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Designing and Evaluating an Adaptive Virtual Reality System using EEG Frequencies to Balance Internal and External Attention States

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ABSTRACT

Virtual reality (VR) finds various applications in productivity, entertainment, and training, often requiring substantial working memory and attentional resources. Effective task performance in VR relies on prioritizing relevant information and suppressing distractions through internal attention. However, current VR systems fail to account for the impact of working memory loads, leading to over or under-stimulation. In this work, we designed an adaptive system using Electroencephalography (EEG) correlates of external and internal attention to support working memory tasks. Participants engaged in a visual working memory N-Back task, where we adapted the visual complexity of distracting elements. Our study demonstrated that EEG frontal theta and parietal alpha frequency bands effectively adjust dynamic visual complexity. The adaptive system improved task performance and reduced perceived workload compared to a reverse adaptation. Furthermore, we trained a Linear Discriminant Analysis (LDA) model and achieved a classification accuracy of 79.4% for distinguishing internal and external attention states using EEG frequency features, demonstrating the feasibility of EEG-based models for real-time attention state detection. These results highlight the potential of EEG-based adaptive systems to balance distraction management and maintain user engagement without causing cognitive overload.

1. Introduction

The immersive nature of Virtual Reality (VR) environments allows users to engage with a wide range of lifelike and immersive scenarios, making it an ideal tool for various applications, such as remote collaboration (Knierim et al., 2021), training (Zahabi and Abdul Razak, 2020) and entertainment (Lécuyer et al., 2008). These applications also extend to productivity settings, where specific VR applications have been shown to improve productivity by enabling higher focus and multitasking capabilities (Gonzalez-Franco and Colaco, 2024; Aufegger and Elliott-Deflo, 2022; Chiossi et al., 2024). Here, productivity settings benefited from specific VR applications. However, VR environments' inherent predominant visual nature can challenge users' capacity to process information. For example, users have been overwhelmed when the VR system provided excessive visual stimuli for training in visual tasks (Ragan et al., 2015), spatial memory (Huang and Klippel, 2020), and immersive analytics (Bacim et al., 2013; Gonçalves et al., 2022).

Researchers have proposed adaptive systems that aim to detect if a user is overwhelmed and adjust the VR environment. One promising approach to detect such *overload* states , i.e., a state where the cognitive demands placed on a user exceed their capacity to process information effectively (da Silva Cezar and Maçada, 2023; Kosch et al., 2023a), is to employ physiological measures, potentially allowing for online adaptation. A robust approach is detecting the relationship between internally-oriented (Hutchinson and Turk-Browne, 2012) and externally-oriented (Jiang et al., 2021a) attention using EEG as when the attentional state of the user changes, the electrophysiological activity is unintentionally altered and this physiological signal can be employed for implicit adaptations, i.e., cognitive fatigue detection in pilots (Dehais et al., 2018)). Internal attention involves focusing on stimuli within oneself or stored in working memory (WM), or episodic memory (Chun et al., 2011), while external attention allows the processing of stimuli in the external environment, such as visual or auditory cues (Jiang et al., 2021a). This is specifically relevant, as many VR tasks can share internal attention (Rowe et al., 2000; Magosso et al., 2019) and external attention features (Ricci et al., 2022; Magosso et al., 2019). Users might become overwhelmed, distracted, and lose focus if external attention is prioritized over internal attention. On the other hand, users may miss important external cues if they are in a predominant internal attention state, leading to suboptimal performance in VR. Thus, balancing internal and external attention processes in VR settings is crucial. Therefore, it is not a matter of whether a task employs internal or external attention exclusively but

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rather how to balance one in the face of the other. This is consistent with Chun's taxonomy that internal and external attention are part of a continuum (Chun et al., 2011).

Internal and external attention share specific EEG features in this continuum (Putze et al., 2016; Benedek et al., 2014; Cona et al., 2020), i.e., alpha and theta frequency bands. Alpha power is associated with enhancing relevant sensory information processing and concurrent suppression of irrelevant information. Theta mediates WM and cognitive control processes (Pastötter et al., 2013). In the context of VR systems, they have also been associated with increased immersion and engagement with the VR task (Magosso et al., 2019; Ricci et al., 2022). Previous work has employed alpha and theta frequency bands in adaptive VR systems focused on neurofeedback for concentration (Kosunen et al., 2016), cognitive training (Dey et al., 2019) and immersion enhancement (Woźniak et al., 2021). However, most physiologically-adaptive systems focused on main task features, such as visual search targets (Dey et al., 2019), learning material (Walter et al., 2017) or secondary task difficulty (Chiossi et al., 2022a). However, it is important to note that while alpha and theta oscillations are key markers for attention and WM (Klimesch, 2012, 1999), other frequency bands, also play roles in such cognitive processes (Harmony et al., 2004; Fernández et al., 2021). The most closely related to our work is the paper by Vortmann et al. (2019), that, even if in Augmented Reality (AR), used alpha and theta bands for offline classification of internal and external attention states. Thus, the next step is to employ alpha and theta bands for online adaptation of distracting features of the environment from calibrating and allocating the user's attention.

In this work, we designed and evaluated two VR adaptive systems based on EEG correlates of external and internal attention, i.e., alpha and theta frequency bands, that either balance for external or internal attention.These bands were selected due to their strong links with attention and WM, although they are not the sole indicators, nor are they exclusively tied to attention processes. We engaged participants in a visual WM task that required both internal and external attentional resources. We adjusted the peripheral visual distractors based on their detected attentional state. We demonstrated that balancing for internal attention during a WM task enables dynamic adaptations of visual distractors, resulting in improved WM task performance. This indicates that our approach helped users avoid distracting external attention states while staying engaged with the virtual environment and maintaining an optimal internal attention state.

1.1. Contribution statement

We make the following key contributions through our study. Firstly, we designed a VR adaptive system that employs visual complexity to dynamically support task performance and engagement. This system leverages the dynamic adaptation of peripheral environmental factors to implicitly balance the user's attentional state and overall experience without altering the main task features. Secondly, our study demonstrates that online adaptation of EEG correlates of external and internal attention results in efficient user modeling. We focused on adapting peripheral environmental factors using these EEG correlates, ensuring that the primary task remains consistent while effectively managing the user's attentional state. Furthermore, we make the VR adaptive system openly available along with a recorded dataset of behavioral, qualitative, and EEG data, facilitating further research and development. This open access promotes replication studies, comparative analyses, and further innovation, contributing to the broader scientific community. Our study introduces several novel contributions that significantly advance the field of EEG-based adaptive VR systems. Unlike previous studies that primarily focus on neurofeedback or cognitive training, our approach integrates real-time EEG-based adaptation to balance internal and external attention states during complex tasks in VR. This real-time adaptation is achieved by dynamically adjusting peripheral environmental factors, providing a subtle yet effective enhancement of task performance and user engagement.

2. Related work

In the following, we highlight the relevance of investigating internal and external attentional states for VR, and then we discuss their EEG correlates in terms of alpha and theta frequency bands. Finally, we summarize previous work that employed EEG as input for adaptation in VR.

2.1. Relevance of internal and external attentional states in VR

When immersed in VR, our senses are continuously stimulated, allowing us to interact with the virtual environment. Sensory inputs, particularly vision and hearing, strongly influence attention. Vision, in particular, has garnered the most interest (Hutmacher, 2019), as it is the primary channel stimulated in VR (Hvass et al., 2017) and significantly influences the orientation of human attention (Souza and Naves, 2021).

Attention orienting refers to the process of directing cognitive focus toward specific stimuli, whether internal, such as thoughts and memories, or external, such as visual and auditory cues (Chun et al., 2011), see Fig. 1.

External attention is drawn to external stimuli. Task demands can voluntarily drive external attention in a top-down manner, such as when we focus on a specific spatial location or feature of sensory stimuli that is goal-relevant (Verschooren et al., 2019). Alternatively, external attention can be captured involuntarily in a bottom-up manner, which occurs when attention is drawn to salient stimuli or unexpected events in the environment, even without the intention to focus on them (Cona et al., 2020). This bottom-up attention is driven by the inherent properties of the stimuli, such as brightness, movement, or sudden changes, which naturally attract our attention (Katsuki and Constantinidis, 2014).

Internal attention reflects the processing of internal representations of information. For example, retrieving information about recent or past events (episodic memory) (Hutchinson and Turk-Browne, 2012), WM (Myers et al., 2017), and mental imagery (Putze et al., 2016).

Recently, Lim and Pratt (2023) challenged Chun's framework due to inconsistencies in how internal breadth affects external perceptual processing. They showed that internal attention does not always impact external attention, contradicting the idea that these forms of attention share identical processes and resources. Their findings suggest that internal and external attention may have different characteristics and may not always compete for the same cognitive resources.

However, it is important to note that internal and external attention, while potentially relying on different cognitive resources, are both crucial processes for successful task performance in VR environments (Souza and Naves, 2021). Currently, Human Computer Interaction (HCI) research mostly focuses on internal and external attention for investigating levels of immersion and engagement in VR systems. For example, Magosso et al. (2019) explored the conflict between external and internal attention in a mental arithmetic task (internal attention) and being immersed in a VR environment (external attention). Here, a highly detailed VR environment recruited external attention resources similarly to a reading task, which requires high levels of external attention, as shown in EEG alpha power. Their result was also confirmed in Ricci et al. (2022), showing how exposure to a VR environment increased their attention to the external environment compared to a relaxation state, i.e., internal attention task.

Attentional states also influence how much users can be engaged in a task. Katahira et al. (2018) investigated different flow experiences in an internal attention task, i.e., mental arithmetic task (Putze et al., 2016). They found that EEG correlates of external and internal attention discriminated between states of overload, boredom, and flow. Thus, investigating the external and internal attentional state can benefit users' level of immersion (Souza and Naves, 2021) and task

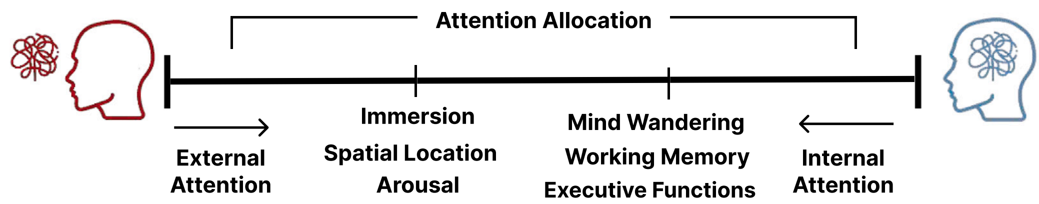


Fig. 1. This figure illustrates Chun's continuum between internal and external attention, depicting the allocation of attentional resources across different cognitive activities. Internal attention encompasses functions such as "Mind Wandering", "Working Memory", and "Executive functions" such as mental calculation, which rely heavily on internally generated information. External attention involves states like "Immersion", "Spatial Location", and "Arousal", which require focus on external stimuli. The continuum demonstrates the fluidity of attention as it shifts between internal and external demands, highlighting the importance of balancing these states for optimal cognitive performance and immersion.

engagement (Katahira et al., 2018).

However, it is important to state that external and internal attention rather than independent states are part of a continuum (Chun et al., 2011). The continuum between external and internal attention provides a fertile ground for developing adaptive systems. This aspect is specifically relevant for settings where the visual components prevail, such as VR. In particular, the visual nature of VR environments makes it challenging to direct internal attention but also creates opportunities to guide external attention. By leveraging this continuum, adaptive systems can tailor the VR experience to the user's attentional needs and goals, supporting them in achieving optimal performance, immersion and engagement.

2.2. Alpha and theta frequency bands as an EEG correlate of external and internal attention

A large number of studies investigated neurophysiological mechanisms underlying external and internal attention. EEG studies, in particular, have strongly supported the functional significance of two brain oscillatory rhythms: theta (4–8 Hz) and alpha (8–12 Hz). Variations in external and internal attention states are strongly linked to the modulation of alpha and theta frequency bands. These relationships highlight the importance of understanding the underlying mechanisms and their implications for designing efficient VR adaptive systems that are grounded in physiological inference (Allanson and Fairclough, 2004).

