and arousal collected while participants were jointly engaged in a visual WM task and in a visual detection task. To evaluate the effect of visual complexity adaptations, we focused our analysis on the adaptive condition, segmenting EDA, ECG, and EEG signals into 20 seconds epochs based on when the Stream of NPCs was adapted. Specifically, two variations in the Stream, based on the adaptation algorithm : (I) *Increase*: based on decreased arousal state compared to baseline; (II) *Decrease* based on increased arousal state as compared to baseline. The VR-physiologically adaptive system performed an average of $M = 4.89$ *Increase* ($SD = 1.691$) while the Stream was decreased on average of $M = 5.06$ ($SD = 1.89$). Depending on the normality testing via Shapiro-Wilk test, we performed paired t-test for normally distributed distributions and Wilcoxon signed-rank test for not-parametric distributions. Second, we compute Pearson correlation to investigate relationships between the extracted physiological features.

3 RESULTS

We present quantitative findings based on the physiological and behavioral data from the dataset. We investigated differences in the signal when participants were either exposed to a *Increase* or a *Decrease* of Stream. Therefore, evaluate the effects of visual complexity adaptation over the extracted dependent variables.

3.1 EDA Results

Results of SCL, and the average amplitude of nsSCRs are depicted in Figure 2a. **Skin Conductance Level (SCL):** Given a violation of normality ($W = .83, p < .001$), a Wilcoxon signed-rank test did not detect any significant differences in the SCL when participants experienced a *Increase* compared to a *Decrease* ($W = 359, p > .05$). **Non-specific Skin Conductance Responses (nsSCRs):** Similarly to the SCL, also the average amplitude of the nsSCRs was not normally distributed ($W = .87, p < .05$). Therefore, a Wilcoxon signed-rank test showed that nsSCRs showed an increased amplitude when participants were exposed to a *Increase* when compared to a *Decrease* ($W = 616, p < .001$).

3.2 ECG Results

We display the results on ECG measures, i.e., Heart Rate and Heart Rate Variability, in Figure 2b. **Heart Rate:** Heart rate (HR) showed a normal distribution ($W = 0.97$, $p > .05$), a paired t-test did not reveal any effect of Stream on HR. ($t = -.62$, $p > .05$). **Heart Rate Variability:** As HR, also HRV was normally distributed ($W = 0.92$, $p > .05$) and not influnced either by *Increase* or *Decrease* ($t = .812$, $p > .05$).

3.3 EEG Results

The results from the comparison between the variations in Stream on EEG features, i.e., Alpha, Theta, and Beta oscillations, are shown in Figure 3 and topographic distribution in Figure 1. Here, we supplement our results with the ratio of Alpha and Theta oscillations. **Alpha Band:** The alpha power was normally distributed ($W = 0.96$, $p > .05$). However, a paired sample t-test did not reveal a statistically significant difference between *Increase* and *Decrease* of Stream ($t = 1.1$, $p > .05$). **Theta Band:** Average Theta power showed a normal distribution ($W = 0.98$, $p > .05$) and showed significantly increased power in the *Increase* as compared to the *Decrease* ($t = 2.06$, $p < .05$). **Beta Band:** Beta power distribution was not normally distributed ($W = .92, p < .05$). Therefore, we submitted Beta scores to a Wilcoxon signed-rank test, which showed a significantly increased Beta power for a *Increase* ($W = 440$, $p < .05$). **Alpha-Theta Ratio:** The ratio between averaged Alpha and Theta powers lead to a not-normal score distribution ($W = 0.91$, $p < .05$),

