Evaluating Cognitive and Emotional Engagement in AI-Assisted Virtual Reality Through EEG

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Abstract. This study proposes an EEG-based evaluation pipeline for an AI-assisted VR platform designed to deliver immersive cultural heritage experiences for elderly people. EEG data is used to evaluate emotional and cognitive responses while performing real-world versus virtual tasks, offering a reusable evaluation framework for future immersive heritage applications.

Keywords: EEG, BCI, VR Systems, Cognitive Load, Emotional State Monitoring, Culturan Heritage.

1 Introduction

European countries are undergoing a demographic shift where the median age of the population is expected to increase from 43.7 in 2019 to 48.2 by 2050 (Eurostat, 2020). This will naturally lead to issues in healthcare, social inclusion as well as cognitive health. Consequently, non-pharmacological treatments such as cultural participation have gained attention due to their potential contribution to mental health, emotional regulation, and quality of life among older adults. Existing studies have demonstrated that exposure to cultural sites can lead to therapeutic advantages for individuals with cognitive disorders such as dementia (Belver et al., 2018). Nevertheless, most of these cultural heritage sites lack accessibility due to geographical, physical, or socio-economic obstacles.

Immersive VR technologies have had several uses in science, technology, and the arts over the last decades. It is particularly characteristic of digital art forms that have emerged through rapid technological progress (Albuquerque et al., 2012). VR has evolved its distinctive visual grammar, enabling the development of new narrative forms (Spampinato, 2021). Moreover, digitisation, including the 3-D representation and its usages in immersive technologies, has become a key strategy for preserving cultural heritage and enhancing its public accessibility (El Debuch et al., 2024, pp. 149 -164). In order to address the aforementioned issues, our research team proposed a novel platform using AI-assisted virtual reality (VR) that performs historical storytelling and provides high-fidelity 3D reconstructions to enable immersive and inclusive access to heritage spaces such as the ancient city of Karkemish.

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However, the quantitative and objective assessment of the impact of VR technologies on perception and emotion is still an open question (Petukhov et al., 2020). Although the proposed system aims to improve cultural access and cognitive-emotional engagement through digital means, its successful implementation requires rigorous evaluation to validate its cognitive impact. Prolonged use of immersive technologies may pose challenges for individuals with cognitive vulnerabilities, making it necessary to assess both usability and neurological safety (Kourtesis, 2024).

This study introduces an EEG-based evaluation pipeline as part of an AI-assisted VR platform for cultural heritage. Mental workload, emotional states, and sensorimotor embodiment will be monitored using electroencephalography (EEG). Through EEG recordings collected during real-world and virtual experiences as well as during AI-generated storytelling segments within the virtual environment, the evaluation will quantify the system's cognitive effects and guide iterative improvements. The primary aim of the proposed EEG evaluation pipeline is to ensure that the platform is not only accessible and engaging but also cognitively appropriate and neurologically safe for the aging population.

2 EEG-based BCI Systems Integrated with VR

EEG measures electrical activity of the brain through electrodes placed on the scalp. These signals capture neural oscillations within specific frequency bands (delta, theta, alpha, beta, and gamma) where these oscillations are associated with specific emotional and cognitive states (Attar, 2022). Although recording modalities such as functional magnetic resonance imaging (fMRI) and magnetoencephalography (MEG) provide a higher spatial resolution, EEG is the most preferred approach in both research and applications as it is non-invasive, more affordable, portable and has a high temporal resolution (Biasiucci, 2019). The EEG recording systems range from high-density clinical arrays to lightweight mobile devices such as Emotiv, Muse and OpenBCI. Thanks to these devices, researchers run experiments in controlled lab settings as well as physical and virtual environments (Sabio et al., 2024).

EEG forms the foundation of brain-computer interface (BCI) systems which enable direct communication between the brain and external devices. Depending on their design, BCI systems work by detecting a range of mental states. So called mental states are evoked through a range of tasks including cognitive tasks (i.e. mental arithmetic, stroop and n-back tasks), attention tasks (i.e. oddball, sustained attention and vigilance tasks), motor imagery tasks (i.e. left hand, right hand and foot movement tasks) and emotion tasks (i.e. emotion induction through external stimuli such as images or video clips). Accordingly, BCI systems can work in active (intentional control) and passive modes (state monitoring) depending on the application (Gu et al., 2021; Zander and Kothe, 2011).

In recent years, there has been an increasing interest in combining Virtual Reality (VR) Systems with BCI systems to create intelligent and adaptive environments (Gholizadeh et al., 2024). BCIs in VR can function in offline and online settings. Offline settings are typically used for post-hoc analysis where neural responses of participants, such as EEG spectral power and event related potentials are compared for testing the validity and realism of VR experience. On the other hand, online settings enable real-time feedback supporting a natural experience, such as adjusting environment based on attention, mental workload and emotional state of users. Thus, BCI systems are not only control interfaces but are also valuable evaluation tools to be used with VR systems that reveal users' cognitive and emotional engagement with AI-enhanced VR experiences (Sun et al., 2009; Nwagu et al., 2023).

To determine the extent to which virtual reality reflects real-life cognitive demands, researchers typically use within-subjects designs in which participants complete the same tasks in both environments. Recent research comparing graphic VR simulations and real-life scenarios showed that graphic VR led to a much higher frontal theta activity, whereas parietal alpha was higher for the real task, emphasizing the influence of fidelity on mental workload (Nwagu et al., 2023). Darfler et al. (2022) created a virtual classroom and measured physiological and neural signals such as event related potentials and spectral power extracted from EEG signals in both conditions. The participants performed memory tasks with and without avatar in the VR classroom, the presence of avatar reduced response times significantly while the accuracy did not change. Furthermore, the theta-band activity in the dorsolateral prefrontal cortex and occipital cortex was increased during visual working memory tasks, reflecting increased cognitive demands and attentional control.

