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Inter-brain synchrony in real-world and virtual reality search tasks using EEG hyperscanning

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This study investigates inter-brain synchronization during a collaborative visual search task performed in Virtual Reality (VR), and compares it to the same task executed in a real-world environment. Previous research has demonstrated that collaborative visual search in real-world settings leads to measurable neural synchrony, as captured through EEG hyperscanning. However, limited work has explored whether similar neural dynamics occur in immersive VR. In this study, we recorded EEG hyperscanning data from participant pairs engaged in a joint visual search task, conducted in both VR and physical settings. Our results reveal that inter-brain synchronization occurred in the VR condition at levels comparable to the real world. Furthermore, greater neural synchrony was positively correlated with better task performance across both conditions. These findings demonstrate that VR is a viable platform for studying inter-brain dynamics in collaborative tasks, and support its use for future team-based neuroscience research in simulated environments.

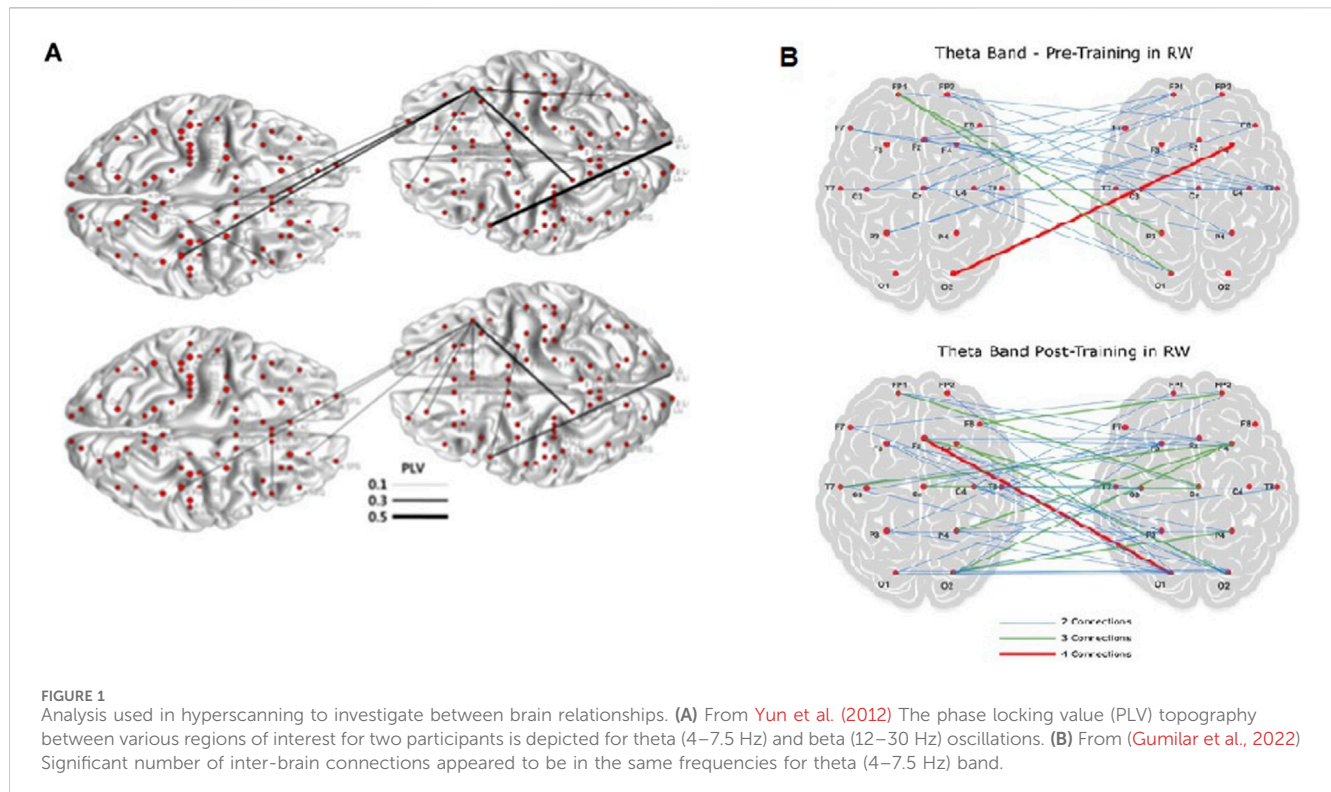
KEYWORDS

hyperscanning, brain synchronization, virtual reality, remote collaboration, social neuroscience, social facilitation, EEG, joint attention

1 Introduction

This paper explores brain synchronization between people in Virtual Reality (VR) and compares it to brain synchronization in the real world. Recent neuroscience research has shown that brain activity can synchronize between people engaged in a cooperative task (Williams Woolley et al., 2007; Mu et al., 2018; Toppi et al., 2016). The synchronization level can be a measure of efficiency in collaboration, that may enhance the utility of standard outcome measures such as response time, accuracy and engagement. Brain synchronization may provide feedback for facilitating collaboration, enhancing learning and improving team performance (Szymanski et al., 2017). This is because successful teams have a “shared attention” resulting from more functional connectivity between the neuroelectric activities of the team members (Astolfi et al., 2011).

Brain synchronization has been extensively studied in wide range of tasks involving social interactions, particularly in cooperative and competitive scenarios (Park et al., 2022; Mendoza-Armenta et al., 2024; ?). However, there has been very little study of brain



synchronization in VR. Previous research suggests that we tend to behave similarly in both the real-world and VR (Bailenson et al., 2003; Gillath et al., 2008). So a key question is: “does brain synchronization occur in VR in a similar manner to in the real world”? This is important because there may be perceptual and cognitive differences between reality and VR that may make it more difficult to observe brain synchronization.

Relatively little research has been conducted on brain synchronization in VR, but preliminary results are promising as they show collaborative tasks in VR can significantly impact inter-brain synchrony. Gumilar et al. (2022) found that that gaze direction plays a crucial role in inter-brain synchrony during collaboration in VR (see Figure 1). Furthermore, collaborative design behavior in VR based on inter-brain synchrony has been explored, highlighting the differences in collaborative design behavior between VR and the real world, and providing objective evidence for studying human neural activity in natural environments (Ogawa and Shimada, 2023). For example, Gumilar et al. (2021b) reports on a hyperscanning study in VR that replicates a previous study on hyperscanning in a real world finger tracking task (Yun et al., 2012), finding that brain synchronization also occurs in VR. Similarly, emerging work in the field of hyperscanning and VR by other researchers (Barde et al., 2019; Hajika et al., 2019) demonstrates that hyperscanning can be used across a range of applications to improve collaborative experiences in VR. Overall, VR has shown a similar impact on inter-brain synchrony in comparison to the real world environment during collaborative tasks, offering promising avenues for future research and improvements in collaborative VR experiences.

These studies have focused on joint action tasks in VR, such as finger tracking (Gumilar et al., 2021b) and elevating collaborative artistic experiences (Hajika et al., 2019), but not

many study have been conducted on joint attention tasks. Joint attention refers to the coordinated focus of two or more individuals on a common target simultaneously. This concept plays a crucial role in social interactions, aiding in understanding others’ intentions and goals (Battich et al., 2021). Research suggests that joint attention can enhance visual information encoding and processing, potentially impacting multisensory integration tasks (Lee et al., 2021). Previous research has showed that brain synchronization occurs in real world joint attention tasks, such as a visual search activity (Szymanski et al., 2017). In this paper we report on brain synchronization in a VR joint attention task and compare it to brain synchronization in the same task conducted in the real world.