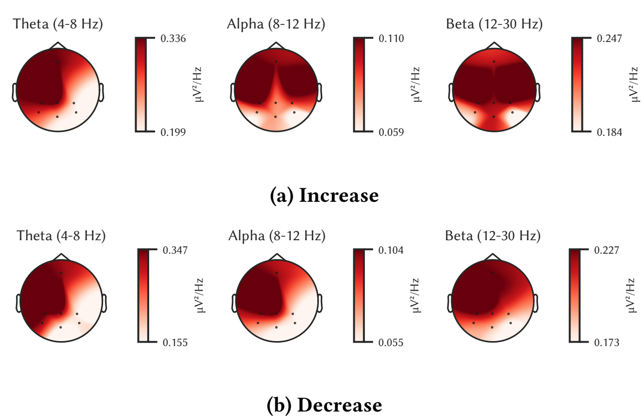
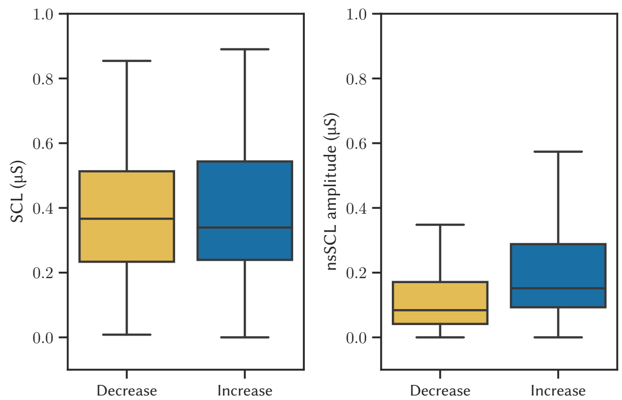
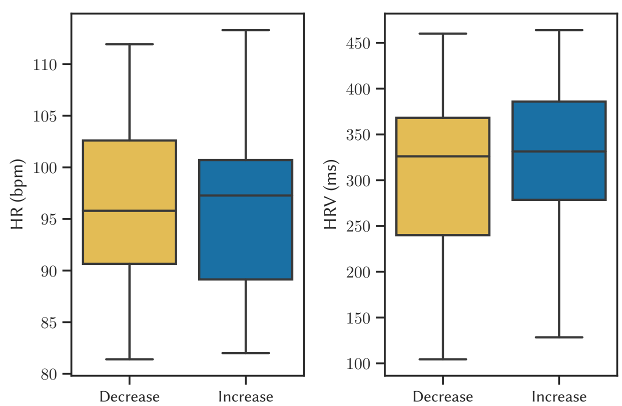


Figure 1: Topographic maps for the increase and decrease variations of secondary task difficulty for the EEG oscillations of interest. View is top looking down with nose at top.

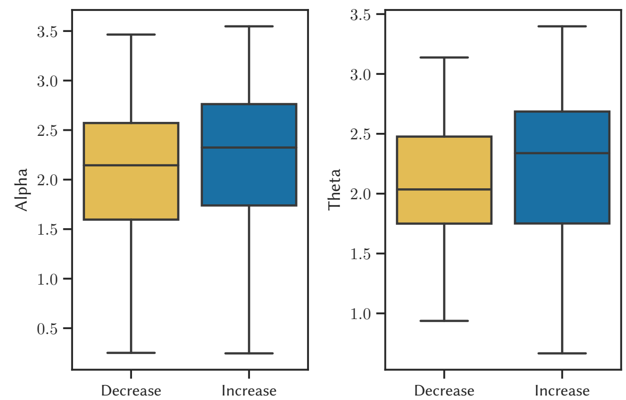


(a) EDA

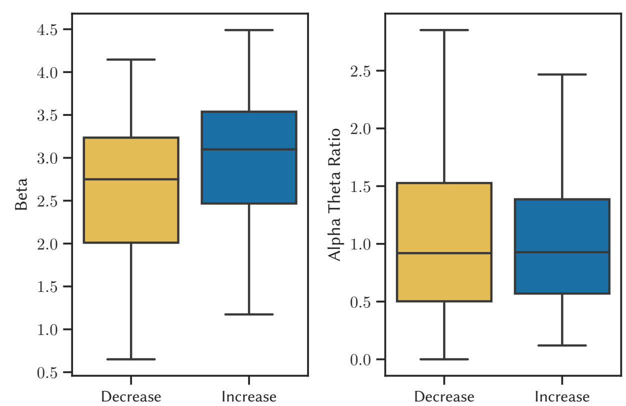


(b) ECG

Figure 2: EDA and ECG results. On the left, we depict the results for Skin Conductance Level (SCL) and average nsSCRs amplitude. On the right, we show results for Heart Rate (HR) and Heart Rate Variability (HRV). The only significant difference is detected in the nsSCRs, which are increased in the Increase.



(a) Alpha/Theta



(b) Beta/Alpha-Theta-Ratio

Figure 3: EEG oscillations results. In order, we present the differences in alpha, theta and, beta oscillations in the two variations of secondary task difficulty. In the last plot, we plot the A/T Ratio. Beta and Theta oscillations are significantly increased in the Increase.

a Wilcoxon signed-rank test did not detect any difference between the two Stream variation ($W = 337$, $p > .05$).