Furthermore, by interpreting mental workload, attention, and emotional responses during task performance in both real-world and VR environments, it is possible to determine how effectively VR is replicating real-world cognitive demands. For instance, Ajami et al. (2024) conducted a study where the participants were involved in a VR training with forklift operators. The results indicated that increasing task difficulty led to a higher frontal theta and parietal alpha power, pointing to a higher cognitive load in the virtual task. Furthermore, the results have shown that highly realistic VR environments demand lower cognitive load and therefore a natural and comfortable experience. However, graphical VR environments that can be less immersive but more visually stimulating, demand a higher cognitive load making it a better candidate for learning and training applications where cognitive activation is desirable.

In another study by Tremmel et al. (2019) where an n-back task was performed in VR demonstrated that traditional low-frequency EEG bands could distinguish between different cognitive workload levels. Similarly, real-world tasks such as flight simulation (Hamann and Carstengerdes, 2022) and air traffic control (Shou and Ding, 2013), showed increased frontal theta activity with increasing workload supporting its validity as a robust marker of mental workload. These findings highlight EEG's ability to monitor mental workload in both real-world and virtual environments.

In addition to mental workload assessment, EEG enables monitoring of emotional states and embodiment during immersive interaction. For instance, frontal alpha asymmetry is considered a biomarker for valence (Harmon-Jones et al., 2010), while alpha/theta ratio is correlated with cognitive fatigue or relaxed attention (Chen et al., 2020). Some VR experiments also examine somatosensory and visual cortex activation in order to determine the degree of embodiment and sensorimotor immersion, particularly when performing motor tasks or full-body simulations. These EEG markers can contribute to the development of adaptive VR systems, where real-time modifications in the virtual experience are prompted by BCI (Porssut et al., 2023; Kober et al., 2022). For instance, when mental workload increases, the AI can decrease task demands or diminish visual complexity. Such bidirectional feedback loops enabled by EEG-based BCI systems can lead to development of smart and responsive VR systems (Chiossi et al., 2025).

3 EEG-Based Evaluation Pipeline for Cognitive and Emotional Assessment

To evaluate the cognitive and emotional impact of the proposed AI-assisted VR system, we introduce an EEG based evaluation pipeline that is suitable for older adults. Through this evaluation, we aim to perform a neuroscience informed assessment of how VR experiences influence mental workload, emotional states, and sensory engagement. This evaluation is carried out by analyzing EEG data collected during both real-world and virtual tasks.

Real-world and VR recording phase: The EEG data will be collected while participants perform a reference task in a natural physical environment. These EEG recordings will serve as a neural benchmark representing mental workload, attention and emotional engagement under typical conditions. In the next step, the EEG data will be recorded again as the participants perform the same or equivalent task within immersive VR environment. This setup will enable a within-subject comparison of brain electrical activities for verification of the validity and fidelity of the VR system.

AI-based storytelling VR phase: The EEG data will also be recorded while participants engage with the immersive storytelling experience generated by the AI system. During this phase, participants will be exposed to narrative content that reconstructs the cultural and historical background of the Karkemish site. The aim is to assess users' cognitive and emotional responses to AI-generated narratives, particularly in terms of mental workload, attention, emotional engagement, and immersion. This setting is especially important for understanding how the system supports cultural learning and emotional connection in older users.

In terms of EEG analysis, both spectral and event-related features will be analyzed. For instance, frontal theta activity will be used to evaluate cognitive workload (Nwagu et al., 2023), while frontal alpha asymmetry will be used to assess emotional valence (Harmon-Jones et al., 2010). The alpha/theta ratio will be evaluated as a marker to assess cognitive fatigue or relaxed attention (Chen et al., 2020). Moreover, the EEG signals recorded from sensorimotor regions will be analyzed to assess participants' embodiment and interaction with the virtual environment. ERP's such as P300, which is related to attention and stimulus presentation (Gray et al., 2004), and N400, which is related to semantic processing, will be used to assess participants' cognitive responses to task-specific or narrative stimuli (Kutas et al., 2004), particularly during the AI-generated storytelling segments of the experience.

EEG data will be supplemented by subjective and behavioral measures to assess the interpretability and user relevance. The NASA-TLX questionnaire will be used to assess perceived workload (Hart and Staveland, 1988), and Self-Assessment Manikin (SAM) scale will be used to measure emotional responses (Bradley and Lang, 1994). Furthermore, all EEG data will be managed and stored using privacy-preservation protocols to ensure the anonymity and privacy of participants. This modularity-based evaluation pipeline enables repeated refinement of the VR experience so that the system is cognitively and emotionally safe and appropriate for especially elderly participants. It should also be noted that the proposed framework is reusable for future cultural heritage systems that combine AI and VR.

4 Conclusions

This study proposes a pipeline combining AI-augmented storytelling, an immersive VR environment and cognitive testing using EEG in order to enhance accessibility of cultural heritage, specifically among older adults. By combining AI-based narrative generation with historical foundations and high-fidelity virtual reconstruction, the system provides not only an engaging platform but also a scientifically grounded approach to examine its cognitive and emotional impact. The proposed EEG evaluation procedure, reinforced by both real-life and VR comparisons, aims to validate fidelity, emotional responses and mental workload demands of the proposed AI-assisted VR system. To have a more comprehensive understanding of user experience, behavioral and self-report measures will also be utilised. In addition, privacy preservation protocols are incorporated into the pipeline to protect sensitive user information.

Future research will focus on implementing the proposed evaluation approach in a case study for the AI-assisted VR model of the ancient city of Karkemish. As the next stage, an open-source tool will be developed to generalize this approach to other cultural heritage contexts.

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