The main contributions of this paper are:

1. Presenting the first known example of a brain synchronization study completed in VR for a joint attention task.
2. Providing a comparative study comparing brain synchronization in both VR and the real world for the same joint attention task.
3. Demonstrating empirical evidence of correlation between task performance and inter-brain synchrony.

In the remainder of the paper we first provide an outline of related work and how it informs our study. Then we describe the methods used to conduct the study. This is followed by reviewing the data analysis techniques used for the study and the results obtained following data processing. Next, we present a discussion section where we put the results we have obtained into context and discuss on the limitations. Finally, we conclude with the ways in which this research can be further extended.

2 Background

Our research is based on earlier studies in hyperscanning, visual search tasks, and inter-brain synchrony across virtual reality (VR) and real-world settings. In this section, we review pivotal related work in each domain, elucidating how our investigation extends beyond these foundations to explore neural alignment in immersive VR environments.

2.1 Inter-brain synchrony in VR and real-world

Inter-brain synchrony (IBS) refers to the way brain activity syncs up between people during social interactions, helping them understand and feel for each other. Mental effort, social signals, and virtual characters can have a big impact on how well this brain connection works.

High cognitive load can weaken the ability to process social cues by reducing inter-brain synchrony. For instance, research has shown that conflicting social signals can elicit neural correlates of cognitive conflict, as measured by alpha and mid-brain theta oscillations, highlighting the impact of cognitive load on neural alignment during interactions (Abubshait et al., 2022; Gumilar et al., 2021c). Also, inter-brain synchrony aligns neural activity during social interactions, enhancing understanding and empathy, with eye gaze increasing gamma-band IBS in real-world (RW) settings and alpha-band IBS in virtual reality (VR), although VR's effectiveness lags due to technological limits like delayed feedback (Luft et al., 2022; Gumilar et al., 2022).

Recent studies on team training and performance, including research using dual-EEG recordings, suggest that theta and alpha brainwaves play a key role in how we think during tasks (Cross et al., 2022). Theta waves, often tied to working memory and staying focused, seem to predict how well people do in group activities (Aleksichuk et al., 2016). In real-life situations, stronger inter-brain synchrony is related to improved teamwork, such as making decisions together or coordinating smoothly (Reinero et al., 2021; Mu et al., 2018). However, in VR, things become more complicated. The difficulty of the task and how real the VR world feels can affect these brainwaves. For example, while engaging VR setups can keep theta-driven focus sharp, issues such as clunky embodiment, slow feedback, or awkward eye-contact simulations might throw off the natural rhythm of alpha and theta waves between teammates (Pan et al., 2024).

In addition, research revealed that resting-state EEG markers—those brain signals captured when someone is at rest—can predict how well individuals will perform and even tell team members apart in a two-person group. Moreover, during simpler tasks, theta and alpha brainwaves proved to be solid clues about how someone would handle tougher training scenarios later on. These results highlight just how crucial brain oscillations are for teamwork, both in thinking and moving together, supporting what earlier studies have found about brain activity during cooperative efforts (Cross et al., 2022; Schwartz et al., 2022).

2.1.1 Insights from VR-Mediated neural coupling

Inter-brain synchrony reflects the degree to which neural oscillations align between individuals during social exchanges.

The differences in synchrony observed between virtual reality and real-world contexts may stem from the distinct neurophysiological mechanisms underlying these interactions. In everyday social interactions, the combination of sensory information and environmental social cues helps forming a clear perception, enhancing attention, and strengthening brain-to-brain connections (Seijdel et al., 2024; Cuomo, 2025). Virtual reality environments, however, can either support or hinder inter-brain synchrony depending on factors like immersion level, perceptual consistency, and attention demands. High-immersion VR setups can improve synchrony by increasing shared attention and sensorimotor feedback (Tarr et al., 2018). However, low-quality VR systems or poor visual-auditory alignment may cause attentional distractions, reducing neural coordination. This highlights the complex role of technology in influencing inter-brain dynamics.

Also, visual immersion and embodiment within virtual environments significantly enhance inter-brain synchrony by aligning participants' sensory experiences and reinforcing neural coupling (Hu et al., 2017). Studies indicate that immersive settings with shared visual perspectives elicit synchronized neural activity, strengthening interpersonal connections during collaborative tasks (Gumilar et al., 2022). Furthermore, embodiment, defined as the perception of inhabiting a virtual body, modulates neural responses, influencing both perceptual and motor processes during interactions (Khalil et al., 2022). Perceptual coherence, facilitated by synchronized sensory inputs, promotes unified experiences, enhancing the smoothness of interactions and the robustness of neural alignment (Pérez et al., 2017). These findings highlight the necessity of integrating these factors to design virtual environments that effectively support collaborative neural dynamics.

2.2 Hyperscanning

Hyperscanning is the simultaneous acquisition or recording of neural activity from two or more individuals who are interacting during a particular motor or cognitive task (Babiloni and Astolfi, 2014). This can be done using several recording techniques. For example, functional near-infrared spectroscopy (fNIRS) hyperscanning uses InfraRed (IR) light shone into the head as a method to measure inter-personal interactions in a natural context (Scholkmann et al., 2013). Functional Magnetic Resonance Imaging (fMRI) images deeper into the brain, and is a technique which was used for hyperscanning for the first time in 2002 (Montague et al., 2002). However, the most common method is to use multiple electroencephalographic (EEG) recordings for simultaneous measurement of brains during a cooperative task (Babiloni et al., 2006).

The primary purpose of using hyperscanning is to look for synchronization of brain activity, which tends to occur when two or more people collaborate to achieve a common goal. For instance, by using hyperscanning in a training scenario, it is possible to accurately assess neural connectivity between brains in real-time which can enable the trainer to make dynamic and more accurate decisions about the approach to be taken during the training process (Barde et al., 2020a). Accurate real-time analysis is one of the overarching goals of the research that is being pursued in the use of hyperscanning and VR. However, advances in this field have only been possible in recent years.

The number of hyperscanning studies have increased owing to the growing availability of low cost, high quality EEG hardware and software tools. In recent years, EEG hardware has evolved from being an unwieldy and wired piece of equipment to a wireless and easy-to-use tool. Modern day EEG headsets enable researchers to run studies in more real-world environments (i.e., outside the lab) and even allow for ambulatory studies to be carried out (Liebherr et al., 2021).

A common thread that links a majority of the hyperscanning studies is that they were mostly carried out in a traditional lab setting (Saito et al., 2010; Yun et al., 2012) or were set-up to mimic a real-world scenario (Babiloni et al., 2006; Toppi et al., 2016). Some studies attempted to investigate the effect of face-to-face interactions between participants using a variety of different tasks, including finger pointing/tracking exercises (Yun et al., 2012), music performance (Acquadro et al., 2016) and economic exchange (?). The finger tracking task is especially popular among researchers because gesture is thought to represent the most basic form of social interaction, besides eye gaze (Yun et al., 2012). Finger tracking allows us to look at synchrony from a neural as well as physical perspective, i.e., physical manifestation of inter-brain synchrony by means of identical or mirrored body movements among participant pairs.

