ML-Driven Cognitive Workload Estimation in a VR-based Sustained Attention Task

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Introduction

- The purpose of cognitive training is to improve and enhance working memory and executive functions such as attention or multitasking through targeted exercises and activities (Smithers et al. 2018).
- Sustained attention allows the maintenance of a consistent focus over continuous and extended periods of time and is thus essential for learning and performing daily activities (Cohen 2014).
- Two limitations key to designing sustained attention interventions – capacity (the amount of information attended to) and selectivity (how much of the unattended information is processed regardless) (Cochrane, 2020):

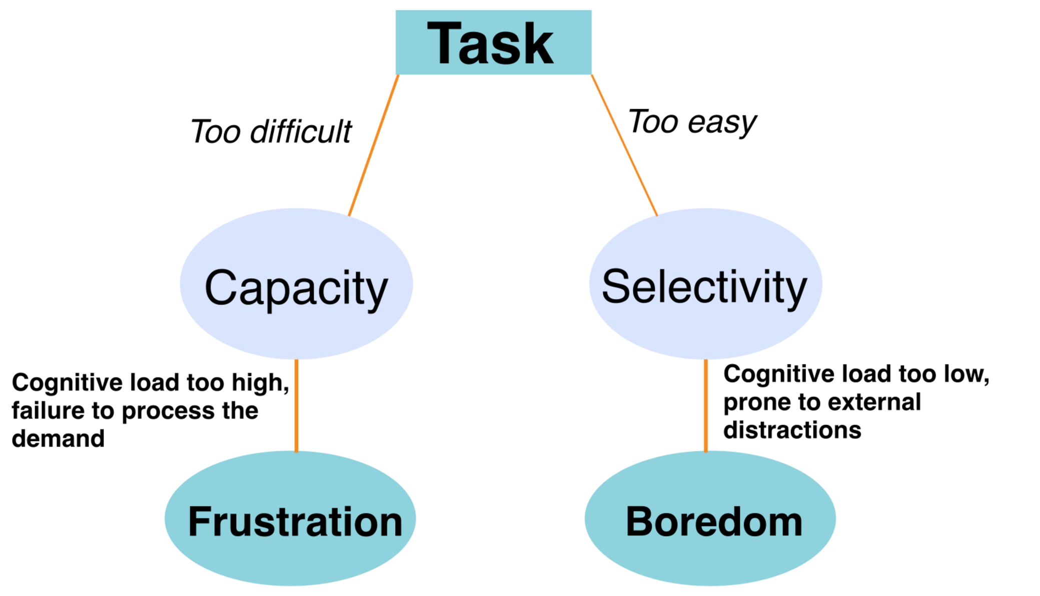

Figure 1. The relationship between capacity and selectivity.

Research questions:

1. **Is eye tracking suitable as a proxy for cognitive load estimation in dynamic, ecologically valid Virtual Reality environments?**
2. **How do cognitive load induced states (boredom and frustration) relate to objective difficulty adjustments across participants?**

Methods

Participants and Task:

- 51 participants aged 18-58 (M=29.82, SD=9.5, 27 female, 6 left-handed).
- Novel sustained attention VR task adapted from continuous performance tasks (Cohen, 2011), where participants are required to respond or withhold response to stimuli over a sustained period, built using Unity.
- **3 sessions – 8 levels each – 60s per level – 10s breaks between levels – 4 difficulties – each difficulty twice in a session – order randomised – feedback provided verbally during breaks**

Materials:

- HTC VIVE PRO EYE headset with an integrated eye-tracker at 90Hz frequency and a Shimmer sensor collecting GSR and PPG at 45Hz