3.4 Behavioral Performance Results

Here, we report the results of the variation in performance when the Stream was either increased or decreased for both primary (N-Back) and secondary (Visual Detection) tasks. Results are shown in Figure 4. **Primary Task Performance:** Accuracy scores did not show a normal distribution ($W = .925$, $p < .05$). Here, a Wilcoxon signed-rank test did not show any further significance ($W = 103.5$, $p > .05$). **Secondary Task Performance:** Secondary task accuracy was normally distributed ($W = .982$, $p < .05$). However, as primary task performance, change in Stream did not show any significant change ($W = 301$, $p > .05$).

3.5 Correlation Analysis

The correlation matrix depicted in Figure 5 displays the Pearson coefficients between EDA, ECG, and EEG measures and behavioral performance in the N-Back (primary) and VD (secondary) tasks together. Results suggest that 21 out of 44 correlations were statistically significant and were greater or equal to $r = .35$, $p < .05$. Correlation between Beta and Theta oscillations was reported to be strongly positive ($r = .96$, $p < .001$), while Alpha oscillations strongly significantly correlated with Theta ($r = .7$, $p < .005$) and Beta ($r = .71$, $p < .005$). Regarding EDA features, SCL, and nsSCRs amplitude were significantly positively correlated ($r = .63$, $p < .001$), and similarly SCL strongly correlated with Alpha oscillations ($r = .75$, $p < .005$). Finally, HR and HRV showed a significant negative correlation ($r = -.683$, $p < .001$). HR showed low positive correlations with Theta ($r = -.417$, $p < .05$), with A/ T Ratio ($r = .352$, $p < .001$) and negative with Beta oscillations ($r = -.403$,

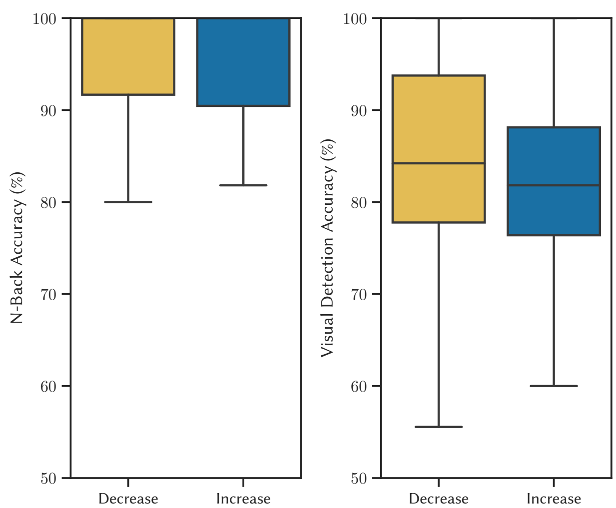


Figure 4: Behavioral performance results. Boxplots for the accuracy of the primary task (N-Back) and secondary task (Visual detection task). No significant differences are detected in the two measures.

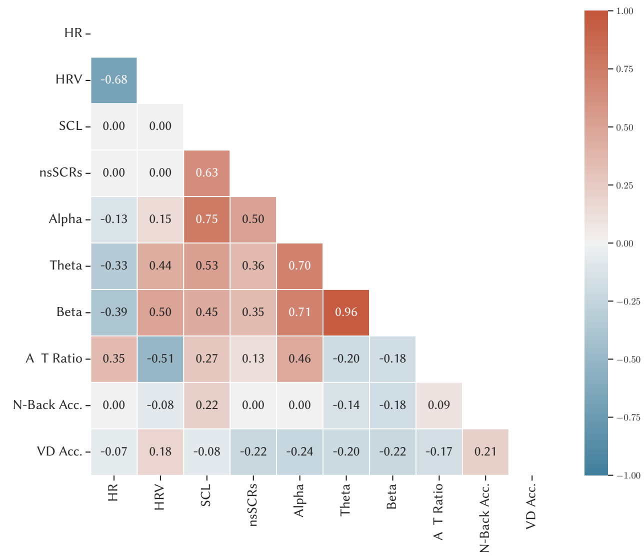


Figure 5: *Correlation Matrix.* Colors indicate the strength of Pearson correlation coefficients. HR = heart rate; HRV = Heart Rate Variability; SCL = Skin Conductance Level; nsSCRs = average amplitude of the nonspecific skin conductance responses; Alpha = average Alpha power; Theta = average Theta Power; Beta = average Beta power; A T Ratio = ratio between average Alpha and average Theta power; VD Acc. = average performance in the visual detection task; N-Back Acc. = average performance in the N-Back task.

$p < .001$). Finally, HRV showed a moderate positive correlation with an EEG arousal correlate, i.e., Beta ($r = .544$, $p < .001$) and low positive correlations with Theta ($r = .493$, $p < .05$) and A/T Ratio ($r = .352$, $p < .05$).