Hyperscanning has been used to explore collaboration in the real world, but there has been little research that applies it in VR (Barde et al., 2019, 2020a; Gumilar et al., 2021a). In one of the few examples, Gumilar et al. (2021b) conducted a finger tracking task in VR, extending an earlier work Barde et al. (2019). Both of these previous work report that they were able to observe brain synchronization in VR that matched brain activity in the same real world task. However, they were based on joint action tasks, not on joint attention task. A related study demonstrated that inter-brain synchrony can occur in cooperative online gaming without physical co-presence, using EEG to measure brain activity during a multiplayer game (Wikström et al., 2022). The findings showed that synchronization across frequency bands decreased during a playing session but was elevated in the second session, indicating that virtual environments, though not specifically VR, can support inter-brain synchrony dynamics. This study highlights the potential for virtual settings to facilitate neural alignment, although it notes the dependence on task design and session progression. Another study used hyperscanning EEG to show that collaborative spatial navigation in VR involves neural synchronization, with distinct delta, theta, and alpha band patterns reflecting role-specific strategies and increased delta causality, but reduced theta/gamma couplings in faster dyads (Chuang et al., 2024). Moreover, a research found that real-like avatars in VR produced the highest number of significant EEG sensor pairs, followed by full-body and head-hand, suggesting that more realistic avatars enhance neural synchronization (Yigitbas and Kaltschmidt, 2024). Furthermore, a study using EEG hyperscanning demonstrated that a shared mixed-reality (MR) environment enhances inter-brain synchronization during cooperative motor tasks compared to individual tasks, with a significant correlation between task performance and synchronization, validating MR's effectiveness for collaboration (Ogawa and Shimada, 2023). Lastly, a study in an Augmented Reality (AR) setting showed that performing synchronized movements beforehand in remote AR education improves quiz

scores, brain synchrony between students, and feelings of closeness, compared to unsynchronized movements, with a clear link between quiz scores and brain synchrony, indicating that synchronized movements improve learning (You et al., 2024).

Given the lack of extended research in this area, we attempt to bridge this gap by studying how VR and neural activity measurements can be combined to investigate cognitive tasks in collaborative VR environments. Our study attempts to gather information on how monitoring neural activity in VR can measure inter-brain synchrony in VR environments on a joint attention task, and how it is comparable to measuring inter-brain synchrony in the real-world environment. In particular we explore brain synchronization in a collaboration on a visual search task in VR, extending earlier work done in the real-world (Szymanski et al., 2017).

2.3 Joint attention and visual search tasks

Vision is considered the most dominant of our senses (Krishna, 2012). We rely on it to navigate through environments we encounter, and it also serves as a way to corroborate what the auditory sense detects in an environment (Witkin et al., 1952; Jackson, 1953). The visual faculty relies on a host of complex cues—color, depth, motion *etc.*, – in order to make accurate judgements regarding regions or objects of interest, and the environments in which these are based. Visual search tasks involve finding specific objects among distractors in a visual display, whether in 2D or 3D environments, with varying levels of cognitive demand (Santos, 2023; Anderson and Lee, 2023; Zhang and Pan, 2022). These tasks can range from routine searches like locating keys on a table to more critical searches like identifying tumors in medical images (Samiei and Clark, 2022). The efficiency of visual search can be influenced by factors such as the size and eccentricity of the target object, with larger and more eccentric targets being found faster with fewer fixations (Wolfe, 2010).

It is the complexities encompassing the visual sense which makes visual search tasks a great tool to analyze a number of factors that affect interaction, cognition and other processes. For example, researchers have used visual search tasks to explore the difference between how visual and auditory cues are assimilated in order to locate a target in an environment (Barde et al., 2020). Other researchers have looked at how motivation and the strategies employed by users affect performance in a visual search task (Boot et al., 2009).

In the neuroscience domain, visual search tasks have been used to induce neural activity of a given band of frequencies (Tallon-Baudry et al., 1997), to study memory (Postle, 2021; Peterson et al., 2001) and to study the effect of visual distractors on task performance (Won et al., 2020; Tanrikulu et al., 2020), among other things. While an exhaustive review is beyond the scope of this paper, we can clearly see that the visual search is a popular method employed by researchers. Visual search tasks can also be adapted to study a range of cognitive and neurological processes that affect our functioning as humans. Employing visual search tasks in VR offers a valuable method for studying human attention processes. Studies have shown that VR can provide a more ecologically valid setting for visual search experiments, allowing

for improved visual realism and participant interaction (Hadnett-Hunter et al., 2022). Also, research has demonstrated that immersive VR technology can effectively evaluate spatial and distractor inhibition attention using complex 3D objects, replicating previous findings and supporting the use of VR for such assessments (Ajana et al., 2023). Additionally, distractions in VR activities can impact task performance, with task-oriented selective attention enhancing performance without compromising the flow experience (Bian et al., 2020). So, this collective evidence reveals the potential of VR for investigating visual search tasks and its connection to attention mechanisms, including joint attention systems.

There are a number of papers that have used hyperscanning to explore brain synchronization in joint attention tasks in the real world (Lachat et al., 2012; Szymanski et al., 2017). For example, Lachat et al. (2012) performed a hyperscanning study and used an eye-gaze task in a face-to-face setup to find the relation between joint attention and alpha and mu bands. Szymanski et al. (2017) provided evidence that during joint attention in a visual search study, local and inter-brain phase synchronization increases and behavioral team performance is correlated with phase synchronization. They also found that neural phase synchronization correlates to social facilitation, which may reveal neural correlates for better performance among some teams when compared to others. In our work, we make a novel contribution by presenting results from the first known joint attention brain synchronization experiment in VR, and compare them with the real world studies. In the next section we describe our experimental method, including the hypothesis, task, and participants.

3 Method

3.1 Hypothesis

The main purpose of our study was to evaluate inter-brain synchrony in a VR environment in a representative joint visual search task, comparing the results of a real-world study with those obtained in VR. We believe that such comparisons are good indicators of how real-world tasks translate to VR by maintaining similar neural activity as seen in the real-world (Gumilar et al., 2021b). They also provide empirical evidence that demonstrates neural inter-connectivity can be achieved in a manner similar to that in the real-world. Furthermore, use of VR has shown positive impacts on collaboration efficiency (Xanthidou et al., 2023). Previous studies have highlighted that virtual knowledge sharing positively influences team effectiveness, especially when supported by collaborative technologies (Farooq and Bashir, 2023). Additionally, remote collaboration in virtual reality, particularly through head-mounted displays (HMD), enhances the sense of co-presence among users, indicating improved collaboration effectiveness (Latini et al., 2022; Bayro et al., 2022). So, we can investigate if brain synchronization in VR collaborative tasks is higher than similar tasks in the “real-world” environment.

To that end, the three hypotheses for our research are:

- H1: Inter-brain phase synchronization will increase during visual search task cooperation in the real-world (reproducing the result of previous real world studies).
- H2: Phase synchronization will occur during a visual search task in VR in a manner which is not significantly different than the real-world.
- H3: Task performance in VR will be higher than in the real-world.

3.2 Participants

Twenty-eight individuals (9 female, 19 male) were recruited via flyers, university mailing lists, social media advertisements and personal contacts. Participants were mostly university students or staff aged between 21 and 39 years ($M = 29.11$, $SD = 6.27$). All dyads knew each other previously (i.e., were classmates or colleagues). All participants were right-handed, presented normal or corrected-to-normal visual acuity, and provided informed written consent to participate in the study. No neurological, psychiatric or psychological problems or brain injury history were reported by any of the participants, as determined in a preliminary screening phase. They were also asked if they have previous experience with VR. Nine out of 28 participants (32%) didn't have any experience with VR while 51.5% used VR several times per month.

Prior to conducting the experiment we calculated the required sample size to achieve an acceptable power in the analysis using G*Power version 3.1. We found that to achieve a power of 0.85, 24 participants were required. Hence, our sample size is sufficient for the experimental validity. Participation was voluntary, and each of the participants were given a \$40 gift voucher as compensation for taking part in the study.

3.3 Task and Procedure

The visual search task for participants involved locating target objects within a static scene. This static scene included 82 distractor objects usually found in an office or home (e.g., toys, kitchenware, office stationary and small home objects). The objects used and the experiment method followed was adapted from a similar real world study reported in Szymanski et al. (2017).