Figure 3. Equipment

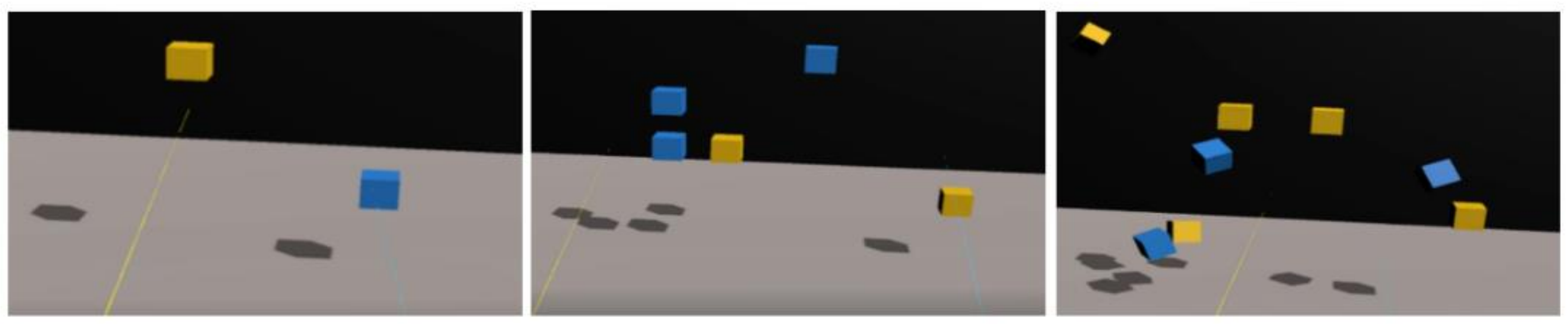

Figure 2. In-game view of progressively increasing difficulties.

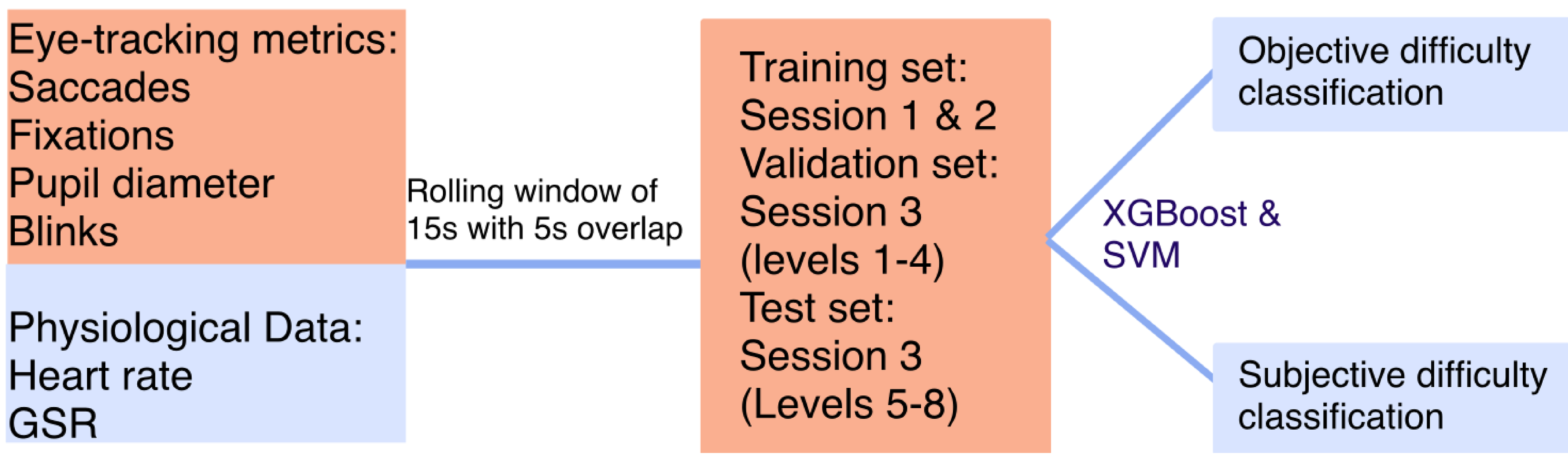

Figure 4. Predictors, target variables and data processing.

Results

Model performance for different validation protocols comparing objective and perceived difficulty predictions using different combinations of data types:

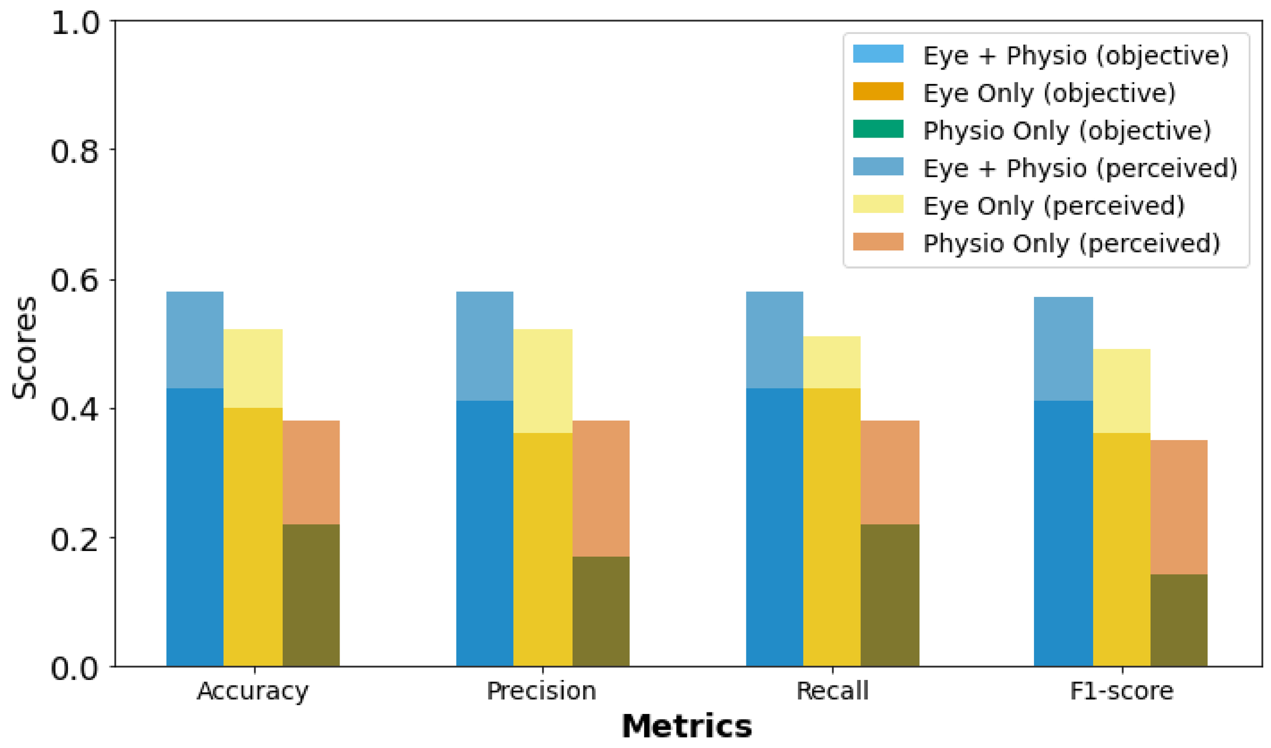

Figure 5. Within Subject Cross-Validation Protocol (same participants seen during testing and training).