The alpha rhythm is the dominant oscillatory rhythm of the human brain and is traditionally linked to attentional load changes (Foxe and Snyder, 2011). Alpha band power is thought to act as a sensory gating mechanism by enhancing relevant sensory information processing and suppressing irrelevant information processing (Jensen and Mazaheri, 2010; Foxe and Snyder, 2011). Thus, alpha activity plays a crucial role in regulating attention processes, both within and outside the focus of attention. Studies have explored posterior alpha as a possible index of internal and external attention, with external attention linked to alpha power decrease and internally directed attention primarily associated with alpha power increase (Cona et al., 2020; Benedek et al., 2014). Specifically, alpha increase aims at preventing external, irrelevant sensory information from interfering with internal processes. On the other hand, when individuals enter an external attention state, alpha power tends to decrease in the occipital region. This decrease in alpha frequency band reflects increased excitability of the visual cortex, which in turn enhances the processing of external sensory information (Van Diepen et al., 2019).

Regarding theta frequency band, its increased power has been linked to WM engagement and cognitive control, particularly in frontal regions (Harmony, 2013). Both WM and cognitive control involve internal attention features. WM requires temporarily maintaining and manipulating internal representations of information (Rerko and Oberauer, 2013). Cognitive control refers to the ability to regulate thoughts and actions to achieve specific goals (Braver, 2012), and therefore ignoring task-irrelevant or distracting information (Lavie, 2010). The theta activity could be indicative of a balance between external and internal attention (Cona et al., 2020) and their competition (Magosso et al., 2021). Theta decrease may signify the act of shifting attention towards external stimuli, allowing for the processing of potentially distracting information. In contrast, an increase in frontal theta underlies protection and prioritization of ongoing internal processing (Lorenc et al., 2021; de Vries et al., 2020).

In conclusion, alpha and theta changes can index different levels of the continuum between external and internal attention, namely, their competition. In the next section, we review adaptive and passive BCI (pBCI) systems that employ such frequency bands as input for VR systems.

2.3. EEG as an input for adaptation in virtual reality

EEG frequency bands have been used as the primary input for interaction in pBCI systems. A pBCI system derives an output from automatic, involuntary, spontaneous brain activity, interpreted in the given context (Lotte et al., 2018). Historically designed for communication and control for patients with severe disabilities, pBCIs recently found new applications for patients and healthy users when combined in VR settings (Lécuyer et al., 2008). pBCIs and VR can see reciprocal benefits as pBCI can become more intuitive than traditional devices. At the same time, VR can enrich interaction and provide more motivating feedback for pBCI users than traditional desktop settings (Aricò et al., 2018). Therefore, VR-pBCI or physiologically-adaptive VR systems could support system learnability, i.e., reduced time required to learn BCI skills or increased classification performance (Leeb et al., 2006; Ron-Angevin and Díaz-Estrella, 2009), and allow for an extensive range of applications (Chiossi et al., 2022b).

In VR adaptive systems, alpha and theta were the basis for designing adaptive systems for meditation (Kosunen et al., 2017) and adaptation of task difficulty based on cognitive interference (Wu et al., 2010). Another related work focused specifically on alpha for cognitive training is the study by Dey et al. (2019), where authors modulated the visual task difficulty in a VR visual search task. Finally, frontal theta power has also been employed in adaptive systems to index the continuum between overload and optimal motivational engagement (Ewing et al., 2016). Closer to our work, even though applied to AR settings, are the adaptive systems developed by Vortmann et al. (2022), Vortmann and Putze (2020). Here, the authors employed the entire EEG frequency spectrum and eye tracking to categorize internal and external attention with an 85.37% accuracy in a special alignment task.

Previous work explored alpha and theta EEG frequencies for adaptation in human factors, VR and AR environments, but mostly for interaction methods and monitoring cognitive load or task engagement. However, only a few works investigated the use of EEG for external and internal attention in VR settings (Magosso et al., 2019, 2021) and adaptive systems have been designed only in AR settings (Vortmann et al., 2019). Our research is the first that investigates how to develop an adaptive VR system to balance for internal attention, grounded in physiological inference (Allanson and Fairclough, 2004), and validated in a user study.

2.4. Summary

The immersive nature of VR technology has revolutionized how we interact with digital content. However, VR is primarily designed around visual information that challenges users' capacity to process information (Bacim et al., 2013; Gonçalves et al., 2022), leading to an unbalanced allocation of external attention resources at the expense of internal attention (Vortmann and Putze, 2021). Thus, the design of an adaptive VR system grounded in EEG correlates of external/internal attention state, leveraging the amount of task-irrelevant elements in the internal–external attention continuum (Chun et al., 2011), can impact subjective workload, engagement, and task performance (Aricò et al., 2018). Here, we compare two adaptive systems, one balancing for external attention (Negative Adaptation) and one for internal attention (Positive Adaptation) while participants engaged in a visual N-Back, a task that primarily recruits internal attention but also features both attention components, which act along a spectrum. Based on related work, we designed an adaptive system to support performance by balancing the two attentional components. However, given the inherent trade-off, we designed two systems that balance for external or internal attention, we hypothesize that:

- **HP1**: An adaptive system designed for balancing the attention competition towards internal attention should positively impact WM task performance.
- **HP2**: An adaptive system designed for balancing the attention competition towards external attention should negatively impact WM task performance.
- **HP3**: By balancing the visual complexity and achieving a balanced allocation of internal and external attention resources, the adaptive system designed for internal attention is hypothesized to increase subjective engagement in the WM task.
- **HP4**: If the adaptive system balancing for external attention has a detrimental effect on WM task performance, we expect increased subjective workload ratings.

Moreover, detecting and understanding a user's attentional state could significantly enhance the utility of VR systems and enable novel use cases that are purposefully designed to react, detect and balance it (Allanson and Fairclough, 2004). Therefore, drawing from AR settings (Vortmann et al., 2019; Vortmann and Putze, 2021) and considering how much internal and external attention are recruited in VR settings, we expect that:

- **HP5**: External and internal attentional states in VR can be reliably classified.

We explore classification-based differentiation of external and internal states as an alternative to literature-driven selection of adaptation variables from the EEG signal. Potentially, machine learning can better balance multiple such variables in one model and deal better with EEG trial-by-trial fluctuations (Lotte et al., 2018). As this approach requires more tuning and is less predictable, we explore its potential for future adaptation approaches.

3. Architecture of the EEG-adaptive VR system

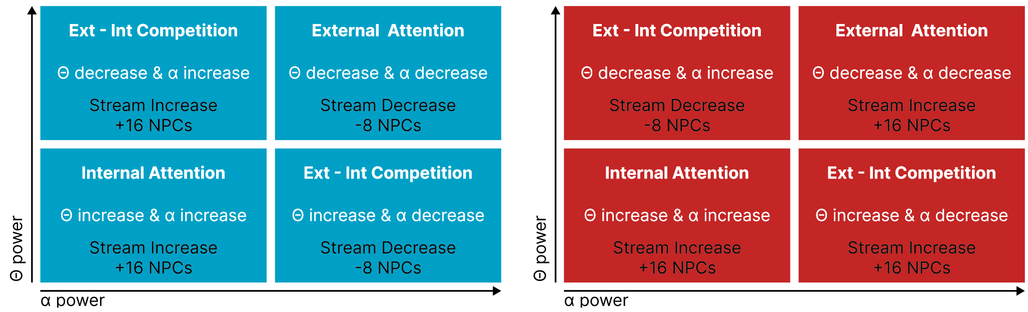
VR environments are often designed to be immersive, realistic, and engaging, making it easy for users to become distracted or overwhelmed by external visual stimuli. Thus, we might see a constant competition between internal and external attention when engaged in VR scenarios. Here, an EEG-adaptive system can monitor users' attentional states and balance attentional processing to improve internal task performance in VR settings by adapting surrounding visual information. We define the goal of balancing attentional processing as enhancing the efficiency and effectiveness of attentional processing necessary for a given task. This goal requires identifying and achieving an ideal balance between external and internal attentional processes to improve task performance while maintaining engagement with the virtual environment. The critical aspect is not whether a task exclusively relies on internal or external attention, but rather how to achieve an optimal balance between the two. For example, during a mostly internal task, the goal is to provide external attention as much as possible without compromising the focus on the internal processing of the task. This aligns with Chun et al. (2011) perspective that internal and external attention are interconnected along a continuum, and their interaction must be considered when balancing attentional processing.

In this work, we designed and compared two VR adaptive systems based on EEG correlates of internal and external attention. We frame the adaptive systems from the perspective of a situation in which being in a state of internal attention is desirable. Specifically, the system called from here on Positive Adaptation is designed to balance the internal attention state. In contrast, the system defined as Negative Adaptation aims to balance externally-directed attention. We used the visual WM N-Back task developed by Chiossi et al. (2022a) for both adaptive systems. We chose the VR N-Back task as it recruits WM resources and results in changes in alpha and theta frequency bands (Chiossi et al., 2023a; Tremmel et al., 2019). The N-back task is a continuous performance task used to assess working memory, where participants are presented with a sequence of stimuli and must identify when the current stimulus matches the one from N steps earlier (Mallett and Lewis-Peacock, 2018). The task can vary in difficulty; for instance, in the 1-back task, participants must match the current stimulus with the one immediately preceding it. In the 2-back task, they must match the current stimulus with the one from two steps before.

The N-back task is particularly well-suited for balancing internal and external attention because it inherently requires the management of both types of attentional resources. Internally, participants must continuously update and maintain information in their WM, reflecting internal attention processes. Externally, they must remain vigilant to new stimuli presented during the task, engaging their external attention. This dual demand makes the N-back task an ideal candidate for studying and balancing the balance between internal and external attention states.

Furthermore, implementing the N-back task in a VR environment provides significant advantages. VR enhances the immersion and engagement of the N-back task by incorporating 3D spatial cues and interactive elements, making the task more realistic and ecologically valid than traditional 2D presentations. VR's rich, multisensory environment allows for a comprehensive assessment of cognitive functions, as it integrates visual, auditory, and haptic inputs. This heightened realism ensures that the task better reflects real-world scenarios, providing more accurate data for adapting the VR environment in real-time.

We adapted the surrounding visual complexity of the VR environment in the form of non-player characters (NPCs) that were passing next to the participant. We denote the number of NPCs passing by the participants per minute as Stream. NPCs were used as colorful, dynamic, and task-irrelevant distractors to introduce controlled visual complexity, allowing for systematic testing of the system's adaptive mechanisms. NPCs provide a controlled and consistent way to validate the system's functionality and evaluate its potential effectiveness in balancing internal and external attention. However, while NPCs serve as a proof-of-concept implementation, they are not an essential component of the system. The adaptive framework can be applied to other forms of distracting or task-irrelevant stimuli in real-world applications, tailored to specific scenarios and requirements. The Stream of NPCs was constant, making NPCs appearing/disappearing at the same rate. The Stream of NPCs contributes to the general amount of detail, clutter, and objects in the scene, namely its visual complexity (Olivia et al., 2004). NPCs are task-irrelevant elements, and for the purpose of this task, they act as distractors.



(a) Positive Adaptation (b) Negative Adaptation

Fig. 2. Adaptation Methodology for the two adaptive systems based on the increase and decrease of the alpha and theta frequency bands and their relevance to internal and external attentional states.

3.1. EEG adaptive system

Both adaptive systems shared the same apparatus encompassing four components: (I) an R-Net 64 channel EEG with two wireless LiveAmp amplifiers (BrainProducts, Germany), (II) Transmission Control Protocol (TCP)/Internet Protocol (IP) for online EEG data preprocessing (III) the Unity 3D (Version 2022.1) game engine for VR development; and (IV) HTC Vive Pro (HTC, Taiwan) VR HMD for the display of the VR environment. For online adaptation, we first applied a notch filter at 50 Hz and then performed a band-pass filtering between (1–70 Hz) to remove high and low-frequency noise. Then, we extracted alpha and theta EEG powers via Welch's periodogram method using a Hamming window of .1 s (50 samples) at 10% overlap (5 samples) to obtain a 10 Hz frequency resolution. For determining the alpha frequency range, we computed the Individual Alpha Frequency (IAF) via the method developed by Corcoran et al. (2018). Then, based on the individual alpha lower bound, we defined the theta frequency range, using the alpha lower bound as the high theta bound and defining the theta lower bound by subtracting 4 Hz from the alpha lower bound. For computing alpha power we used parieto-occipital channels (P3, Pz, PO3, POz, PO4, O1, O2) (Benedek et al., 2014; Magosso et al., 2019), while for theta, we chose frontal channels (Fp1, Fp2, AF3, AF4, F1, F2, F3, Fz, F4, FC1, FC2) (Magosso et al., 2019). Electrode FCz was set as an online reference.