The object combinations were displayed on a wall using a video projector for the real-world condition (RW) and were presented in a head mounted display (HMD) for the VR condition (Figure 2). Participants could see a blank scene displaying an object name in the VR environment asking them to count a specific target object on the shelves in front of them, which could be zero, one or two objects amongst a collection of random objects. The same object never appeared as a target more than once in the same display condition, either VR or RW, and each time a different combination of random objects was displayed for them. This was done to prevent participants from being able to memorize and predict the placement of target objects during the experiment. These conditions were designed for both the RW and VR environments. Users had the freedom to look around in the VR environment as they normally would in the real-world. This was

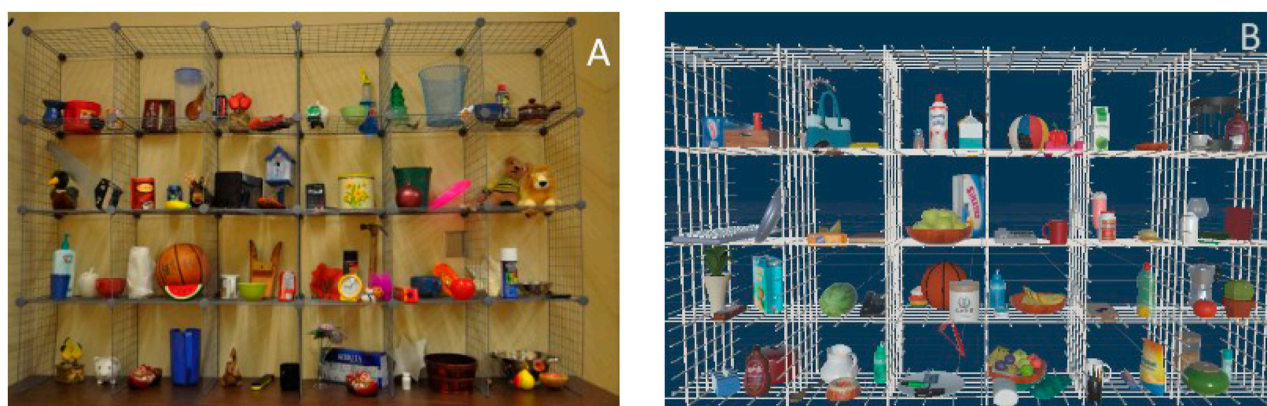


FIGURE 2
A set of 82 distracting objects in (A) the real world adapted from Szymanski et al. (2017) and (B) the VR environment.

done to mimic, as closely as possible, the task carried out in the real-world condition.

The study was designed as a 2×2 within-subjects experiment with two factors: 1) environment and 2) cooperation. Participants experienced four conditions in total; in each environment (VR or RW) there were two conditions where participants performed the task individually, or completed the task as a team. In team conditions, participants sat side by side in the same room, having the same view and they were given a question about the object which they had to look for in the next scene, and to find the number of occurrences of that specific object. Participants were instructed in team condition to decide on a strategy to collaborate and find the objects faster and in a more accurate way. For example, they could divide the shelves in 2 sections (i.e., top/down or left/right of the shelves) and each participant looked for the objects only in half of the shelves. In both individual and team conditions, each participant was asked to find 14 objects in 14 different scenes of random placements in each environment condition (VR and Real-world). In the VR mode, participants had to wear an HTC VIVE VR HMD and experienced the same number of scenes. The VIVE headset featured a 110 field of view, a refresh rate of 90 Hz and built-in headphones.

In this study, the order of environments and conditions for study groups was randomly selected to counterbalance the experiment, however the order of questions was the same for each group. In the individual condition in both environments, participants were given the same set of questions and objects placement while each participant could not see the other participants' scenes and questions during the experiment in the study room.

After three practice trials, the main task started in which participants saw three scenes with collections of objects from where the participants were asked to find target objects and count their number. The target object that was required to be found was communicated to them in advance by showing a message on the screen asking to find a certain object. Once reading the question, participants pulled the trigger on a handheld controller which showed a scene in which a shelf of objects was displayed. Participants were required to search this

scene to decide on the number of targets they had found. Following this, they moved to the next scene by pressing the trigger on a handheld controller which showed the same question again and they had to call out the answer, i.e., the number of objects they found. EEG signals were recorded at the beginning of the search task and paused at the end of the task so the synchronization was based on the starting and ending time of the activity (Figure 3). This ensured that neural activity that was recorded only represented the time that was spent on collaborative search tasks which was mostly less than 20 s to answer each question.

After each team condition, subjects were surveyed on how they felt about their partner's presence and cooperation during the visual search task. This was done by asking them to complete a short Likert scale survey (see Figure 4), where they rated items on a scale of 1 (totally disagree) to 7 (totally agree). This questionnaire was adapted from a study by Gupta et al. (2016).

3.4 EEG data acquisition

During the tasks, neural activity was recorded using two sets of 32 electrodes (Ag/AgCl) Brain Vision LiveAmp EEG devices¹. Separate amplifiers with individual ground electrodes were used for each person linked to two PCs to collect synchronized brain signals. For the placement of EEG electrodes on scalp, the international 10–20 system was used. The EEG channels were recorded at a sampling rate of 512 Hz. Two other computers with multiple synchronized screens were used for stimulus presentation. Prior to data collection, we adjusted electrode placements until all signals indicating optimal impedance $< 10 \text{ k}\Omega$ and minimizing the proportion of bad channels to near zero across conditions. While we did not quantify impedance variations *post hoc*, we assessed signal quality by comparing alpha power spectra (8–13 Hz) between conditions, finding no

¹ <https://pressrelease.brainproducts.com/liveamp/>



FIGURE 3
EEG hyperscanning during the study in (A) the real world and (B) the VR environment.

Q#	Statement
Q1	I felt connected with my partner.
Q2	I felt I was present with my partner.
Q3	My partner was able to sense my presence.
Q4	My partner (<i>or for Remote Helper: I</i>) could tell when I (<i>or for Remote Helper: my partner</i>) needed assistance .
Q5	I enjoyed the experience.
Q6	I was able to focus on the task activity.
Q7	I am confident that we completed the task correctly.
Q8	My partner and I worked together well.
Q9	I was able to express myself clearly .
Q10	I was able to understand partner's message.
Q11	Information from partner was helpful .

FIGURE 4
Likert scale rating questions on co-presence and cooperation adapted from Gupta et al. (2016).

significant differences (RW: $M = 1.8 \mu V^2$, $SD = 0.4$; VR: $M = 1.7 \mu V^2$, $SD = 0.5$; $t(23) = 0.82$, $p = 0.42$). These values align with typical resting-state EEG norms, suggesting that technical limitations from the VR headset did not introduce substantial biases in our data.

3.5 Behavioral analysis

The accuracy of answers was calculated for each individual and team conditions using the data analysis methods provided in prior work (Szymanski et al., 2017). Efficiency was calculated based on the number of correct answers, and the time participants took to find the objects was also recorded. These were compared between the team and the individual sessions as well as VR and RW environments.

3.6 EEG data analysis

Two pairs (one male-male and one female-female) were excluded from the analysis due to technical issues with EEG recording hardware. As a result, only data from 24 participants (twelve pairs) was analysed. The recorded data was processed using MNE Python² and the HyPyP library for Python (Ayrolles et al., 2021). This was done to determine which environment showed a higher neural synchrony in social sessions. Prior research suggested that the Circular Correlation Coefficient (CCorr) offers enhanced robustness in detecting artificial inter-brain associations (Burgess, 2013). Therefore, we utilized CCorr (Jammalamadaka and Sengupta,

² <https://mne.tools/stable/index.html>

2001) to evaluate the synchrony between the two cerebral signals. The integration of this equation into the HyPyP library facilitated its application for analyzing inter-brain synchronization data.

