Into the Zone: Flow State EEG Analysis in the VR game "Cubism"

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ABSTRACT

Numerous studies have identified EEG patterns associated with Flow states. This study investigates whether playing *Cubism* in a VR headset induces Flow, assessing its suitability for a follow-up experiment. Flow states were measured using a standardized questionnaire, and EEG data were analyzed for correlations with established literature. Preliminary results suggest a positive relationship between Flow scores and expected EEG patterns. However, significant data loss due to noise—likely from improper wet electrode placement—raises concerns about reliability. Poor electrode contact may have compromised signal quality, limiting interpretability. Despite these challenges, the findings contribute to understanding Flow states in immersive virtual environments and their detection through EEG.

Index terms: EEG, Flow State, Virtual Reality, Cognitive Neuroscience, Cubism.

1 INTRODUCTION

Flow state is described as the "sweet spot" between a person's skill level and task difficulty, characterized by a distorted sense of time, optimal performance, and deep task engagement. Understanding Flow could lead to operationalized, controllable methods for enhancing performance across dynamic tasks. Flow states have been studied in various activities, including sports, music, and gaming. However, research on Flow in puzzle-based gameplay is limited, and even fewer studies have explored Flow in VR games—no known studies have investigated a game which utilities both.

Existing literature on Flow in visuomotor tasks, puzzle games, and mental calculations suggests that Flow states correlate with specific EEG power changes: decreased delta [1,5] and alpha [1,3,5] waves, increased theta [3,4,5] waves, and inconsistent findings regarding beta waves—some studies report an increase [1], while others report a decrease [3,5].

This study explores whether EEG can detect Flow states during gameplay of Cubism in VR. The goal is to assess the game's suitability for a follow-up experiment in which difficulty dynamically adjusts based on EEG-estimated Flow levels, aiming to maximize time spent in Flow. To achieve this, EEG data was recorded during gameplay, and Flow states were quantified using a standardized questionnaire.

2 METHODS

2.1 Participants

The study included 11 right-handed participants (5 males and 6 females) aged 22 to 28, all of whom had little to no VR experience. However, the data from 2 participants had to be excluded due to unusually high levels of noise, rendering it unusable.

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2.2 Apparatus

Participants played the game Cubism using a Meta Quest 2 headset for the immersive experience. EEG data was recorded using 19-channel EEG system with wet electrodes placed according to the 10-20 system. The EEG signal was collected at a sampling rate of 250Hz, and data was processed for analysis using Python.

2.3 Experimental Design

The experiment followed a within-subject design, where each participant played Cubism in a VR environment for 20 minutes. Participants were first familiarized with the game mechanics before starting the main task. A baseline EEG measurement was taken before gameplay, afterwards EEG data was recorded continuously during the gameplay.

2.4 Flow State Measurement

To quantify Flow state, participants completed the LONG Dispositional Flow Scale (DFS-2) [2], immediately following their gameplay session. DFS-2 is designed to assess the subjective experience of Flow by evaluating factors such as engagement, enjoyment, and immersion.

2.5 EEG Data Processing and Analysis

The EEG data was preprocessed by applying a notch filter to remove 50 Hz power line noise and using high-pass (1 Hz) and low-pass (40 Hz) filters to isolate relevant frequency bands. The power spectral density (PSD) for each band was calculated, and any power values exceeding 200 $\mu V^2/Hz$ were considered noise and removed.

The power data for each subject were averaged across five brain regions (frontal, central, temporal, parietal, and occipital) and plotted to visualize changes in power (Fig. 1); change in power was calculated by subtracting the baseline power value from the task power value, then dividing the result by the baseline power value [5]. "Good data" was identified by counting power changes that matched expected flow-related patterns from the literature. The percentage of "good data" was calculated by dividing the number of "good data" points by the total data for each subject, which was plotted against their flow score (Fig. 2 and Fig. 3).

Due to uncertainties in beta wave behavior, two interpretations of beta changes were tested: a positive change (Fig. 3) and a negative change (Fig. 2) as "good data". Each approach was analyzed separately to compare the results.

2.6 Statistical Analysis

Statistical analysis was conducted to examine the relationship between flow scores and EEG power changes. To assess the correlation between flow scores and the percentage of "good data", Pearson's correlation coefficient was calculated. Additionally, separate analyses were performed for the two interpretations of beta power changes, and the results were compared using scatter plots with regression lines.

2.7 Initial Results

The analysis revealed a moderate correlation between EEG power changes and participants' flow scores. When beta power decreases were considered as the expected pattern, the correlation coefficient was r = 0.49. In contrast, when beta power increases were assumed to be the expected pattern, the correlation coefficient was slightly higher at r = 0.51.