For data streaming and online preprocessing, we transmitted the data through a Transmission Control Protocol (TCP)/Internet Protocol (IP) client to a TCP/IP server implemented via Python network programming. This implementation enabled us to exchange data between Lab Streaming Layer[1] and the VR Unity environment in both forward and backward directions. We utilized a Network Time Protocol (NTP) service to time-synchronize the VR Unity scene's time and the bridge server's operating system time.

3.2. Adaptive system architecture

Adaptive system architecture was grounded on previous work on the functional significance of alpha and theta frequency bands (Putze et al., 2016; Benedek et al., 2014; Vortmann et al., 2019) as input for the VR adaptive systems. First, we used a continuous adaptation, continuously comparing the mean alpha and theta bands over two consecutive time windows, w_1 and w_2, both of 20 s duration, based on previous work (Chiossi et al., 2022a, 2023a). Second, we compute the mean alpha and theta power for w_1 and w_2. Here, we compare the direction of change (defined as exceeding a 15% threshold) of both mean alpha and theta in w_2 to the average power in w_1. We determined the threshold after multiple sessions (N = 14, $M = 25.62$, $SD = 2.52$; 7 female, 7 male, none diverse) to identify a threshold allowing the system to balance external attention while avoiding overshooting, i.e., always performing the same adaptation response or undershooting, i.e., not reacting to changes in alpha and theta EEG frequencies. We tested multiple thresholds (5% steps from 5%–30%) and evaluated system performance. If the change from w_1 to w_2 of both alpha and theta exceeded the decision threshold, depending on the direction of the frequency band, a change in Stream of NPC is performed. We define our adaptation goal as biased toward a specific type of attention (internal or external) while maintaining a balance between the two states. This balance is crucial, as attention operates along a continuum, and users often need to shift fluidly between internally and externally directed attention based on context and task demands (Vortmann and Putze, 2021). To support this balance, our systems dynamically adjust environmental factors (e.g., peripheral visual complexity) to gently guide users toward the desired attentional state while avoiding extreme shifts that may disrupt task performance or cognitive engagement.

On average, the Stream in the Positive Adaptation condition stabilized at 133.17 NPCs per minute (SD = 14.86). Participants executed a mean of 152.25 (SD = 73.19) WM trials in the Positive Adaptation condition, compared to 167.33 (SD = 68.04) in the Negative Adaptation condition and 182.96 (SD = 68.53) in the baseline condition. The Positive Adaptation methodology is depicted in Fig. 2(a) and the architecture in Fig. 3.

3.2.1. Rationale and parameters

Parameters are based on previous work on adaptive system design, accounting for the task irrelevance and distracting effect of the NPCs (Chiossi et al., 2023a,b). They also ensure that the number of distracting NPCs does not drop to zero per minute, maintaining a consistent level of visual complexity. Participants began the adaptive blocks with a Stream set at 115 NPCs entering the scene per minute, chosen as the mean value between the lowest possible value and the highest (230) based on Chiossi et al. (2023b). The 15% adaptation threshold was selected to ensure a balance between sensitivity to attentional changes and stability in the adaptation process. Multiple sessions determined this threshold by identifying a level that allows the system to balance external attention without overshooting or undershooting (Chiossi et al., 2023b).

Analysis of EEG alpha frequency spectra over 20-second sliding windows supported this choice, aligning with prior findings that alpha activity fluctuates dynamically within short intervals. For example, studies have shown periodic shifts between synchronized and desynchronized EEG states (Tirsch et al., 2004) and task-relevant cortical excitability changes (Klimesch et al., 2007). These dynamic oscillatory patterns, along with observed pilot results, informed the selection of a 15% threshold to ensure responsiveness while avoiding excessive adaptation triggers.

[1] https://labstreaminglayer.org/

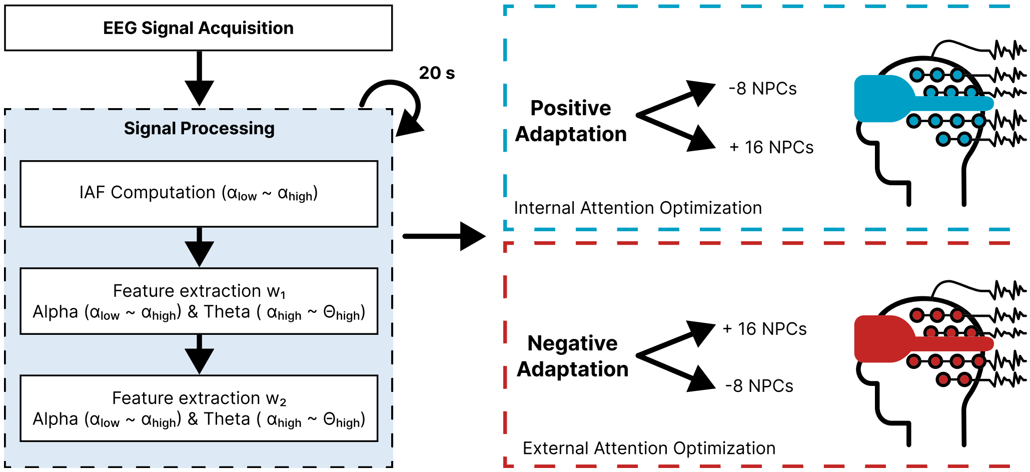
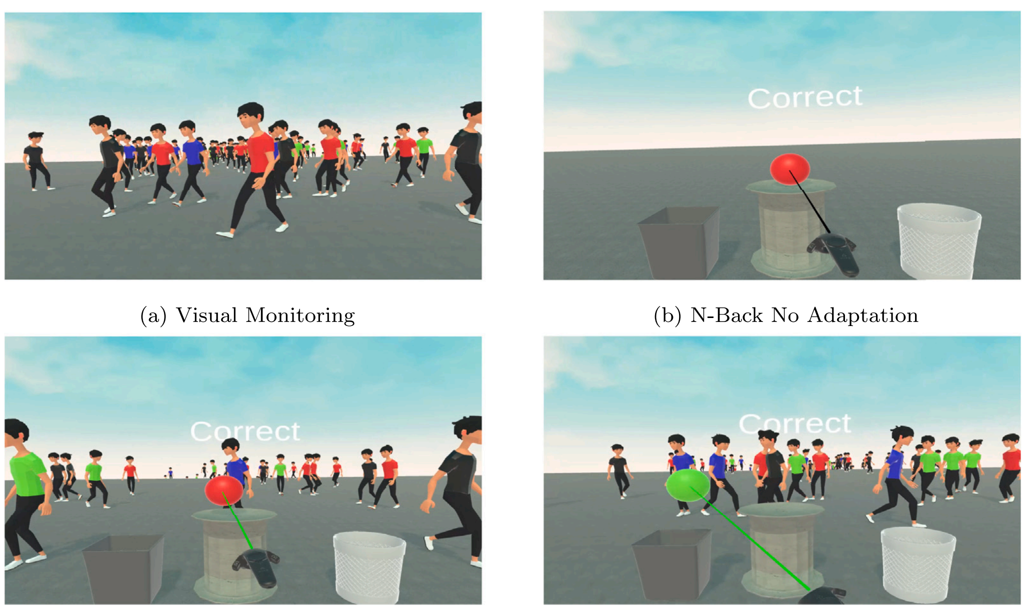


Fig. 3. Architecture of the two adaptive systems. The Stream of NPCs adapts based on alpha and theta variation in two different time windows (w_1 and w_2), each lasting 20 s. If the change is bigger than the decision threshold of 15%, the NPC stream is either increased by +16 or decreased by −8 NPCs. The Positive Adaptation system (a) aims at balancing internal attention, while the Negative Adaptation system (b) targets external attention.



(a) Visual Monitoring

(b) N-Back No Adaptation

(c) N-Back Positive Adaptation

(d) N-Back Negative Adaptation

Fig. 4. Game VR Capture of the experimental tasks. In the Visual Monitoring task (a), participants are exposed to a stream of NPCs and are required to monitor, i.e., follow with their gaze, NPCs of a specific color. In the N-Back No Adaptation task (b), participants interact with a sequence of spheres presented on a marble-like pillar. They must place each sphere into either the left or right bucket based on its color and the color of the sphere presented two steps prior (N = 2). If the current sphere's color is different from the sphere two steps ago, it is placed in the left bucket; if the same, it goes in the right bucket. In (c) and (d), we depict the participants' point of view while interacting with the two adaptive systems. While interacting with the two systems, participants perform the N-Back task while being exposed to NPC that act as distractors.

3.3. Positive adaptation

The Positive Adaptation system dynamically adjusts the visual complexity of the VR environment based on real-time changes in the user's alpha and theta EEG bands. The system monitors these EEG signals over two consecutive 20-second time windows, w_1 and w_2, and makes adjustments to the number of non-player characters (NPCs) passing by the participant, referred to as the Stream.

3.3.1. Decision tree

The Positive Adaptation system operates using a decision tree to interpret changes in the user's EEG bands and adjust the visual complexity as follows.

Internal attention state. When a shared 15% increase in both alpha and theta bands is detected in w_2 compared to w_1, the system interprets this as the user being in an internal attention state. To find an optimal level of visual complexity and test the tradeoff between internal attention and external visual complexity, the system increases the Stream by 16 NPCs. This adjustment allows us to investigate how individuals adapt to a dynamic environment where attentional demands are subject to change.

External attention state. Conversely, when both alpha and theta bands decrease by at least 15% in w_2 compared to w_1, the user is assumed to be in an external attention state. To support the internal attention state, the system removes 8 NPCs from the scene. This decision is grounded in research indicating that internal attention is associated with increases in alpha (Benedek et al., 2014; O'Connell et al., 2009) and theta (Cona et al., 2020), reflecting increased WM engagement (de Vries et al., 2020).

Divergent attention states. In cases where alpha and theta bands show opposite directions, the system makes specific adjustments based on the type of attentional state inferred as follows.

Alpha Decreases and Theta Increases. When alpha decreases and theta increases by 15%, it is assumed that the user has entered an external attention state. This is indicated by the alpha band (Benedek et al., 2014) and increased cognitive control due to the effort to maintain focus while ignoring distractors (Braver, 2012). In this scenario, the Stream is decreased by 8 NPCs.

Alpha Increases and Theta Decreases. Conversely, if alpha increases and theta decreases, it is theorized that the user is increasing internal attention with decreased WM engagement. Therefore, the system increases the Stream by adding 16 NPCs.

3.4. Negative adaptation

The Negative Adaptation system dynamically adjusts the visual complexity of the VR environment to balance for external attention. It operates by monitoring the user's alpha and theta EEG bands over two consecutive 20-second time windows, w_1 and w_2, and adjusting the number of non-player characters (NPCs) passing by the participant, referred to as the Stream.

3.4.1. Decision tree

The Negative Adaptation system uses a distinct set of rules to modify the visual complexity based on EEG band changes.

External attention state. When a decrease of at least 15% in alpha power is observed in w_2 compared to w_1, it indicates that the user is in an external attention state. To further promote external attention, the system increases the Stream by adding NPCs, thereby increasing the visual complexity.

Internal attention state. On the other hand, if both alpha and theta bands show a 15% increase in w_2 compared to w_1, it suggests that the user is in an internal attention state. To counteract this and shift attention externally, the system also increases the Stream.

Divergent attention states. When alpha and theta bands change in opposite directions, the system makes specific adjustments. A decrease in alpha combined with an increase in theta indicates that the user is maintaining focus despite distractors, reflecting an external attention state. In this case, the Stream is increased to heighten visual complexity. Conversely, if alpha increases and theta decreases, it suggests an increase in internal attention with reduced WM engagement. To prevent boredom and ensure continued engagement, the system decreases the Stream by 8 NPCs (Ewing et al., 2016). This choice is meant to evaluate if adaptation can still impact the user's WM performance without improving it, demonstrating that BCI-based adaptation cannot be replaced equivalently with a purely performance-based one. If participants already exhibit an internal focus of attention, this might decrease engagement with the task, enforcing such an internal state. Finally, when alpha and theta have the same direction, indexing an internal attention state, the system increases the visual complexity by adding 16 NPCs to the Stream.