To reduce electrical interference, the EEG data were initially pre-processed using a 50 Hz notch filter and a band-pass filter (1–60 Hz). The filters were implemented using the MNE-Python library (Gramfort et al., 2013), employing finite impulse response (FIR) filters to preserve phase information critical for PLV calculations. Default filter orders were used as provided by MNE-Python version 22.3.0, ensuring minimal distortion of the phase relationships between signals.

Motion artifacts induced by the VR headset, along with eye movement and muscle (EMG/EOG) noise, were addressed using a machine learning technique from MNE-Python integrated into the HyPyP module, a Python tool for inter-brain synchrony research as well as independent component analysis (ICA). To assess signal quality, the signal-to-noise ratio (SNR) was estimated post-preprocessing for a subset of data, yielding an average SNR of approximately 3.2 dB (SD = 0.8 dB) across conditions, indicating acceptable signal clarity for phase synchronization analysis despite the challenges posed by VR headset movements. An automatic rejection threshold, implemented via the auto-reject package (Jas et al., 2017), rejected approximately 5%–10% of epochs across participants, with paired rejection ensuring synchrony analysis integrity. When a participant's data was rejected, the corresponding epoch for the other participant was automatically rejected as well.

3.7 Phase locking value (PLV) analysis

The Phase Locking Value (PLV) is a measurement of the relative phase difference between two signals (Lachaux et al., 1999). In EEG hyperscanning, the PLV is used to analyze the phase of pairs of simultaneous EEG signals. This is one of the most frequently used methods to demonstrate that brain-to-brain coupling exists between individuals in social interactions (Haresign et al., 2022; Gumilar et al., 2021a). The PLV takes values on the scale of [0, 1] in which 0 being the situation where there is no phase synchrony and 1 reflecting the situation where relative phases are identical in all trials. From filtered and pre-processed EEG data, the phase value of the signal using the Hilbert transform can be extracted. As originally proposed by Lachaux et al. (1999), PLV is derived from this phase information by calculating a time-varying value for neural synchrony and is computed as:

$$PLV_{ij} = \left| \frac{1}{N} \sum e^{(\phi_i - \phi_j)} \right| \quad (1)$$

Where N indicates the total number of epochs (the data organized into equal parts according to a specified time frame) and ϕ_i and ϕ_j indicates the phase of the signals for the electrodes i and j and $\phi_i - \phi_j$ are the electrode phase differences. Inter-brain synchrony analysis calculates the PLV value for each pair of electrodes i and j , each belonging to a different subject.

In this study, we began by calculating the PLV, denoted as the “real” PLV for this analysis, for each set of 1024 (32×32) connections, performed according to Equation 1. For the control

measure, random PLV scores were generated by randomizing the epoch of the recorded data prior to PLV calculation. This randomization process was iterated 200 times for each electrode pair, resulting in a distribution of 200 randomized PLV scores. Subsequently, the “real” PLV score for each electrode pair was compared to the distribution of randomized PLV scores. This comparison allowed for the evaluation of whether the observed PLV score exceeded the level of random chance synchronization (Yun et al., 2012), and if it was significant.

4 Results

4.1 Statistical analysis

In this study we adopted the PLV method using the HyPyP package and used the analysis method of Gumilar et al. (2022) to find the functional connectivity between the two interacting brains. Before processing raw data, the MNE-Python package (Gramfort et al., 2013) and the HyPyP package were utilized for pre-processing the raw EEG signals. According to their method, there were 1024 electrode pairs (32×32 electrodes) for each pair of participants. So, there were 1024 PLV scores between 0 and 1 that indicated the magnitude of inter-brain synchrony for all possible pairs. By applying a cut-off ($p < 0.05$) to a distribution of the PLV scores (1024 PLV scores for each pair of subjects), we extracted only those scores that were below the threshold. Pairs with PLV scores above the 95% confidence interval were retained as significant PLV scores which reflect the top 5% highest synchronization and we call them significant connections or significant connectivity. The total number of aligned electrode pairs (significant connections) were counted (out of 1024 total pairs) for each condition along with the frequency bands (i.e., theta, alpha, beta, and gamma) within which they were observed. Tables 1, 2 presents an overview of the total number of connections that were observed along with a band-wise breakdown of the inter-brain connections.

4.2 EEG data analysis results

4.2.1 Individual vs team conditions

Tables 1, 2 summarises the results of each conditions. Our data analysis using paired t-tests shows that the number of significant connections between participants' brains in the team condition (mean = 283.8, SD = 27.3) was significantly higher ($t(11) = 17.395$, $p < .001$) than the individual condition (mean = 241.7, SD = 26.2) in the RW condition. This result supports H1, which is confirming the findings from prior work (Szymanski et al., 2017). In support of H2, the results from the VR conditions also indicated the number of significant connections significantly increased ($t(11) = 18.655$, $p < .001$) in the team condition (mean = 300, SD = 23.8) compared to the individual condition (mean = 263.1, SD = 26.4). Finally, the results comparing the team conditions between VR and RW, shows a menainful increase ($t(11) = 3.249$, $p = .007$) in number of significant connections in VR (mean = 300, SD = 23.8) compared to the RW condition (mean = 283.8, SD = 27.3).

TABLE 1 Number of strong brain connections in team condition (VR vs RW environments).

Group	Alpha low		Alpha high		Theta		Beta		Gamma		Total	
	VR	RW	VR	RW	VR	RW	VR	RW	VR	RW	VR	RW
G1	29	29	64	52	38	36	68	56	66	54	265	227
G2	29	29	58	64	52	48	76	76	84	80	299	297
G3	29	31	64	68	52	58	88	58	80	80	313	295
G4	31	29	72	66	58	50	92	88	86	78	339	311
G5	33	29	70	58	60	50	68	72	88	66	319	275
G6	31	31	68	68	50	38	78	72	66	52	293	261
G7	29	29	66	64	64	46	84	78	74	72	317	289
G8	29	29	68	64	48	48	78	78	74	76	297	295
G9	31	29	72	72	48	58	82	74	70	70	303	303
G10	31	31	70	64	48	54	78	82	76	72	303	303
G11	31	31	72	64	42	40	60	58	44	48	249	241
G12	33	31	68	64	54	56	60	82	88	76	303	309
Average	30.5	29.8	67.7	64	51.2	48.5	76	72.8	74.7	68.7	300	283.8
SD	1.51	1.03	4.16	5.05	7.31	7.49	10.23	10.39	12.49	11.29	23.84	27.34

TABLE 2 Number of strong brain connections in individual condition (VR vs RW environments).