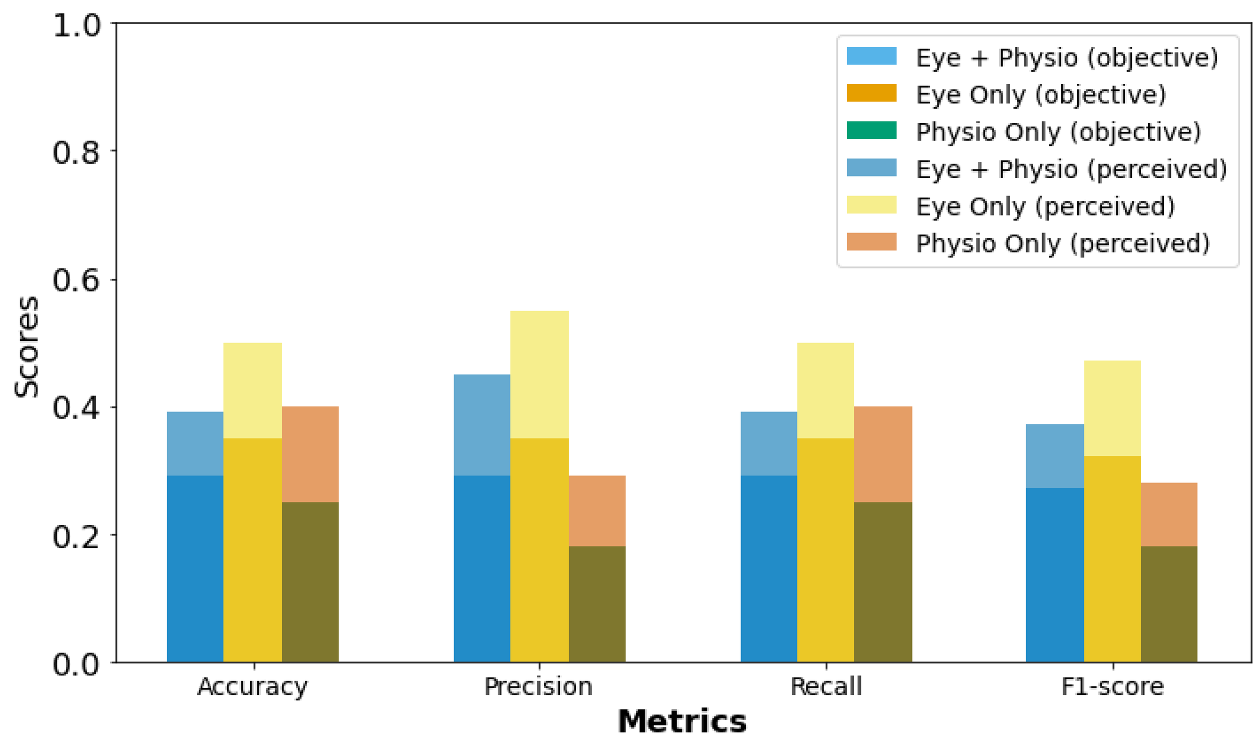

Figure 6. Across Subject Cross-Validation Protocol (participants left out during training and seen only during validation and testing)

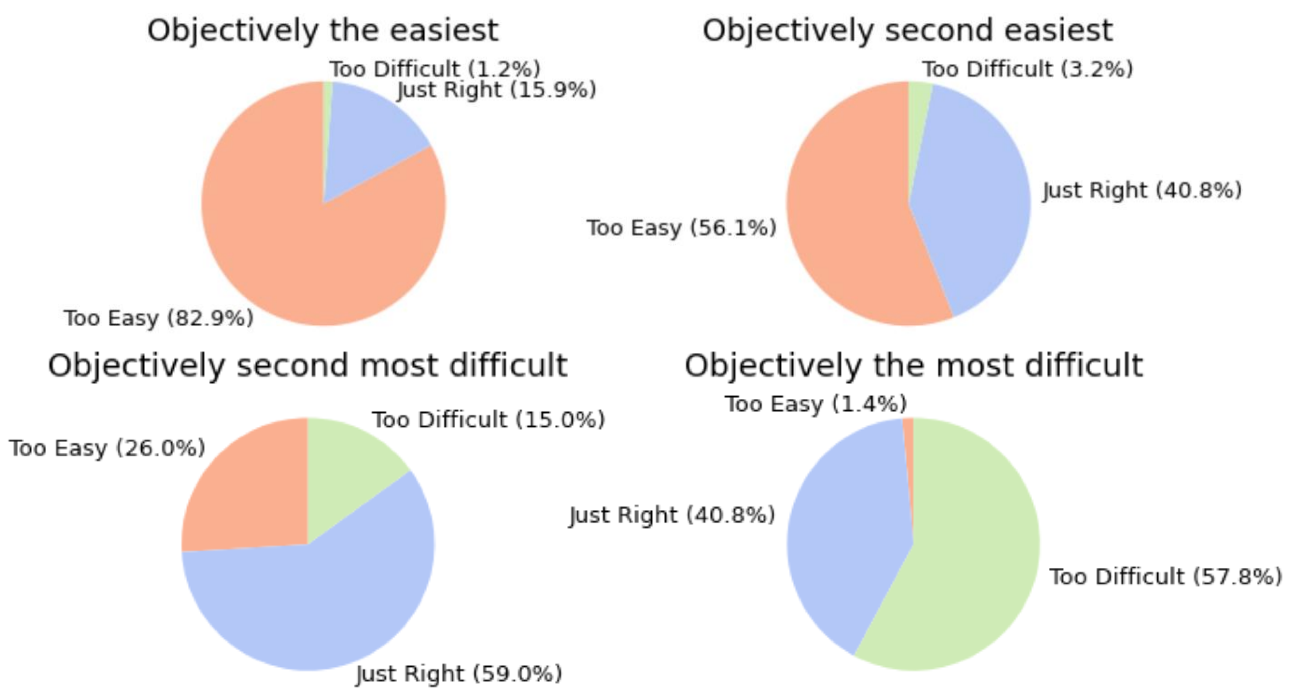

Figure 7. The frequencies of perceived difficulties mapped over objective difficulties (objective difficulty is balanced for each participant).