4. User study

The study evaluated if adaptation of visual complexity, based on EEG correlates of internal and external attention, can balance behavioral WM performance and subjective engagement ratings compared to a system designed to balance for external attention. As the main task, we chose the established N-Back task (Soveri et al., 2017) in the VR version as adapted from Chiossi et al. (2022a). The task involved updating the information in WM and paying continuous attention to the presented spheres while retaining the previously presented information. We selected this task because it evokes external and internal attention processing, making it ideal for balancing one of the two processes in adaptive systems.

4.1. Design

To examine differences in behavioral performance, perceived workload and engagement and alpha and theta frequency bands, we performed a within-subjects study for the system's adaptability factor (Positive vs Negative Adaptation). The experiment encompasses six blocks, of which four are the experimental ones and either recruit only external (Ext-Att Task : Visual Monitoring Task) or internal attention (Int-Att task : N-Back No Adaptation), and two adaptive blocks which have a competition between the two processing with two different adaptive systems (Ext/Int Task: N-Back Negative Adaptation and Ext/Int Task: N-Back Positive Adaptation). The first two blocks are the Individual Alpha Frequency Block (IAF computation Block), which lasted 2 min and is necessary for computing the IAF for each participant, and the Resting State block, used as a basal condition for normalization to the experimental blocks. The Ext-Att Task (Visual Monitoring task) requires participants to inspect the VR scene, identify and follow with the gaze NPCs of a specific color, see Fig. 4(a). The Int-Att Task (N-Back No Adaptation) is a visual N-Back task (N=2) where the participants have to retain information regarding the color of a sphere and internally direct attention towards the memory of the color of the sphere and compare it to the color of the current sphere, and place in a specific bucket depending on the match of the color, see Fig. 4(b). The two "adaptive" experimental conditions required participants to perform the N-Back task while being exposed to a Stream of NPCs, i.e, an adaptation of the visual complexity through changes in the participant's alpha and theta EEG frequency bands. In the two adaptive tasks, NPCs serve as distractors as they are elements that are not relevant to the task at hand (see Fig. 4(c) for the Positive Adaptation and see Fig. 4(d) for the Negative Adaptation). Respectively, positive adjustments of Stream (Increase) resulted in adding 16 NPCs to the scene, while negative adjustments of Stream (Decrease) resulted in removing 8 NPCs from the scene. In Fig. 6 we depict the Stream variation over time in both adaptive systems across participants, while in Fig. 10(a) and in Fig. 10(b) we display the Stream variation for a representative participant together with alpha and theta powers for the Positive and Negative adaptive systems, respectively.

4.2. Participants

We recruited 24 participants (M = 26.33, SD = 5.12; 12 female, 12 male, none diverse) via convenience sampling and social media. Participants self-reported the gender they identified with. However, we removed 2 participants due to technical interferences, resulting in a total population of 22. Participants provided written informed consent before participating. We surveyed participants' familiarity with AR, AV, and VR devices as in previous work (Chiossi et al., 2024d,a). All participants reported prior experience with VR ($M = 4.23$, $SD = 1.27$) on a scale from 1 (not at all familiar) to 7 (extremely familiar). None of the participants reported a history of neurological, psychological, or psychiatric symptoms.

4.3. Task

Participants executed two types of tasks, i.e., Visual Monitoring task and N-Back task. In the Ext-Att block, participants were exposed to a fixed Stream (334 NPCs per minute) and were asked to monitor and follow with the gaze approaching NPCs of a randomized color (blue, green, black, and red). This Visual Monitoring task is expected to recruit external attention resources as it only requires visual processing and externally directed attention to participants. This block acts as a control

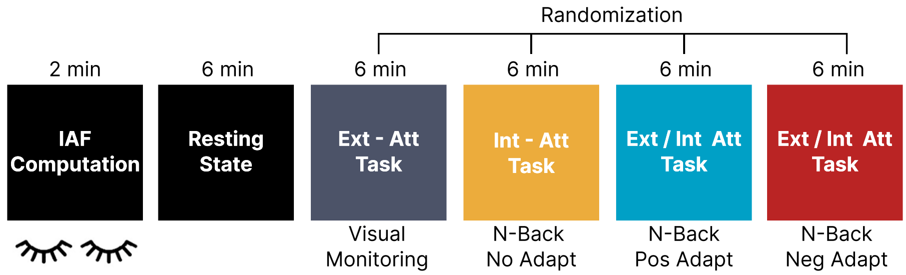


Fig. 5. Experiment Procedure. The experiment encompassed six different blocks. In between blocks, participants filled in NASA-TLX and GEQ subscales and observed a three-minute pause in VR. Blocks order was randomized for the Visual Monitoring, N-Back with No Adaptation and N-Back with Positive or Negative Adaptation. In the first block, participants maintained their eyes closed to compute the Individual Alpha Frequency (IAF). In the Resting state block, participants relaxed in the neutral VR environment without distracting elements. After those two blocks, participants experienced the experimental tasks (Visual Monitoring, N-Back No Adaptation, N-Back Positive Adaptation, N-Back Negative Adaptation block) in a randomized order. Refer to Section 3 for a complete description of the adaptive systems.

condition as it is the only one in which participants performed a task that mainly required external attention.

In the Int-Att Block and in the two adaptive blocks, participants executed the N-Back (N = 2) as adapted from Chiossi et al. (2022a). Here, participants are presented with a sequence of spheres over a marble-like pillar that has to be placed in one of two buckets on the left and the right, respectively. Spheres could have been spawned in four possible colors (green, red, blue, and black), according to McMillan et al. (2007), in a randomized sequence. Participants were required to pick up the spheres with an HTC Vive Pro controller and place them in the correct buckets. The placement of each sphere depended on its color and the color of the sphere presented two steps before. If the colors matched, the participant had to place the sphere in the right bucket. If the colors did not match, the participant had to put the sphere in the left bucket. New spheres would appear either after the current sphere was placed in one of the two buckets or after 4 s. Participants received accuracy feedback every 20 sphere placements and were instructed to maintain a performance level of 90%. The feedback frequency and performance target were informed by previous work in VR n-back tasks, demonstrating that periodic feedback supports engagement and prevents cognitive overload (Chiossi et al., 2022a, 2023b; Tremmel et al., 2019). Errors were computed by the proportion of times the sphere was positioned in the wrong bucket.

4.4. Procedure

Upon participants' arrival, we provided them with information regarding the study's procedure and addressed any inquiries they had before having them sign the informed consent form. Participants were provided with instructions for each task to ensure they understood the requirements and objectives. For the N-Back, they were specifically instructed to balance accuracy and speed, rather than prioritizing one over the other, to achieve an optimal performance tradeoff based on Rival et al. (2003). This approach was designed to encourage participants to focus on both the quality and efficiency of their responses, ensuring a balanced performance. Additionally, participants were not informed about which adaptive system they were interacting with during the experiment. This was done to avoid any persuasive effects on their performance that could arise from their awareness of the intelligent system's presence (Kosch et al., 2023b). In the experiment, participants were seated comfortably in a chair while performing the tasks. The study began with a trial phase to enable participants to acclimate to the VR environment. During the VR trial phase, participants practised the 2-back task until they achieved a minimum accuracy level of 95% while identifying a sequence of 80 spheres (Chiossi et al., 2022a). Next, the experimenter set up the water-based EEG cap. The experimental procedure started with the IAF Block, where participants kept their eyes closed for 2 min and 10 s. We describe the IAF computation in Section 4.6 . Then participants observed 3 min of rest for physiological adaptation (not included in the analysis) and started the Resting State Block for 6 min. They sat comfortably in the VR environment without NPCs or N-Back task elements, keeping their hands on their thighs without moving. After the Resting State, participants moved to the experimental phase consisted of four randomized experimental blocks (Ext-Int task, Int-Att Task, Positive Adaptation and Negative Adaptation), lasting six minutes each. In between blocks, participants fill the NASA TLX questionnaire to evaluate perceived workload (Hart and Staveland, 1988) and the Game-Experience Questionnaire (GEQ) In-Core Module, choosing the Competence, Immersion, and Positive Affection subscales for validated content validity for perceived engagement (Law et al., 2018). Immersion and Competence subscales measure the level of engagement participants experience with the task at hand which is related to challenge immersion (Burns and Fairclough, 2015). The Immersion subscale evaluates the extent to which participants feel absorbed and involved in the task, reflecting their level of engagement and the VR environment's adaptations in maintaining their focus. The Positive Affection subscale assesses participants' emotional responses to the task, indicating their overall satisfaction and enjoyment, which is important for understanding their motivation and sustained engagement. The Competence subscale measures participants' perceived effectiveness and skill in performing the task, which is crucial for assessing how well they manage the attentional demands of the N-back task. Again, between questionnaire completion, participants rest for 3 min in the VR scenario for physiological adaptation. Overall, the experiment lasted one hour and thirty minutes. The experiment procedure is depicted in Fig. 5.

4.5. Offline EEG recording and preprocessing

EEG data were recorded from 64 Ag-AgCl pin-type passive electrodes mounted over a water-based EEG cap (R-Net, BrainProducts GmbH, Germany) at the following electrode locations: Fp1, Fz, F3, F7, F9, FC5, FC1, C3, T7, CP5, CP1, Pz, P3, P7, P9, O1, Oz, O2, P10, P8, P4, CP2, CP6, T8, C4, Cz, FC2, FC6, F10, F8, F4, Fp2, AF7, AF3, AFz, F1, F5, FT7, FC3, C1, C5, TP7, CP3, P1, P5, PO7, PO3, Iz, POz, PO4, PO8, P6, P2, CPz, CP4, TP8, C6, C2, FC4, FT8, F6, F2, AF4, AF8 according to the 10–20 system. Two LiveAmp amplifiers acquired EEG signals with a sampling rate of 500 Hz. All electrode impedances were kept below ≤ 20 kΩ. We used FCz as an online reference and AFz as ground. For offline preprocessing we used MNE Python (Gramfort et al., 2013). We first notch-filtered at 50 Hz followed by a band-pass filter between 1–70 Hz to eliminate noise at high and low frequencies. Next, we re-referenced the signal to the common average reference (CAR) and applied the Infomax algorithm for Independent Component Analysis (ICA). We utilized the "ICLabel" MNE plugin Pion-Tonachini et al. (2019) for automatic classification and correction of ICA components. On average, we removed 2.97 (SD = 5.19) independent components within each participant.

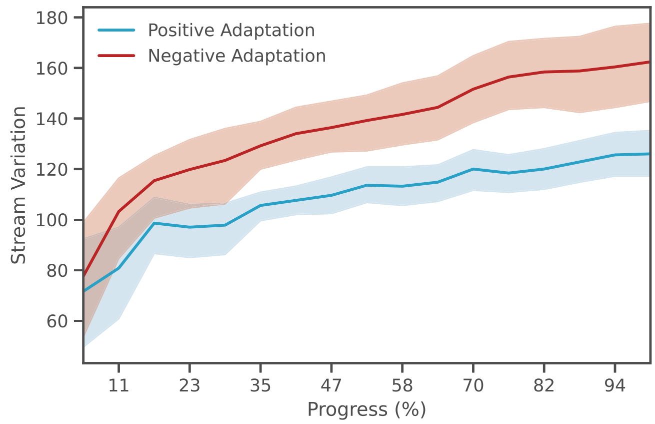


Fig. 6. Stream Visualization. Here, we depict the average evolution over time of the STREAM for the two adaptive systems. The POSITIVE ADAPTATION averaged on 133.17 NPCs per minute while the NEGATIVE ADAPTATION on 161.48 NPCs. The line shading represents the standard deviation, providing a visual indication of the variability in the STREAM over time.