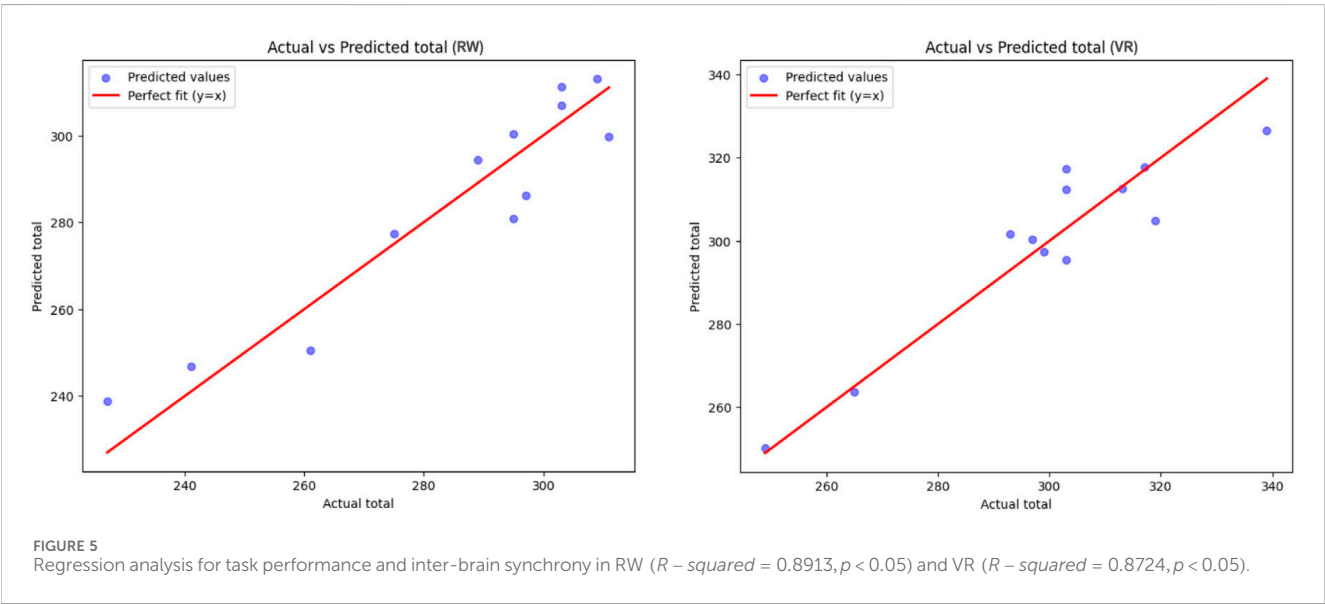
Group	Alpha low		Alpha high		Theta		Beta		Gamma		Total	
	VR	RW	VR	RW	VR	RW	VR	RW	VR	RW	VR	RW
G1	22	19	54	44	29	22	56	54	59	49	220	188
G2	23	25	45	50	45	32	67	65	78	75	258	247
G3	21	12	56	55	46	56	76	53	77	76	276	252
G4	34	13	65	61	46	54	79	76	79	70	303	274
G5	23	17	63	54	54	43	65	68	79	64	284	246
G6	26	22	58	47	45	29	76	65	60	53	265	216
G7	19	19	57	57	60	39	78	64	65	71	279	250
G8	23	19	57	52	45	39	77	70	69	71	271	251
G9	19	18	64	49	37	50	76	68	63	59	259	244
G10	26	22	65	56	38	54	73	78	56	61	258	271
G11	30	23	60	56	35	36	49	54	34	34	208	203
G12	25	23	59	52	57	38	58	78	77	67	276	258
Average	24.3	19.3	58.6	52.8	44.8	41.0	69.2	66.1	66.3	62.5	263.1	241.7
SD	4.4	4.0	5.6	4.7	9.1	10.8	10.1	8.9	13.3	12.3	26.4	26.2

We also found that the average response time of each pair in the RW environment in the individual condition was significantly less than the response time in the team condition in the same environment ($t(11) = 4.01$, $p = 0.0002$). However, the difference between the average response time of each pairs in the VR environment compared to the team condition was not

statistically significant ($t(11) = 1.07$, $p = 0.3$) (Table 3). The answers in team conditions in both environments were more accurate (Team-VR: mean = 12, SD = 1.8; Individual-VR: mean = 11, SD = 1.3; Team-RW: mean = 11.4, SD = 1; Individual-RW: mean = 10.7, SD = 1.3) with a paired t-test analysis showing a statistically significant increase in correct

TABLE 3 Response time for individual condition comparing to team condition in both VR and RW environments.

Group	RW-T	VR-T	RW-I (P1)	RW-I (P2)	VR-I (P1)	VR-I (P2)
G1	16.7	15.1	12.6	13.6	13.5	14.1
G2	13	12.5	11.8	11.7	12.8	13.3
G3	12.8	10.7	12	12.3	12.1	12
G4	11.5	9.2	8.9	8.6	8.6	9.9
G5	13.2	12.5	11	11.7	10.2	11.3
G6	15.4	11.5	9.8	9.2	11	10.1
G7	12.1	9.5	9	8.7	8.6	9.4
G8	10.6	11.8	11.3	10.8	12.6	11.6
G9	10.2	9.6	9.7	8.9	8.5	9.2
G10	11.5	12.5	8.9	10.7	13.6	11
G11	15.8	16.5	14.5	11.5	15.1	13.8
G12	10.8	11.2	9.3	12	12.7	12.1
Average	12.8	11.9	10.7	10.8	11.6	11.5
SD	2.1	2.2	1.8	1.6	2.2	1.7



answers in team condition compared to individual condition in VR ($t(11) = 2.07$, $p = 0.02$) while in the RW condition the significance level was statistically significant ($t(11) = 2.07$, $p = 0.05$).

4.2.2 Regression analysis

Regression analysis results demonstrate a significant positive relationship between task performance and inter-brain synchrony in RW condition ($R - squared = 0.8913$, $p < 0.05$) as well as VR condition ($R - squared = 0.8724$, $p < 0.05$). This significant correlation supports our findings with further evidence on the relationship between neural alignment and performance outcomes in both RW and VR [Figure 5](#).

The regression model for real-world condition is articulated as follows:

$$TotalConnections = 315.38 - 8.91 \times Time + 7.22 \times correct\ answers$$

The regression model, with an R-squared value of 0.8913, accounts for approximately 89% of the variance in total, indicating robust predictive capability. The Mean Squared Error (MSE) of 74.46 reinforces the model’s correctness by signifying a comparatively minor average squared deviation between observed and projected values.

For VR dataset, the regression model is expressed as:

$$TotalConnections = 260.48 - 4.26 \times Time + 7.51 \times correct\ answers$$

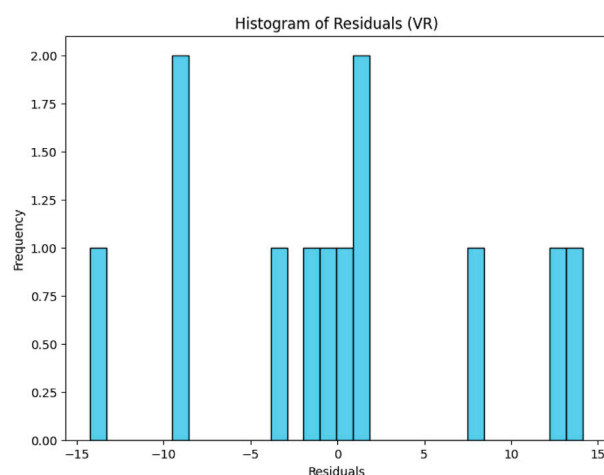
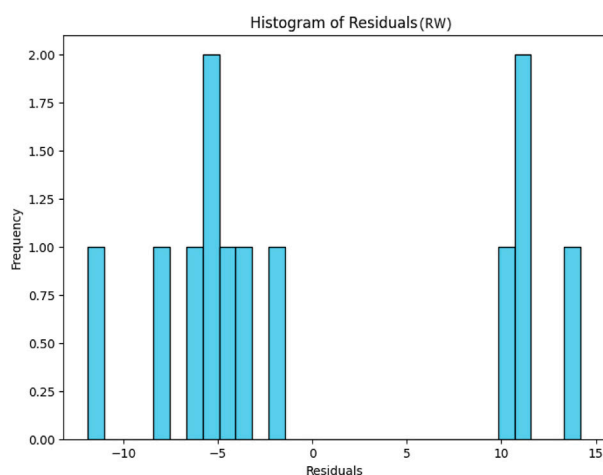


FIGURE 6
Residuals histograms in the RW and VR conditions.