4 DISCUSSION

In this work, we evaluated the effect of secondary task difficulty adaptation over different physiological measures coregistered during interaction with a VR physiologically-adaptive system.

We first hypothesized (**H1**) that INCREASE in task difficulty for the VD task would have increased the arousal response in the form of beta oscillations and EDA measures, i.e., SCL and nsSCRs. We partially verified this hypothesis by finding increased arousal for beta and nsSCRs, but not for SCL. This difference in the EDA can be explained by the fact that nsSCRs are a phasic component and therefore show faster responses to environmental stimuli than its tonic counterpart and similar time dynamics as brain patterns [51]. We can therefore argue that for evaluation purposes, a phasic component might be a better candidate than tonic components to evaluate physiological reactivity to adaptations that occur at a fast pace ($\sim 20s$). Similarly, we can draft a similar conclusion regarding **H4**, where ECG-related measures, i.e., HR and HRV, failed to discriminate between the two levels of secondary task difficulty adaptation. HR and HRV are able to discriminate to different task demands but only at the overall task level. In fact, HR discriminated between highest and lowest task load but in two different conditions [56], or between tasks but not for task difficulty [59].

Regarding results from EEG oscillations, we verified **H1** and **H2**, but not **H3**. We replicate results from Deiber et al. [19], which found increased beta and theta oscillations with increased WM load. Thus, an increased VD task difficulty impacted the WM load over the N-Back task as participants had to allocate more attentional resources to the VD task and put more effort into updating the WM information. Theta oscillations are in fact, one of the most robust indicators of WM engagement and cognitive control [36, 54, 55]. This result is also supported by the strongest correlation we reported in our analysis between beta and theta. Alpha oscillations, instead, were not significantly affected by the difficulty adjustment. We can explain this as an insufficient increase in the visual load given the adaptation parameters chosen by Chiossi et al. [12] (-2 / +4 variation in visual complexity). Alpha increase has been classically related to increasing visual and attentional load [37, 49], even in adaptive systems [20]. Hence, future adaptive systems aiming at adjusting visual complexity and employing alpha oscillations should optimize adaptation parameters with larger difference. Although prior research has been exploring optimizing system behavior based on human inputs [46], our results are related to the evaluation of difficulty adjustments; such outcomes should motivate future researchers to investigate optimizing physiological features [22] by adapting system parameters, which could be a more reliable measure that complements subjective functions [47] using Bayesian optimization.

Finally, correlations provided two specific interesting results, showing high correlations between Theta and Beta oscillations, SCL and Alpha oscillations and moderate between SCL and nsSCRs amplitude. Even though our results are related to the evaluation of difficulty adjustments, such outcomes should motivate future researchers to investigate these features as input and to improve adaptation algorithms in hybrid systems. Furthermore, our results show how multimodal evaluation of physiological reactions to adjustments in adaptive systems is feasible and can be a promising side tool to improve adaptation algorithms in hybrid systems.

5 CONCLUSION

We presented an explorative analysis and evaluation of an existing dataset acquired during an interaction with a physiologically-adaptive VR system. Our results show how theta, beta, and nsSCRs are promising indicators for evaluating the outcomes of adaptations. While evaluating a variety of physiological data as input for adaptation is undoubtedly a fundamental research goal, multimodal evaluation is promisingly emerging. Further research is needed to explore the use of multiple physiological measures for adaptation and to optimize other aspects of the system, such as the timing and duration of system adaptations.

6 OPEN SCIENCE

Our collected datasets and analysis scripts are openly accessible on GitHub (https://github.com/mimuc/vr-adaptation-eeg-evaluation) for researchers to replicate and build upon our findings and analysis methods.

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REFERENCES

[1] Fabio Babiloni. 2019. Mental workload monitoring: new perspectives from neuroscience. In *International Symposium on Human Mental Workload: Models and Applications*. Springer, Cham, Switzerland, 3–19. https://doi.org/10.1007/978-3-030-32423-0_1

[2] Hubert Banville and Tiago H. Falk. 2016. Recent advances and open challenges in hybrid brain-computer interfacing: a technological review of non-invasive human research. *Brain-Computer Interfaces* 3, 1 (2016), 9–46. https://doi.org/10.1080/2326263X.2015.1134958

[3] Anthony J Bell and Terrence J Sejnowski. 1995. An information-maximization approach to blind separation and blind deconvolution. *Neural computation* 7, 6 (1995), 1129–1159. https://doi.org/10.1162/neco.1995.7.6.1129