4.6. Individual alpha and theta frequencies bands range computation

We employed the methodology established by Corcoran et al. (2018) to calculate IAF, based on Klimesch (2012). This method enables us to determine the alpha band at the individual level, taking into account the differences between individuals, thereby facilitating a more accurate and detailed online adaptation and offline analysis. We removed the first and last four seconds of data from the beginning and end of each IAF recording to remove signals unrelated to cortical activity and impacted by eye blinks. For IAF computation, we use posterior electrodes (P3, Pz, PO3, POz, PO4, O1, O2). Overall, the lower alpha range stabilized across participants on an average of 8.02 Hz (SD = .09), while with the higher bound, we obtained an average of 12.99 Hz (SD = 1.03). After determining the IAF for each participant, we utilized this information to calculate the alpha power for parieto-occipital electrodes employed for adaptation, see Section 3.1. For Theta power, we applied to a window of 4 Hz falling below the alpha lower bound computed from the IAF. Participants showed an average lower theta bound of 4.02 Hz (SD = .09) and an average upper theta bound of 8.02 Hz (SD = .09). We then computed the Theta power from the frontal electrodes selected for adaptation, see Section 3.1.

4.7. Statistical analysis

For EEG power bands, behavioral accuracy, and subjective scores on perceived workload (NASA-TLX) and engagement (GEQ), we use Repeated measures ANOVA or Friedman's test for not data not coherent with a normal distribution, as evaluated by the Shapiro–Wilk test. For post hoc comparisons, we use Conover's tests with Bonferroni correction. We compared the effect of BLOCK (N-Back No Adaptation, N-Back Positive Adaptation, N-Back Negative Adaptation) over measured dependent variables. For subjective measures, we also include the Visual Monitoring task for comparison.

We employ Linear Mixed Models (LMMs) for analyzing reaction times because they can handle skewed distributions and account for both fixed and random effects (Lo and Andrews, 2015). LMMs enable us to consider individual differences and repeated measures within participants, avoiding the averaging that can obscure meaningful variability. They are particularly suited for nested data structures, allowing us to model participant and condition variability accurately.

Specifically, for LMMs we use a Restricted Maximum Likelihood (REML) and a nloptwrap optimizer[2] for variance component estimation to account for the loss of degrees of freedom associated with estimating fixed effects. This results in less biased estimates, particularly in models with complex random effects structures or when the sample size is not large.

For reaction times, see Section 5.2.2, we fitted an LMM on raw correct reaction times (`RTs`) with BLOCK (N-Back No Adaptation, N-Back Positive Adaptation, N-Back Negative Adaptation) as a fixed effect and participant and the amount of visual distractors per trial as random effects. We selected the formula `rt ~ Block + (1|participant) + (1|distractor)` based on a model selection procedure using the Bayesian Information Criterion (BIC) to ensure the best fit. Several alternative models were evaluated, and the one associated with the lowest BIC value was selected (Peng and Lu, 2012; Barr et al., 2013). This procedure and detailed results are included in Fig. 5. Outliers were removed by excluding values exceeding three standard deviations above the mean (Berger and Kiefer, 2021).

For Repeated Measures ANOVA, we report the effect sizes using partial eta squared (η_p^2), while for the Friedman test, we use Kendall's W. We compared the effect of BLOCK (N-Back No Adaptation, N-Back Positive Adaptation, N-Back Negative Adaptation) over measured dependent variables. For subjective measures, we also include the Visual Monitoring task for comparison. For LMMs, we report the effect sizes using marginal R^2.

4.8. Classification

We performed a binary classification task to predict internal and external attention states using EEG data. We performed the classification using the frequency features of the EEG signals, specifically alpha, theta, delta, beta, and gamma bands, as input data. Based on recommendations from Lotte et al. (2018), we used a Linear Discriminant Analysis (LDA) model for this purpose. The classification task involved mapping a vector of frequency features to one of two labels: internal attention or external attention.

4.8.1. Data preparation

For class labeling, EEG data from the Visual Monitoring task was used for the External Attention label, and data from the N-Back No Adaptation task was used for the Internal Attention label. As the feature vector for each 20-second interval, we used the mean power values of the alpha, theta, delta, beta, and gamma bands, as computed from the EEG data.

For the feature vector, we computed EEG frequency bands every 20 s over the 6-minute (360 s) blocks for both the Visual Monitoring and N-Back No Adaptation tasks across 24 participants. This resulted in 18 (360 s/20 s) samples per block per participant. With two blocks per participant, we obtained a total of 36 samples per participant. Therefore, we had 864 samples (432 for internal attention and 432 for external attention) for training, resulting in perfect class balance.

For the data splitting, we followed the recommendation by Le et al. (2020). Here, we divided the data into training, validation, and test sets. Importantly, we employed a participant-wise split to ensure that data from any given participant appeared in only one of the three sets, thereby counteracting potential overfitting and ensuring robust generalization across participants. Specifically, data from 14 participants (63%) were used for training, 6 participants (20%) for validation, and 4 participants (17%) for testing. This process was repeated across

[2] The 'nloptwrap' optimizer (https://search.r-project.org/CRAN/refmans/lme4/html/nloptwrap.html) was used in our analysis to handle the optimization required for fitting the linear model. The 'nloptwrap' optimizer is particularly well-suited for models with random effects structures and large datasets, ensuring efficient and accurate parameter estimation.

1000 bootstrap iterations, ensuring variability and robustness in our evaluations.

Each classifier was trained using data pooled from multiple participants, not from individual participants. For each bootstrap iteration, a single classifier was trained using the training set (14 participants) and validated using the validation set (6 participants). The number of data points per class per fold was consistent across bootstrap iterations, with 252 samples per class (internal and external attention) in the training set, 108 samples per class in the validation set, and 72 samples per class in the test set. This setup ensured a balanced representation of classes in every fold of cross-validation. A total of 1000 classifiers were trained across the bootstrap iterations.

To ensure robustness and generalizability, we employed a bootstrap resampling approach combined with hyperparameter optimization for the classification task. We conducted 1000 bootstrap iterations, where participants were randomly shuffled and assigned to training, validation, and test sets in each iteration. This ensured that the splits accounted for variability in participant-level data, reducing the risk of model overfitting to specific subsets.

We performed hyperparameter search for the LDA classifier. This included variations in the solver (svd, lsqr, and eigen) and the shrinkage parameter (None, auto, and fixed values of .25, .5, .75, and 1). Using a grid search with the validation set, we identified the optimal combination of hyperparameters for each bootstrap iteration. The grid search followed a PredefinedSplit strategy, where training and validation sets were explicitly defined to prevent data leakage. We used accuracy as the metric for hyperparameter selection.

After determining the best hyperparameters, the model was retrained on the training set and evaluated on the validation and test sets. Predictions were made for all three splits, and we computed key performance metrics, including accuracy and F1 scores. To interpret the contribution of each EEG feature (alpha, theta, beta, delta, and gamma) to the classification, we derived LDA weight vectors following the methodology by Haufe et al. (2014), which maps model coefficients to neurophysiologically interpretable feature contributions. These weights inform on the relevance of different frequency bands in discriminating between internal and external attention.

This approach ensures robustness through a combination of hyperparameter optimization and bootstrap resampling, counteracting the bias–variance tradeoff (Guan and Burton, 2022). By conducting 1000 bootstrap iterations, we accounted for variability in training and test splits, simulating diverse data conditions to evaluate the stability of the model's performance. The inclusion of hyperparameter optimization further refined the LDA classifier by systematically exploring parameter settings (e.g., solver type and shrinkage) to select the configuration yielding the highest validation accuracy. This combination minimizes bias while maintaining variance at a manageable level, resulting in a model that generalizes well across unseen data.

Our choice of LDA was based on its proven effectiveness in EEG classification tasks, especially in scenarios with limited training data, cf. Lotte et al. (2018). LDA is particularly suited for EEG data due to its ability to model Gaussian-distributed data effectively and provide interpretable weight vectors that highlight the contribution of individual features. Furthermore, LDA's regularization options, such as shrinkage, reduce the risk of overfitting when the number of features approaches or exceeds the number of samples. These characteristics make LDA an appropriate choice for managing the balance between bias and variance while maintaining interpretability and computational efficiency.

We chose 20-second time intervals for EEG feature extraction and adaptation based on several considerations. First, this interval aligns with the parameters we used in rule-based adaptive systems, ensuring consistency and comparability between different adaptive mechanisms. Additionally, prior research has demonstrated that 20-second intervals provide a stable measure of brain activity, balancing sensitivity and stability in EEG measurements (Jansen et al., 1981). Studies by Vortmann et al. (2019) and similar task settings from Chiossi et al. (2022a, 2023a, 2024b) have shown that this duration is effective for capturing significant variations in EEG signals corresponding to attentional shifts, supporting real-time adaptation in VR environments.

4.8.2. Feature extraction

We extracted EEG features based on the Power Spectral Densities (PSD) via Welch's method. We computed averaged alpha and theta based on the individual frequency range computed (see Section 4.6) and delta (.5–4 Hz), beta (13–30 HZ), and gamma (30–45 Hz) based on the preprocessing pipeline described in Section 4.5. All frequency values were normalized based on the Resting state data. We used electrodes chosen for adaptation for alpha and theta as in Section 3.1. For beta, we used the same frontal electrodes as theta (Putman et al., 2014), while for delta and gamma, we based our choice on previous work in internal–external attention classification (Vortmann et al., 2019; Vortmann and Putze, 2021; Harmony et al., 1996; Darvas et al., 2010).[3] The EEG features were computed on 20 s intervals, mirroring the time window used for adaptation.

The input tensor for the LDA model is composed of five EEG features: *alpha*, *theta*, *beta*, *delta*, and *gamma*. These features were extracted from the EEG data of 24 participants, following the preprocessing steps described in the manuscript. The data was split into training, validation, and test sets across 1000 bootstrapped iterations, ensuring participant-wise separation. Typically, the training set consisted of data from 14 participants (63%), resulting in 504 samples per class (144 total samples per participant across both classes). The validation set included data from 6 participants (20%), resulting in 216 samples per class, while the test set included data from 4 participants (17%), resulting in 144 samples per class. Each sample was represented as a vector with five EEG features, giving shapes of (1008, 5), (432, 5), and (288, 5) for the training, validation, and test sets, respectively.

4.8.3. Classification apparatus

We performed the data analyses using Python (version 3.11) and R (version 4.2.3) environments, ensuring compatibility with widely used data analysis frameworks. All packages and their exact versions are documented in the Open Science Framework (OSF) computational notebooks, publicly available for transparency and reproducibility, see Section 8. The computational environment consisted of two Intel Xeon Gold 6132 CPUs (28 cores, 2.6 GHz each), 754 GB of RAM, and a Tesla V100-SXM2 GPU (32 GB memory). The machine ran on an Ubuntu 20.04 LTS operating system. Despite the availability of these high-performance resources, the analysis and modeling tasks were not computationally intensive.

5. Results

In this section, we first present results on EEG power bands, behavioral accuracy and subjective scores on perceived workload (NASA-TLX) and engagement (GEQ). Finally, we report our results on the classification of the two attentional states based on Visual Monitoring (External Attention) and N-Back task with No Adaptation (Internal Attention) using accuracy and F1 score.

5.1. EEG results

5.1.1. Alpha

The normality of Alpha power was assessed using the Shapiro–Wilk test, which indicated that the data were consistent with a normal distribution ($W = .981$, $p = .176$). A repeated measures ANOVA was conducted to examine the effect of Block on Alpha. The results showed no significant differences ($F(3, 69) = .43$, $p = .73$, $\eta_p^2 = .005$), indicating a negligible effect on Alpha power. As depicted on the left in Fig. 7, the variation in Alpha power across different blocks was not substantial.

[3] For the delta band analysis, we did not use the T3, T4, T5, and T6 electrodes, as these are only available on EEG caps with 256 electrodes. Instead, we limited our analysis to the electrodes shared with our 64-electrode cap.