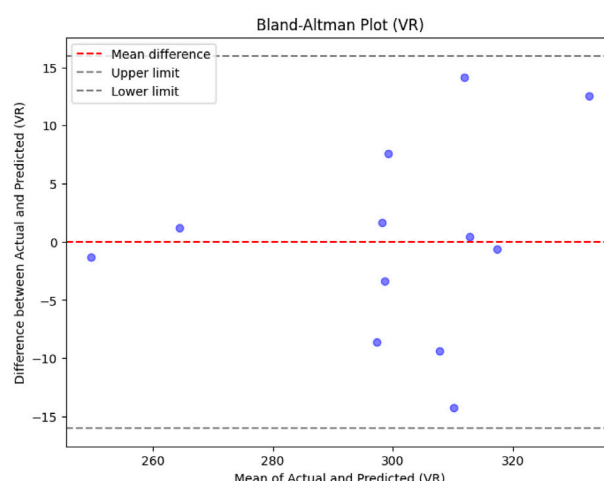
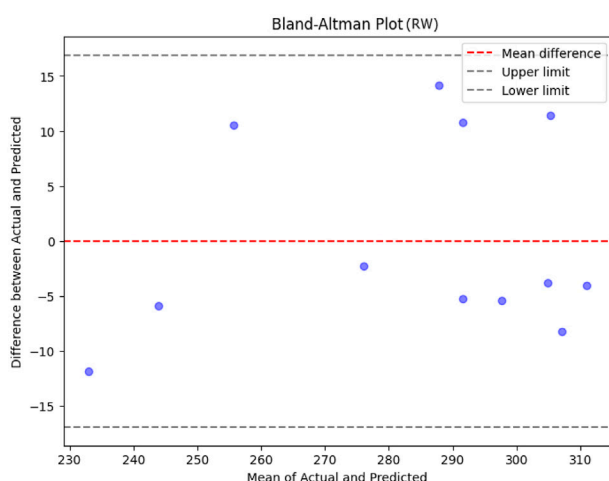


FIGURE 7
Bland-Altman comparison of measurement agreement in RW and VR conditions.

The regression model explains about 87.24% of the changes in the data, as shown by an R-squared value of 0.8724, which means it fits the data well. The Mean Squared Error (MSE) of 66.47 shows that the average difference between predicted and real total scores is quite small, proving the model predicts steadily. These numbers together show the model works well to find the total score, with Time and correct answers having big but different effects on the result (Figure 6).

More checking with residual analysis and Bland-Altman plots, done in both Real-World (RW) and Virtual Reality (VR) settings, shows the regression models give fair predictions. The average residual is almost zero (-2.37×10^{-15}), meaning no big errors lean one way, and the standard deviation of residuals ($SD \approx 8.63$) shows errors spread out in a normal way. Bland-Altman analysis says most prediction mistakes stay within a good range of -17 to $+17$, proving the models are useful in real situations (Figure 7).

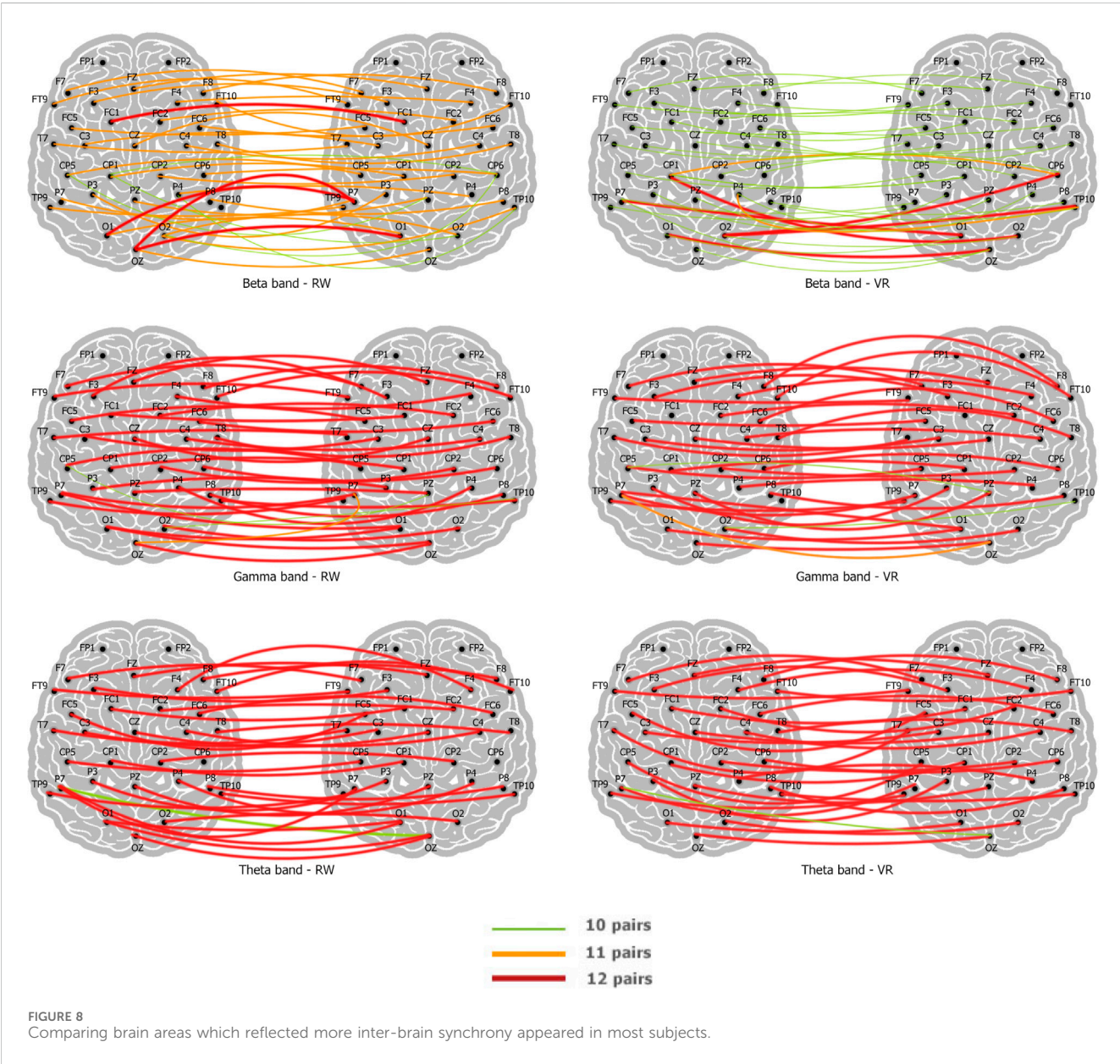
Overall, both models catch the data patterns well, as seen in their high R-squared values and decent prediction correctness. Though the data is a bit off from being perfectly normal, this happens often in real studies and does not ruin the results. Future work could try changing the data or using stronger methods to improve the findings' sureness. Still, for practical use, the models are strong and trustworthy enough.