[4] Mathias Benedek and Christian Kaernbach. 2010. Decomposition of skin conductance data by means of nonnegative deconvolution. *Psychophysiology* 47, 4 (2010), 647–658. https://doi.org/10.1111/j.1469-8986.2009.00972.x

[5] Yati N Boutcher and Stephen H Boutcher. 2006. Cardiovascular response to Stroop: effect of verbal response and task difficulty. *Biological psychology* 73, 3 (2006), 235–241. https://doi.org/10.1016/j.biopsycho.2006.04.005

[6] Anne-Marie Brouwer, Maarten A Hogervorst, Michael Holewijn, and Jan BF van Erp. 2014. Evidence for effects of task difficulty but not learning on neurophysiological variables associated with effort. *International Journal of Psychophysiology* 93, 2 (2014), 242–252. https://doi.org/10.1016/j.ijpsycho.2014.05.004

[7] Anne-Marie Brouwer, Maarten A Hogervorst, Jan BF Van Erp, Tobias Heffelaar, Patrick H Zimmerman, and Robert Oostenveld. 2012. Estimating workload using EEG spectral power and ERPs in the n-back task. *Journal of neural engineering* 9, 4 (2012), 045008. https://doi.org/10.1088/1741-2560/9/4/045008

[8] Niko A Busch and Christoph S Herrmann. 2003. Object-load and feature-load modulate EEG in a short-term memory task. *Neuroreport* 14, 13 (2003), 1721–1724. https://doi.org/10.1097/00001756-200309150-00013

[9] Joey Campbell and Mike Fraser. 2019. Switching It Up: Designing Adaptive Interfaces for Virtual Reality Exergames. In *Proceedings of the 31st European Conference on Cognitive Ergonomics* (BELFAST, United Kingdom) *(ECCE '19)*. Association for Computing Machinery, New York, NY, USA, 177–184. https://doi.org/10.1145/3335082.3335087

[10] Rebecca L Charles and Jim Nixon. 2019. Measuring mental workload using physiological measures: A systematic review. *Applied ergonomics* 74 (2019), 221–232. https://doi.org/10.1016/j.apergo.2018.08.028

[11] Youguo Chen and Xiting Huang. 2016. Modulation of alpha and beta oscillations during an n-back task with varying temporal memory load. *Frontiers in psychology* 6 (2016), 2031. https://doi.org/10.3389/fpsyg.2015.02031

[12] Francesco Chiossi, Robin Welsch, Steeven Villa, Lewis Chuang, and Sven Mayer. 2022. Virtual Reality Adaptation Using Electrodermal Activity to Support the User Experience. *Big Data and Cognitive Computing* 6, 2 (2022), 55. https://doi.org/10.3390/bdcc6020055

[13] Francesco Chiossi, Robin Welsch, Steeven Villa, Lewis Chuang, and Sven Mayer. 2022. Virtual Reality Adaptation using Electrodermal Activity to Support User Experience. https://doi.org/10.18419/darus-2820

[14] Francesco Chiossi, Johannes Zagermann, Jakob Karolus, Nils Rodrigues, Priscilla Balestrucci, Daniel Weiskopf, Benedikt Ehinger, Tiare Feuchtner, Harald Reiterer, Lewis L. Chuang, Marc Ernst, Andreas Bulling, Sven Mayer, and Albrecht Schmidt. 2022. Adapting visualizations and Interfaces to the User. *it-Information Technology* 64, 4-5 (2022), 133–143. https://doi.org/10.1515/itit-2022-0035

[15] Marvin M Chun, Julie D Golomb, and Nicholas B Turk-Browne. 2011. A taxonomy of external and internal attention. *Annual review of psychology* 62, 1 (2011), 73–101. https://doi.org/10.1146/annurev.psych.093008.100427

[16] Jonny Collins, Holger Regenbrecht, Tobias Langlotz, Yekta Said Can, Cem Ersoy, and Russell Butson. 2019. Measuring cognitive load and insight: A methodology exemplified in a virtual reality learning context. In *2019 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)*. IEEE, New York, NY, USA, 351–362. https://doi.org/10.1109/ISMAR.2019.00033

[17] Giorgia Cona, Francesco Chiossi, Silvia Di Tomasso, Giovanni Pellegrino, Francesco Piccione, Patrizia Bisiacchi, and Giorgio Arcara. 2020. Theta and alpha oscillations as signatures of internal and external attention to delayed intentions: A magnetoencephalography (MEG) study. *NeuroImage* 205 (2020), 116295. https://doi.org/10.1016/j.neuroimage.2019.116295