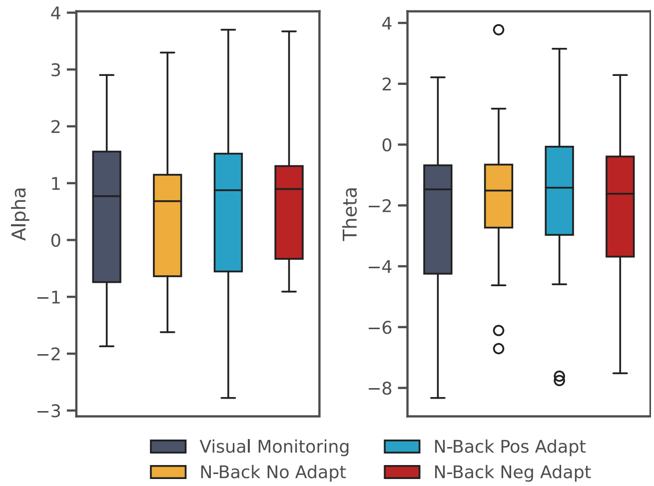


Fig. 7. EEG Alpha and Theta Powers. Boxplots representing average Alpha (left) and Theta (right) frequencies. Frequencies were obtained from the parieto-occipital channels for Alpha, while for Theta, we chose frontal channels. Values are computed for each experimental condition and normalized to the resting state.

5.1.2. Theta

As Theta power was not consistent with a normal distribution (Shapiro–Wilk, W = .965, p = .012), we conducted a Friedman test. The results showed no significant differences ($\chi^2(3)$ = 2.10, p = .552), indicating a negligible effect on Theta power, as depicted on the right in Fig. 7.

5.2. Behavioral results

5.2.1. Accuracy

Shapiro–Wilk test showed accuracy scores were not consistent with a normal distribution (W = .959, p = 0.019). We tested the effect of Block on Accuracy via a Friedman's test. We found a significant main effect ($\chi^2(2)$ = 30.583, p < .001, Kendall's W = .621). Post hoc comparisons with Bonferroni correction revealed that the mean accuracy in Positive Adaptation (M = .88, SD = .06) was significantly increased from the mean score for Negative Adaptation (M = .74, SD = .07), p < 0.001. Additionally, the accuracy in Negative Adaptation was significantly lower compared to the N-Back Block with no distractors (M = .88, SD = .06), p < .001. Results are depicted in Fig. 8(a).

5.2.2. Reaction times

The model's total explanatory power, as indicated by the conditional R^2, was substantial ($R^2_{\text{conditional}}$ = .45), suggesting that both the fixed and random effects explained 45% of the variance in reaction times (RTs). The contribution from fixed effects alone was minimal (R^2_{marginal} = .003). The model's intercept, corresponding to the N-Back - No Adaptation condition, was 2.18, 95% CI [1.91, 2.46], $t(9972)$ = 15.45, p < .001. The effect of Positive Adaptation was statistically non-significant and negative, β = −.06, 95% CI [-.12, .009], $t(9972)$ = −1.69, p = .091; standardized β = −.06, 95% CI [−.12, .009]. The effect of Negative Adaptation was statistically significant and negative, β = −.14, 95% CI [−.20, −.07], $t(9972)$ = −4.08, p < .001; standardized β = −.14, 95% CI [−.20, −.07]. The mean reaction times and standard deviations for each condition were as follows: for the N-Back - No Adaptation condition, M = 1.99, SD = 1.04; for the Positive Adaptation condition, M = 1.92, SD = .999; and for the Negative Adaptation condition, M = 1.83, SD = .953. Results are depicted in Fig. 8(b).

5.3. Subjective results

5.3.1. Perceived workload

As Shapiro–Wilk showed data were consistent with a normal distribution (W = .982, p = .210), an ANOVA indicated that average raw NASA-TLX scores were significantly influenced by Block (F = 4.21, p < .001, Kendall's W = .137). Pairwise comparisons via paired t-tests with Bonferroni correction showed that Negative Adaptation resulted in a significantly higher workload (M = 70.13, SD = 16.97) than Positive Adaptation (M = 57.00, SD = 13.09), N-Back (M = 57.65, SD = 16.94), and Visual Monitoring (M = 54.81, SD = 27.21), all p < .01. No significant differences were detected in other comparisons. Results are shown in Fig. 9.

5.3.2. GEQ-competence

The Shapiro–Wilk normality test indicated data not consistent with a normal distribution for the GEQ competence scores (W = .947, p = .001). A Friedman's test revealed no significant effects ($\chi^2(3)$ = .17, p = .983), see Fig. 9.

5.3.3. GEQ-positive affection

As the Shapiro–Wilk test showed a distribution not coherent with a normal one (W = .954, p = .002), a Friedman rank sum test was conducted to examine the effect of Block on the GEQ Positive Affection scores. The analysis revealed a significant main effect of Block on GEQ Positive Affection scores ($\chi^2(3)$ = 21.20, p < .001, Kendall's W = .397). Pairwise comparisons using a Wilcoxon signed-rank test with a Bonferroni correction showed that GEQ Positive Affection scores in Negative Adaptation were significantly lower (M = 1.11, SD = .79) than in Positive Adaptation (M = 1.86, SD = 0.98) and N-Back (M = 1.86, SD = .99), all p < .05. Identical results were found in comparisons with the Visual Monitoring task, where participants reported significantly lower subjective positive affection (M = 1.13, SD = 0.97) than in the Positive Adaptation and N-Back tasks. No differences were detected in the comparison between Positive Adaptation and N-Back. Results are depicted in Fig. 9.

5.3.4. GEQ-immersion

The Shapiro–Wilk test indicated that the distribution of GEQ Immersion scores was not coherent with a normal one (W = .952, p = .001). A Friedman rank sum test revealed a significant main effect of Block ($\chi^2(3)$ = 32.06, p < .001, Kendall's W = .518). Pairwise comparisons using a Wilcoxon signed-rank test with a Bonferroni correction showed that the GEQ Immersion scores in Negative Adaptation (M = 1.36, SD = 1.36) were significantly lower than those in Positive Adaptation (M = 2.98, SD = .83) and in N-Back (M = 2.48, SD = .71), all p < .005. The Visual Monitoring task condition showed significantly lower Immersion scores (M = 1.52, SD = .96) compared to Positive Adaptation and N-Back (p < .005). No differences were detected in the comparison between Visual Monitoring and Negative Adaptation, see Fig. 9.

5.4. Classification results

5.4.1. Accuracy

The LDA model was trained on data from a subset of participants (N = 14) and validated on data from a separate set (N = 6). We then evaluated the model on the remaining participants (N = 4). The results demonstrated a mean training accuracy of .792 (SD = .047), a mean validation accuracy of .794 (SD = .061), and a mean test accuracy of .759 (SD = .091).

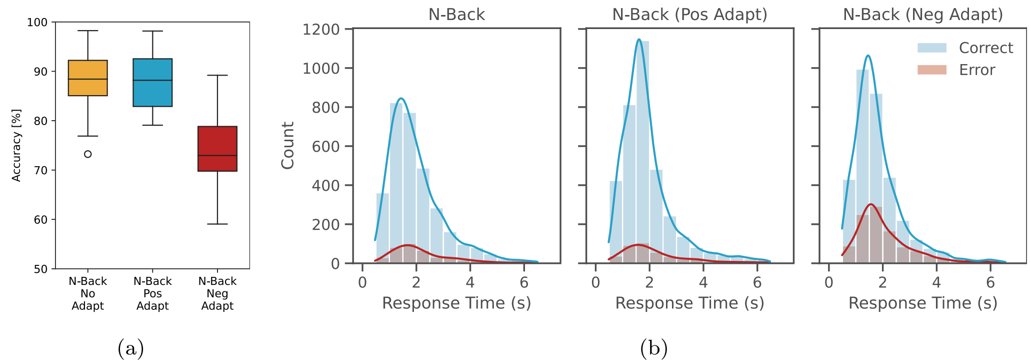


Fig. 8. Behavioral Results. On the left (a), we present the results on Behavioral Accuracy. Here, participants significantly showed higher accuracy in N-Back and Positive Adaptation conditions as compared to the Negative Adaptation. On the right (b), we present an overview of reaction time distributions, separated by correct and error responses. No significant differences were detected in reaction times distributions.

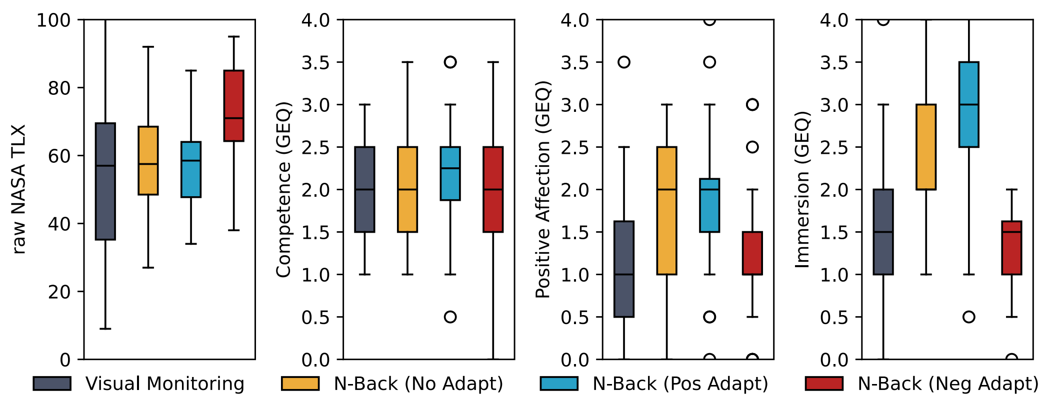
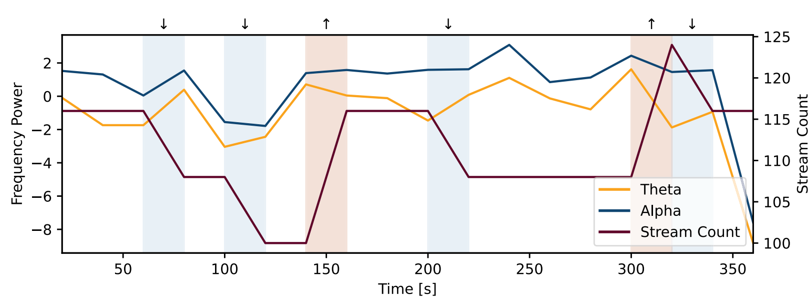
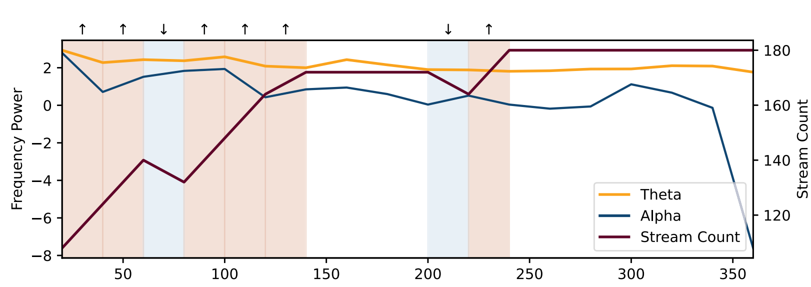


Fig. 9. Subjective Results. Box-plots for perceived workload (NASA-TLX) and engagement (GEQ). Participants reported significantly more workload in the N-Back task with Negative Adaptation. Regarding perceived engagement, we found that participants experienced more Positive Affection and Immersion in N-Back (No Adapt) and N-Back (Pos Adapt) as compared to the Visual Monitoring task and the N-Back task in the Negative Adaptation.



(a) Positive Stream variation for a representative participant



(b) Negative Adaptation Stream variation for a representative participant

Fig. 10. (a) Positive Stream variation and (b) Negative Adaptation Stream variation for representative participants. Yellow and Blue lines indicate the normalized Theta and Alpha frequency bands, while the dark red line represents the Stream Variation. Colored areas indicate whether the system increased (light red) or decreased (light blue) the NPCs Stream in a 20 s time window. On top of each plot, the Stream increase is depicted by an arrow pointing up (↑), while if the Stream decreases, the arrow points down (↓). White areas represent no change in the stream, corresponding to small changes of less than 15 percent.

5.4.2. F1 score

The model's F1 scores demonstrated consistent performance, with a mean training F1 score of .804 (SD = .047), a mean validation F1 score of .803 (SD = .057), and a mean test F1 score of .771 (SD = .090). These metrics illustrate that the model achieved stable and reliable performance, with standard deviations reflecting moderate variance between iterations, particularly in the test set.

5.4.3. LDA weights

To understand which features were most informative for predicting internal and external attention, we examined the weight coefficients of the LDA model. The coefficients indicate the relative influence of each feature in predicting attention. Specifically, a positive coefficient for a feature indicates that higher values of that measure are associated with predicting external attention. In contrast, a negative coefficient indicates that higher feature values are associated with predicting internal attention.