These results suggest that the relationship between EEG activity and flow states remains similar regardless of how beta power changes are interpreted. While both conditions show a moderate correlation, the small difference in coefficients highlights the uncertainty surrounding beta power behaviour in flow states. Further investigation is needed to determine the most appropriate interpretation of beta activity in this context.

2.8 Discussion, conclusion and future work

This study examined the relationship between EEG power changes and flow states, revealing a moderate correlation. When beta decreases were assumed to align with flow, the correlation was r = 0.49; when increases were assumed, it was r = 0.51. These findings suggest a link between EEG and flow but highlight sensitivity to beta power assumptions.

Significant data loss due to noise, likely from poor electrode placement, compromised signal quality and reduced reliability. I have been developing a live impedance measurement feature that could help future studies improve electrode placement and real-time signal monitoring to minimize artifacts.

The uncertainty around beta power behaviour underscores the need for further research with larger samples, varied tasks, and refined EEG processing. Despite limitations, this study provides preliminary evidence linking EEG activity to flow states, warranting further investigation.

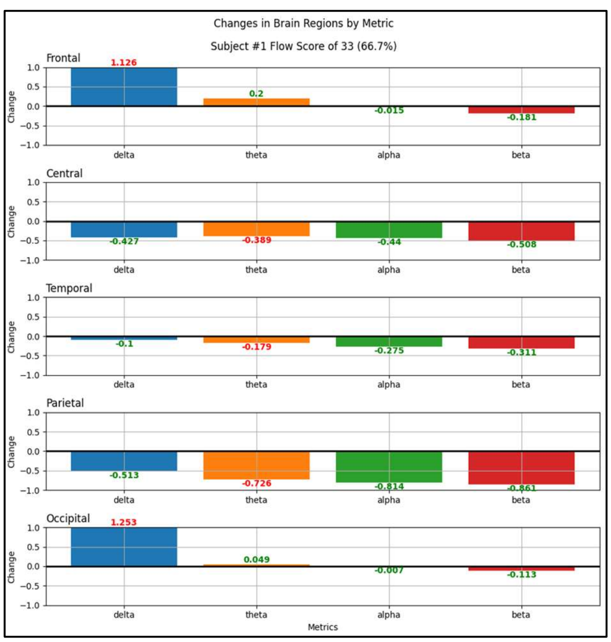

Figure 1: Visualization of EEG power changes (delta: blue, theta: orange, alpha: green, beta: red) for random subjects. Green values represent "good data" used in the correlation plots.

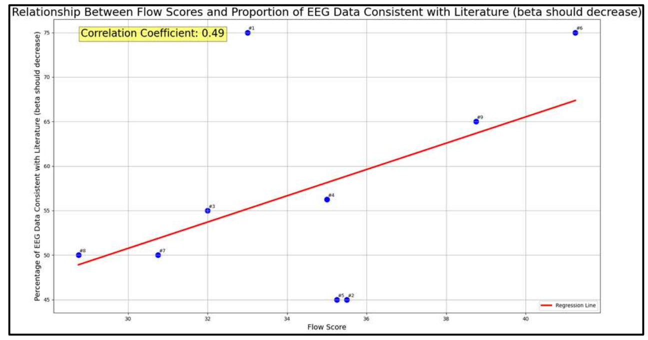

Figure 2: Visualization of the correlation between subjects' flow scores and EEG consistency with the literature, under the condition where beta power shows a negative change.

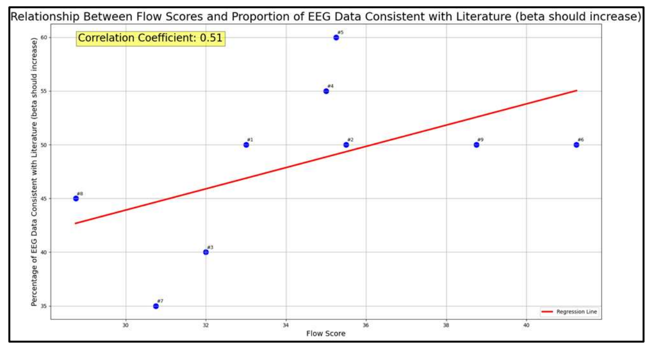

Figure 3: Visualization of the correlation between subjects' flow scores and EEG consistency with the literature, under the condition where beta power shows a positive change.

Acknowledgments

I wish to thank Oren Shriki for supplying all the tools and materials needed for this final project.

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