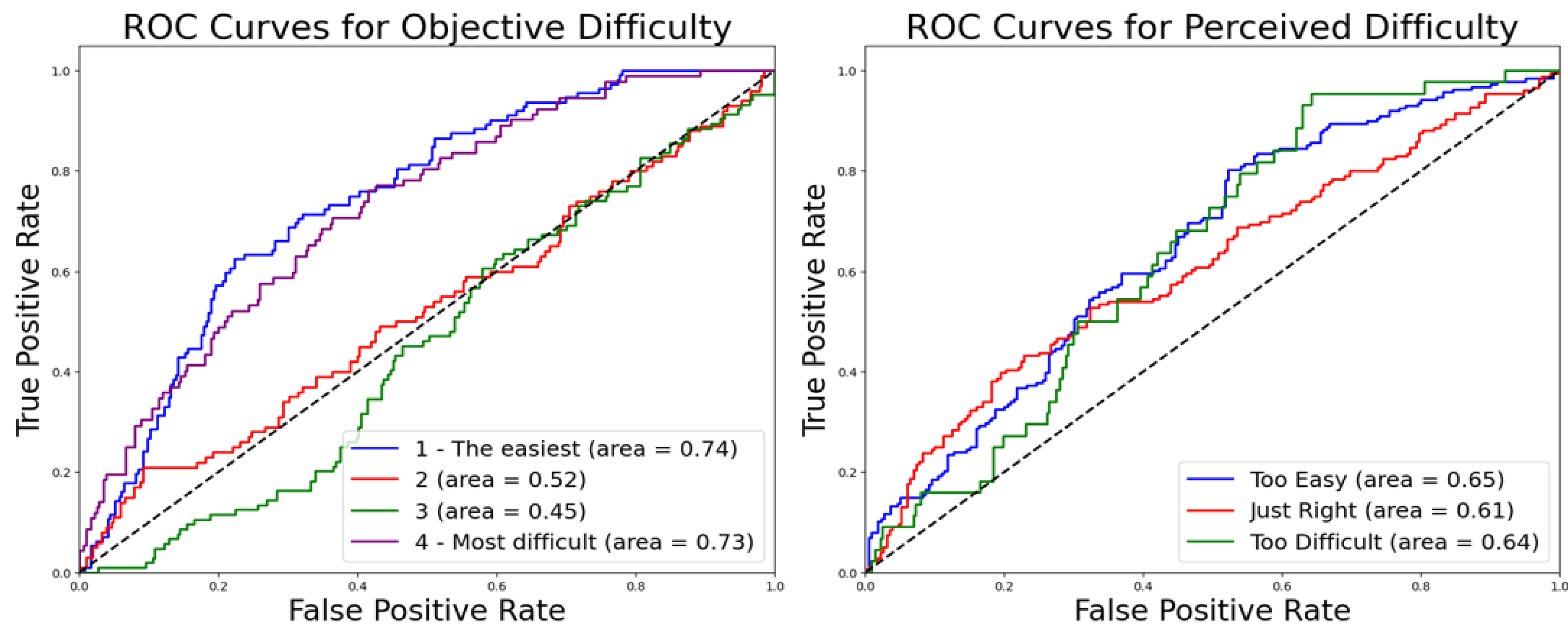

Figure 8. Receiver Operating Characteristic Curves for objective difficulty (left) and perceived difficulty (right) prediction using SVM (eye-tracking data only)

Discussion

- **The aim of the study was to validate automatic cognitive workload detection in a Virtual Reality setting** using only eye-tracking and physiological data for future use in real-time adjustable cognitive training. The task was **adapted with the potential for dynamic modulation, and is ecologically valid in terms of its delivery**, resembling more an actual home-based administration than a highly controlled laboratory environment.
- Perceived difficulty classification yielded better results than objective classification, suggesting that eye-tracking and physiological data is more representative of subjective cognitive load states than objective difficulty of the task.
- The future goal is to develop interactive, AI-driven training environments that will personalise the difficulty automatically to precisely control, in real time, cognitive load based on a combination of eye-tracking and physiological data.

References

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