Our results showed that the alpha measure was predictive of external attention, with a positive mean coefficient of $M = .028, SD = .100$. Delta power was predominantly predictive of internal attention, with a negative mean coefficient of $M = -.273, SD = .280$. The coefficients for the theta, beta, and gamma measures were $M = -.640, SD = .367$, $M = .296, SD = .113$, and $M = -.149, SD = .059$, respectively. These results suggest that theta, gamma and delta were specifically informative for internal attention prediction, while beta and alpha were indicative of external attention.

6. Discussion

We presented a physiologically adaptive VR system that employed EEG correlates of internal and external attention to perform dynamic visual complexity adjustments to enhance task performance. We evaluated the effect of visual complexity adaptations, in the form of NPCs, on task performance, Alpha and Theta power, subjective workload, and engagement. In the study, participants performed a VR N-Back task recruiting WM resources. Here, we discuss our results regarding the outcome of our adaptive algorithms for modeling internal and external attention. Then, we envision applications for online attentional state detection and classification in VR and reflect on limitations and future work.

6.1. Internal and external attention modeling

When users engage in VR tasks that feature both external and internal processing components, we hypothesized that they could benefit from an adaptation that could adjust the number of visual distractors in real-time to balance their attentional state and enhance task performance. To achieve this, we designed two adaptive VR systems based on EEG alpha and theta power to balance external and internal attentional states, respectively.

We identified four initial hypotheses. **HP1** and **HP2** predicted that the adaptive system designed for internal attention would improve WM task performance, while the system designed for external attention would decrease task performance. Our findings supported those two hypotheses, showing that participants performed better on the visual WM task when the adaptive system balanced distractors based on internal attention (**HP1**) and performance decreased when external attention was balanced (**HP2**). These results are consistent with previous research showing that attentional resources are essential for successful WM performance as the balance between external and internal attention can significantly affect task performance (Myers et al., 2017). When we need to recall and manipulate visual information and ultimately perform decisions, adapting task-irrelevant visual information can improve our task performance. Conversely, it could be argued that distracting information could be removed from the environment to balance internal attention for improving task performance. However, our results show that adaptation of visual distractors based on internal attention states enhanced perceived engagement through positive affection and immersion, supporting **HP3**. Participants reported higher levels of engagement when the adaptive system balanced distractors based on internal attention. Conversely, they reported significantly lower levels when interacting with the Negative Adaptation. Incorporating real-time adaptation based on internal attention states into VR systems could lead to more effective and enjoyable user experiences when high-level cognitive processing is involved. Additionally, our findings highlight the importance of considering internal and external attention in designing VR systems. Balancing one at the expense of the other may adversely affect overall user experience and performance. In fact, an increase in engagement could have impacted the increase in task performance. Positive affection, for example, has been shown to enhance the focus of attention (Rowe et al., 2007).

Interestingly, despite lower accuracy, participants were faster when interacting with the negative adaptation system, which emphasized external attention. This was initially counterintuitive, as one might expect slower reaction times with higher error rates. This discrepancy may be explained by the nature of external attention systems inducing a higher arousal state or promoting rapid decision-making in response to increased visual complexity. Such a state could prioritize speed over accuracy, leading to more impulsive responses (Kajimura and Nomura, 2016a).

Alternatively, the continuous need to filter task-irrelevant information might have contributed to cognitive overload, resulting in hasty, error-prone behavior. This aligns with previous research demonstrating that environments requiring heightened external attention can increase perceived workload and degrade performance on cognitively demanding tasks (Rissman et al., 2009). External attention systems inherently shift cognitive resources to process environmental stimuli, often prioritizing sensory processing over executive control. This may explain the observed lower accuracy despite faster reaction times.

In contrast, participants interacting with the positive adaptation system (internal attention) reported higher engagement, positive affect, and immersion, supporting **HP3**. Internal attention systems likely reduced cognitive interference from distractions, allowing participants to allocate more WM resources to the task. This aligns with findings that positive emotions and reduced cognitive load enhance attentional focus and task accuracy (Rowe et al., 2007). These findings highlight the trade-offs between internal and external attention systems: while external systems may stimulate faster responses through heightened arousal and sensory prioritization, internal systems better support precision and cognitive performance by fostering deliberate processing and sustained focus.

Finally, we verified **HP4**, as participants reported significantly higher levels of perceived workload when interacting with the Negative Adaptation as compared to the Positive Adaptation and to the N-Back with no distractors. This finding aligns with previous research showing that increased external attentional demands can lead to a higher perceived workload (Rissman et al., 2009; Kajimura and Nomura, 2016b). The perceived workload might have been associated with the continuous need to actively filter out task-irrelevant information, which can interfere with the processing of relevant information and increase cognitive load. Our results suggest that an adaptive system that prioritizes internal attention can enhance executive performance in a VR environment. In contrast, external attention balancing can have a detrimental effect.

The results of the classification suggest that reliable decoding of internal and external attentional states in VR settings is possible, replicating similar results derived from AR settings (Vortmann et al., 2019; Vortmann and Putze, 2021). Specifically, the main features contributing to the classification were theta and delta for internal states and beta and alpha for external states, with gamma playing a minor role. We can, therefore, state that **HP5** has been verified.

These findings provide further support for the importance of theta and delta in internal attention. Theta power emerged as the strongest predictor of internal attention, with its significant negative weight indicating its critical role in maintaining WM processes and inhibiting distracting information (Sauseng et al., 2005). Delta power, while more variable, also contributed negatively to internal attention classification. This aligns with its established role as a functional modulator of sensory input and its association with internal concentration and phase resetting mechanisms (Harmony, 2013). Additionally, delta's involvement in dynamic switching between internal and external attention states underscores its relevance in balancing attentional processes (Jiang et al., 2021b).

Gamma power, although less influential compared to theta and delta, provided a minor yet stable contribution to internal attention classification. Its negative weight reflects its role in facilitating internal cognitive processes, such as neural synchronization, despite its susceptibility to noise in EEG recordings (Hasib and Vengadasalam, 2023).

Regarding external attention prediction, our results showed that the beta band was the strongest predictor, followed by alpha. Beta power emerged as a dominant positive feature for external attention, reflecting its role in active cognitive processing and alertness. This finding is consistent with previous research showing that beta oscillations are associated with external stimuli processing, increased arousal, and faster response times (Kaminski et al., 2012; Nieuwenhuis et al., 2011). Beta's significant contribution highlights its function in maintaining attentional arousal and sensory engagement, particularly in tasks requiring rapid orienting responses.

Alpha power, with its weak positive weight, indicates a subtle association with external attention, consistent with its role in regulating sensory processing. Alpha decreases are typically linked to attention-demanding tasks, suggesting that lower alpha levels facilitate external sensory engagement (Klimesch, 2012). Its weaker contribution compared to beta reflects its complementary role in external attention allocation rather than a primary mechanism.

Taken together, these results illustrate the distinct roles of EEG frequency bands in predicting internal and external attentional states. Theta and delta bands predominantly support internal cognitive processes, while beta and alpha bands are more associated with external sensory engagement. Gamma contributes minimally but consistently to internal attention, reinforcing the complexity of attentional dynamics. These findings extend our understanding of EEG feature importance and emphasize their utility for adaptive immersive environments.

6.2. Applications for attention-aware VR adaptive systems

Our findings have implications for the design and implementation of VR adaptive systems that aim to balance attentional resources during tasks that jointly require internal and external processing.

6.2.1. Balancing internal attention

We found that we can balance internal attention and improve task performance compared to an adaptive system that can be balanced for external attention. Moreover, we report that the performance with distractors in the Positive Adaptation did not significantly differ from the task executed without distractors. This can be specifically relevant for three application fields: VR productivity and cognitive training in healthy and clinical populations.

Our work showed how internal attention optimization can support task performance when engaged in a WM task. In the context of a virtual office (Knierim et al., 2021), users might be novices to the multitude of visual stimuli, representing the surroundings or human colleagues, i.e. VR human avatars and more prone to distractions and inefficient workflows. Additionally, NPCs function can be adapted to provide cues, prompts, and reminders that can aid users in maintaining their focus and concentration on the task at hand. The design of a system that can minimize distraction while supporting engagement can be valuable for enhancing productivity in virtual environments, particularly in tasks that require WM.

Cognitive training is another application where balancing internal attention in WM tasks can be valuable. WM is essential in many cognitive tasks, such as problem-solving, decision-making, and learning, and is impaired in various clinical populations, including individuals with attention-deficit/hyperactivity disorder (ADHD) (Karbach and Verhaeghen, 2014). Cognitive training interventions aim to support WM performance while generalizing to other cognitive functions and have shown promising results in healthy, ageing and clinical populations, including ADHD (Cortese et al., 2016).

In VR, adapting the system to balance internal attention during cognitive training tasks could enhance the effectiveness of such interventions. Users could more efficiently engage in cognitive training tasks by minimizing distractions and improving focus, leading to better outcomes. Additionally, NPCs can be adapted to provide feedback, coaching, and reinforcement, enhancing cognitive training outcomes (Schroeder et al., 2020).

6.2.2. Balancing external attention

Internal and external attentional mechanisms play a crucial role in determining the effectiveness of VR applications. Even though the central purpose of attentional mechanisms is to facilitate the processing of relevant information over irrelevant one, sometimes internally directed attention can be undesired depending on the VR application and user state scenario. Internal attention might also refer not only to the prioritization of memory-related information but also to mind wandering (Gruberger et al., 2011) and rumination (Chuen Yee Lo et al., 2012).

Therefore, if the user is engaged in a scenario where the visual information is task-relevant, but the user's attention is internally directed, the VR system can increase the perceptual salience to capture the users' attention or pause the interaction until they re-enter the external attention state. Such a scenario can be found in VR content or motor learning and visual analytics (Keim et al., 2008), where users are provided with highly detailed and animated content. Such an interaction paradigm could prevent interrupting task-relevant thoughts and ignoring external information. This type of application could be based on the Optimal theory of learning (Wulf and Lewthwaite, 2016), which postulates that an external focus of attention can result in improved learning skills compared to an internal one. Therefore, balancing for external attention in VR could allow for designing better learning systems.

6.2.3. From heuristic-based to automated attention detection: Rationale and trade-offs

Our heuristic-based system was designed to balance computational simplicity and interpretability. The decision rules were informed by well-established electrophysiological relationships between alpha and theta band power and attentional states (Cona et al., 2020; Long et al., 2024). By explicitly defining rules, we ensured that the system's behavior was transparent, predictable, and suitable for real-time applications, especially in scenarios where computational resources or large datasets for training machine learning models might not be readily available.

While the heuristic approach provides stability and simplicity, future systems could benefit from fine-grained adaptation mechanisms that continuous EEG signals or multiple features. Such systems could employ machine learning models, such as reinforcement learning or neural networks, to dynamically choose and optimize adaptation strategies based on user behavior and physiological responses (Long et al., 2024; Chiossi et al., 2024c). Rather than predefining thresholds for alpha and theta changes, future approaches could utilize unsupervised learning to dynamically identify patterns in EEG data associated with attentional shifts (Vortmann and Putze, 2021; Chiossi et al., 2024c). This could allow for personalized adaptation, accounting for individual variability in EEG responses and attentional needs. However, transitioning to unconstrained systems introduces challenges, such as the need for larger training datasets, computational overhead for real-time learning, and reduced interpretability (Long et al., 2024). These factors must be carefully addressed to ensure the system remains practical and user-centric.

6.2.4. Alternative frameworks for adaptive systems

Our perspective is to enhance performance by manipulating external and task-irrelevant factors without altering the task itself. However, we propose alternative approaches that act on the main task to impact task performance directly. One approach is adaptive object manipulation, where the size of the interactive sphere increases as the user approaches it, facilitating task completion. Implementing an automatic snapping mechanism can help the sphere snap to the correct location, reducing the need for fine motor precision. Additionally, dynamic difficulty adjustment can vary the interval between stimuli presentations based on user performance and cognitive load. Real-time feedback, such as highlighting the correct bucket to prevent mistakes, can also enhance task accuracy, especially when users are either not familiar with the task or in a state of attentional overload. These adaptive features offer a holistic approach, combining environmental and task-specific modifications to support user performance in VR tasks.