[18] Michel De Rivecourt, MN Kuperus, WJ Post, and LJM Mulder. 2008. Cardiovascular and eye activity measures as indices for momentary changes in mental effort during simulated flight. *Ergonomics* 51, 9 (2008), 1295–1319. https://doi.org/10.1080/00140130802120267

[19] Marie-Pierre Deiber, Pascal Missonnier, Olivier Bertrand, Gabriel Gold, Lara Fazio-Costa, Vicente Ibanez, and Panteleimon Giannakopoulos. 2007. Distinction between perceptual and attentional processing in working memory tasks: a study of phase-locked and induced oscillatory brain dynamics. *Journal of cognitive neuroscience* 19, 1 (2007), 158–172. https://doi.org/10.1162/jocn.2007.19.1.158

[20] Arindam Dey, Alex Chatburn, and Mark Billinghurst. 2019. Exploration of an EEG-Based Cognitively Adaptive Training System in Virtual Reality. In *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*. IEEE, New York, NY, USA, 220–226. https://doi.org/10.1109/VR.2019.8797840

[21] Dennis Dietz, Carl Oechsner, Changkun Ou, Francesco Chiossi, Fabio Sarto, Sven Mayer, and Andreas Butz. 2022. Walk This Beam: Impact of Different Balance Assistance Strategies and Height Exposure on Performance and Physiological Arousal in VR. In *Proceedings of the 28th ACM Symposium on Virtual Reality Software and Technology* (Tsukuba, Japan) *(VRST '22)*. Association for Computing Machinery, New York, NY, USA, Article 32, 12 pages. https://doi.org/10.1145/3562939.3567818

[22] Ye Ding, Myunghee Kim, Scott Kuindersma, and Conor J. Walsh. 2018. Human-in-the-loop optimization of hip assistance with a soft exosuit during walking. *Science Robotics* 3, 15 (2018), eaar5438. https://doi.org/10.1126/scirobotics.aar5438

[23] Tolgay Ergenoglu, Tamer Demiralp, Zubeyir Bayraktaroglu, Mehmet Ergen, Huseyin Beydagi, and Yagiz Uresin. 2004. Alpha rhythm of the EEG modulates visual detection performance in humans. *Cognitive brain research* 20, 3 (2004), 376–383. https://doi.org/10.1016/j.cogbrainres.2004.03.009

[24] Stephen H Fairclough. 2009. Fundamentals of physiological computing. *Interacting with computers* 21, 1-2 (2009), 133–145. https://doi.org/10.1016/j.intcom.2008.10.011

[25] Stephen H Fairclough, Louise Venables, and Andrew Tattersall. 2005. The influence of task demand and learning on the psychophysiological response. *International Journal of Psychophysiology* 56, 2 (2005), 171–184. https://doi.org/10.1016/j.ijpsycho.2004.11.003

[26] Society for Psychophysiological Research Ad Hoc Committee on Electrodermal Measures, Wolfram Boucsein, Don C Fowles, Sverre Grimnes, Gershon Ben-Shakhar, Walton T Roth, Michael E Dawson, and Diane L Filion. 2012. Publication recommendations for electrodermal measurements. *Psychophysiology* 49, 8 (2012), 1017–1034. https://doi.org/10.1111/j.1469-8986.2012.01384.x

[27] Alan Gevins, Michael E Smith, Linda McEvoy, and Daphne Yu. 1997. High-resolution EEG mapping of cortical activation related to working memory: effects of task difficulty, type of processing, and practice. *Cerebral cortex (New York, NY: 1991)* 7, 4 (1997), 374–385. https://doi.org/10.1093/cercor/7.4.374

[28] Giorgos Giannakakis, Dimitris Grigoriadis, Katerina Giannakaki, Olympia Simantiraki, Alexandros Roniotis, and Manolis Tsiknakis. 2022. Review on Psychological Stress Detection Using Biosignals. *IEEE Transactions on Affective Computing* 13, 1 (2022), 440–460. https://doi.org/10.1109/TAFFC.2019.2927337

[29] Alexandre Gramfort, Martin Luessi, Eric Larson, Denis A Engemann, Daniel Strohmeier, Christian Brodbeck, Roman Goj, Mainak Jas, Teon Brooks, and Lauri Parkkonen. 2013. MEG and EEG data analysis with MNE-Python. *Frontiers in*