6.3. Limitations and future work

We acknowledge that our work is prone to certain limitations related to the task we designed, their classification and how to improve our designed VR adaptive system.

In our study, we use the VR N-Back task, which inherently features an external shift of attention given its VR nature. This is an inherent limitation of using VR to recruit internal attention, and it must be acknowledged when designing experiments with a prominent visual component. To further evaluate the reliability of this paradigm, we suggest increasing the memory-related demands, such as increasing the amount of information held to be held in WM, i.e., moving from a 2-Back to a 3-Back VR task. Another possibility would be the addition of other internal components, such as episodic memory. Regarding the visual monitoring task, it is worth noting that while we did not explicitly verify whether participants directed their attention towards the NPCs, the task design and instructions provided to participants were based on prior research aimed at recruiting external attention (Cona et al., 2020; Vitali et al., 2019; Arrabito et al., 2015). However, we acknowledge the limitation of not implementing a manipulation check based on eye-tracking. In future work, we plan to address this limitation by incorporating eye-tracking measures to assess participants' attentional focus accurately.

On the other hand, comparing the Visual Monitoring task to a VR version of an established external attention task, such as the visual oddball task (Putze et al., 2016), would allow for better generalization of our results. These limitations and challenges are common in VR research, mainly when designing tasks that have to be ecologically situated.

Improving the generalizability of our results would support the reliability of our classification. Although we have selected tasks that theoretically recruit internal and external attention resources, our classifier could only discriminate between two tasks. Future work will address the training phase on more diverse tasks to validate our results further. Nonetheless, the high accuracy achieved in the between-participant task classification is comparable to previous work in AR (Vortmann et al., 2019; Vortmann and Putze, 2021) and suggests the potential for online implementation to evaluate its performance. Specifically, LDA is a machine learning model that allows for low computation and is successful for online cognitive state detection (Lotte et al., 2018). A new adaptation mechanism could be based on this classification approach, to balance the impact of multiple features and thus increase robustness against trial-to-trial variability.

Furthermore, we recognize the need to address optimal channel selection from the total EEG channels used in our study. While our current approach focused on electrodes placed in the frontal, parietal, and occipital regions, informed by related work on internal and external attention allocation, future work will investigate how each electrode and combination of electrodes can best contribute to classification accuracy.

Methodological approaches such as Recursive Feature Elimination (RFE), Genetic Algorithms (GA) will be employed to systematically evaluate the contribution of individual electrodes. Additionally, we will apply advanced feature importance techniques including Random Forest Importance, Mutual Information, Permutation Importance, Shapley Additive Explanations, and Ablation Study to our dataset. These methods will help us systematically evaluate and identify the most relevant EEG channels. Random Forest Importance ranks features based on their contribution to reducing impurity in decision trees, helping us identify the most critical channels. Mutual Information measures the dependency between EEG features and attention labels, highlighting the channels with the most informative signals.

Permutation Importance assesses the impact of each channel by measuring the increase in prediction error when its values are permuted. Shapley Additive Explanations (SHAP) uses game theory to compute the average contribution of each channel to the prediction model, providing a comprehensive importance ranking. Ablation Study evaluates the decrease in model accuracy when individual channels are excluded, directly indicating their importance.

Recent studies, such as Putze and Eilts (2023), have demonstrated that using these methods can significantly reduce the number of channels without compromising accuracy, specifically in the context of attention prediction. For example, they reduced the number of channels from 32 to 2 while improving accuracy from 60% to 62%. Their findings suggest that minimal channel subsets can maintain or enhance performance.

Finally, our study demonstrated that conventional methods, such as the Welch periodogram computed on a moving time window, can adequately detect temporal variations in non-stationary signals. However, more advanced signal processing techniques like wavelet analysis can further improve the detection of temporal changes (Hillebrand et al., 2016). Thus, implementing and evaluating wavelet analysis in future research may enhance the accuracy of attentional state classification. It is worth noting that efficient wavelet computation algorithms are available, which can be used in real-time applications (Khalid et al., 2009; Xu et al., 2009).

7. Conclusion

In this work, we presented a VR adaptive system based on EEG correlates of internal and external attention to dynamically adjust visual complexity and support task performance in a WM task. Visual complexity adjustments based on alpha and theta bands allowed for modulation of task-irrelevant elements adaptation and increased WM task performance. Furthermore, we showed that successful classification of EEG data in a VR N-Back task based on internal and external attention is possible. Even with linear machine learning algorithm, the classifier could reliably predict offline the attentional state of the participant, allowing for future implementation in real-time adaptive systems.

8. Open science

We encourage readers to reproduce and extend our results and analysis methods. Our experimental setup, collected datasets, and analysis scripts are available on the Open Science Framework via https://osf.io/ar4fs/.

CRediT authorship contribution statement

Francesco Chiossi: Writing – review & editing, Writing – original draft, Visualization, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Changkun Ou:** Writing – review & editing, Visualization, Methodology, Data curation. **Carolina Gerhardt:** Methodology, Investigation. **Felix Putze:** Writing – review & editing, Supervision, Methodology. **Sven Mayer:** Writing – review & editing, Supervision, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Francesco Chiossi reports financial support was provided by German Research Foundation. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Order effects

In examining potential fatigue or learning effects, we tested changes in NASA-TLX scores and Alpha and Theta over the course of the experiment. Before analysis, we tested the normality of NASA-TLX scores and Alpha and Theta for each block using the Shapiro–Wilk test to conduct repeated measures ANOVA (RM ANOVA) or Friedman test, for non-normally distributed data. We depict our order effect results in Fig. A.11.

A.1. Perceived workload

A Shapiro–Wilk normality test was conducted to assess the normality of the NASA scores. The results indicated that the data were normally distributed, $W = .982$, $p = .21$.A repeated measures ANOVA was conducted to examine the effect of presentation order on NASA scores. The results of the ANOVA indicated that there was no significant main effect of order, $F(3, 69) = 2.06$, $p = .113$, generalized eta-squared (η_g^2) = .05. Mauchly's Test for Sphericity indicated that the assumption of sphericity was met ($W = .859$, $p = .655$). Thus, no sphericity corrections were applied.

The descriptive statistics for NASA scores across orders were as follows: Order 0 ($M = 49.8$, $SD = 12.7$), Order 1 ($M = 53.5$, $SD = 14.7$), Order 2 ($M = 59.0$, $SD = 18.5$), and Order 3 ($M = 57.7$, $SD = 18.0$). Although a trend of increasing NASA scores across orders is apparent, the results did not reach statistical significance, indicating that presentation order does not significantly influence NASA scores in this dataset.

A.2. Alpha

The normality of the Alpha power was assessed using the Shapiro–Wilk test, which indicated that the data were normally distributed, $W = .981$, $p = .177$. A repeated measures ANOVA was conducted to examine the effect of order on Alpha power. The results showed that the order of blocks did not have a significant effect on Alpha power, $F(1, 23) = 2.78$, $p = .109$, generalized eta-squared (η_g^2) = .108.

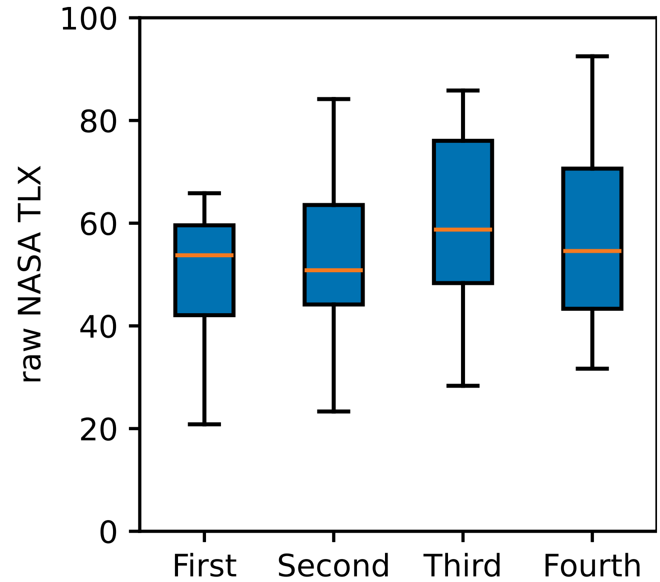

Fig. A.11. Boxplot of raw NASA-TLX scores across presentation orders. The scores show a trend of increasing workload from the first to the third order, with a slight decrease in the fourth order. Descriptive statistics indicate that the mean NASA-TLX scores were $M = 49.8$, $SD = 12.7$ (First), $M = 53.5$, $SD = 14.7$ (Second), $M = 59.0$, $SD = 18.5$ (Third), and $M = 57.7$, $SD = 18.0$ (Fourth). Although a repeated measures ANOVA suggested no significant main effect of presentation order ($F(3, 69) = 2.06$, $p = .113$), the figure illustrates variability in workload perception across different orders. Error bars represent interquartile ranges.

A.3. Theta

The normality of the Theta power was assessed using the Shapiro–Wilk test, which indicated that the data were not coherent with a normal distribution, $W = .965$, $p = .012$. Therefore, a Friedman test was conducted to examine the effect of order on Theta power. The results of the Friedman test indicated no significant differences among the orders, $\chi^2(3) = .95$, $p = .813$.

A.4. Comparison between first and last task order

To address potential confounds arising from the temporal characteristics of EEG rather than task-related activity, we conducted an analysis to compare EEG power bands between the study participants' first and last tasks. This approach helps to determine whether observed EEG changes are due to the inherent temporal dynamics of the EEG signal or the specific task-related activities.

A.4.1. Alpha

The normality of the Alpha power was assessed using the Shapiro–Wilk test, which indicated that the data were normally distributed, $W = .981$, $p = .911$. A paired t-test was conducted to compare the Alpha power between the first and last blocks. The results showed no significant difference in Alpha power between the first and last blocks, $t(11) = -.29$, $p = .779$, 95% CI [-1.65, 1.27]. The mean difference in Alpha power between the first and last blocks was −.19. These results suggest that the temporal order of the tasks did not significantly influence the Alpha power, indicating that observed changes in Alpha power are likely task-related rather than due to temporal characteristics.

A.4.2. Theta

To examine potential order effects on Theta power, we compared the EEG Theta power between the first and last blocks completed by the participants. The Shapiro–Wilk test indicated that the Theta power data for both the first block ($W = .957$, $p = .380$) and the last block

Table B.1
BIC values for candidate models. The best model is Model 3 with the lowest BIC of 24 400.66.

Model	BIC
Model 1	25 896.96
Model 2	25 362.14
Model 3	24 400.66
Model 4	24 420.92
Model 5	24 439.52

($W = .957$, $p = .380$) were normally distributed. A paired t-test was performed to compare Theta power between the first and last blocks. The results showed no significant difference in Theta power between the first and last blocks, $t(11) = -.57$, $p = .582$, 95% CI [−3.25, 1.92]. The mean difference in Theta power between the first and last blocks was −.67. These findings suggest that the sequence of tasks did not significantly affect Theta power.

Appendix B. Model selection for reaction times statistical analysis

To identify the best-fitting model for predicting reaction times (RT) in our study, we performed a model selection procedure using the Bayesian Information Criterion (BIC). The following steps outline the procedure we followed:

B.1. Candidate models

We considered five candidate models, each with different fixed and random effects structures:

1. Model 1: rt ∼ BlockNumber + (1 | PId)
2. Model 2: rt ∼ BlockNumber + CountActual + (1 | PId)
3. Model 3: rt ∼ BlockNumber + (1 | PId) + (1 | distractor)
4. Model 4: rt ∼ BlockNumber + distractor + (1 | PId) + (1 | distractor)
5. Model 5: rt ∼ BlockNumber * distractor + (1 | PId) + (1 | distractor)

B.2. BIC calculation and model comparison

We computed the BIC for each fitted model using the `BIC` function and compared the BIC values to identify the best model. The BIC values for the models are displayed in Table B.1. Overall, the model with the lowest BIC value was selected as the best model. In this case, Model 3 was identified as the best model with a BIC of 24400.66.

B.3. Best model summary

The best-fitting model (Model 3) was a linear mixed model with the formula `rt ~ BlockNumber + (1 | PId) + (1 | distractor)`.

Data availability

We share our data in the Open Science Framework. Link is available in Section 8 in the manuscript.

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