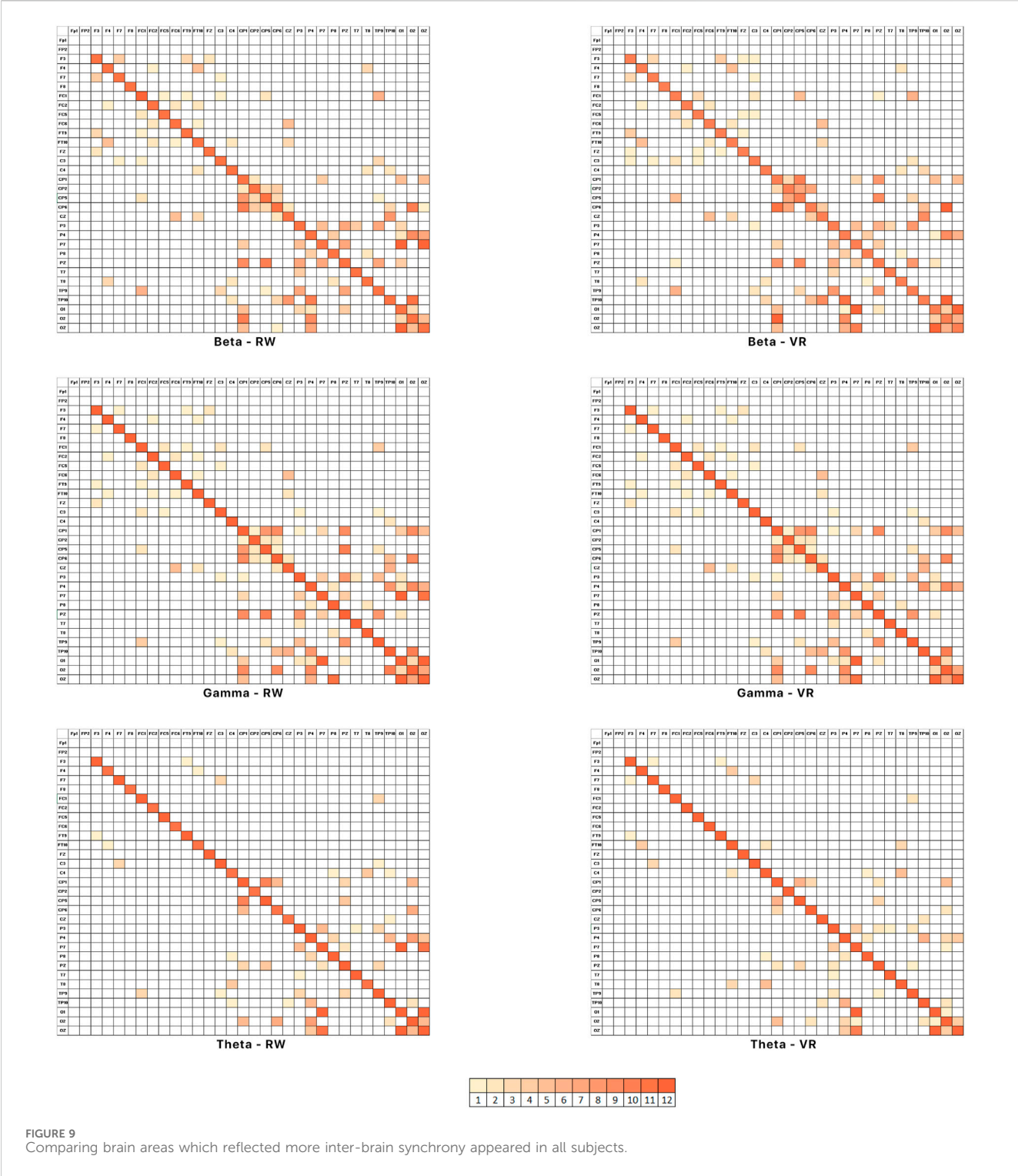
4.2.3 Correlation test

By running data analysis using PLV method and calculating the number of significant connections between all 1024 electrode pairs in each group in both real-world and VR conditions, we noticed a high correlation between the correct answers and number of significant connections in Beta, Gamma and Theta bands in both VR and RW, but no significant correlation was found in alpha-low and alpha-high bands, as expected (Table 4). This is because the

TABLE 4 Correlation test results (*r*: correlation coefficient) between the number of significant connections and correct answers or average response time.

Band	Correlation (Correct answers) - real world	Correlation (time) - real world	Correlation (correct answers) - VR	Correlation (time) - VR
Total	0.85	−0.93	0.91	−0.87
Alpha_Low	−0.01	0.19	0.06	−0.01
Alpha_High	0.3	−0.52	0.09	−0.08
Theta	0.73	−0.83	0.67	−0.71
Beta	0.76	−0.73	0.76	−0.74
Gamma	0.73	−0.8	0.68	−0.61

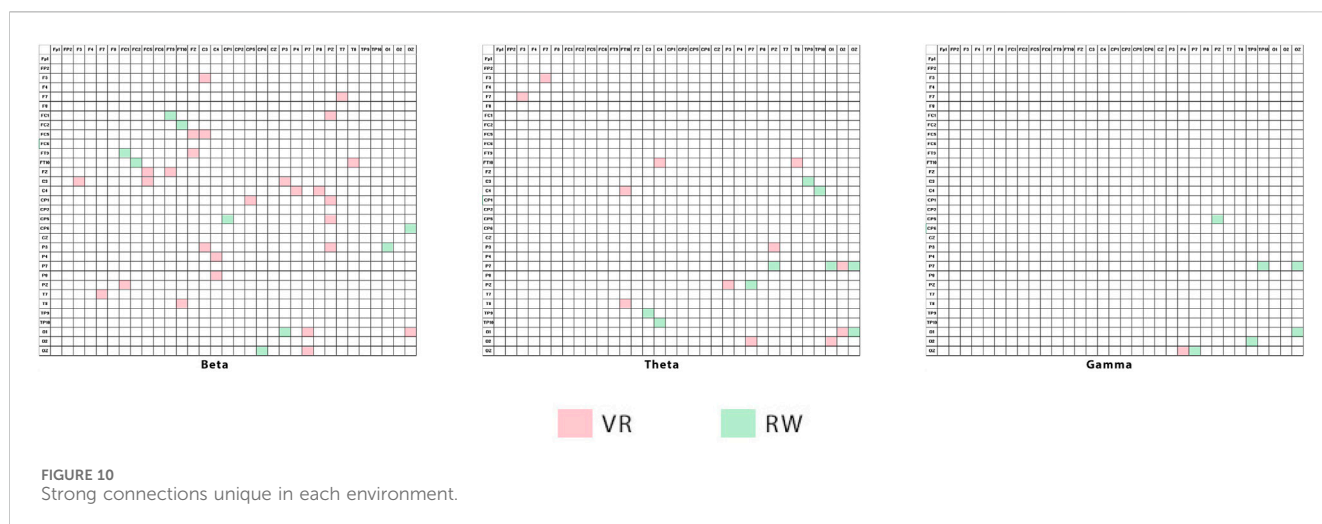




Alpha band is mostly related to relaxation state or slow activity which was not included in our cooperative task.

We also noticed that there was a high number of connections between specific brain areas which appeared in most of participants during the search task in Beta, Theta and Gamma bands (Figure 8) specially in the same electrode pairs. However, the strong connections that appeared in both VR and the RW environments were almost the same. Figure 9 presents all the brain areas with significant correlation

seen in all subjects which represents the similarity of most areas in subject pairs. These heat-map grids also show that there are less connections in the frontal areas of the brain and the strongest connections appears from center to back areas of the brain. Although there were many common areas with strong connections in both VR and the RW environments, some connections were seen distinctively in each environment (Figure 10). In the VR condition more unique active brain areas have been seen in Beta and Theta bands.



4.2.4 Beta band

Based on the correlation analysis, we observed that in the Beta band (13.5–29.5 Hz) the number of significant connections demonstrated a strong correlation with the number of correct answers in both the RW and VR environments (RW = 0.76, VR = 0.76). The Beta band is generally thought to be associated with listening, thinking, analytical problem solving and decision making (Sherlin, 2009). Given that these were activities that the participants were involved in as part of the task, the increased activity in this band, especially for pairs with a greater percentage of correct answers, appears logical and in line with previous literature (Szymanski et al., 2017).

4.2.5 Gamma band

Our analysis also revealed a strong correlation between the Gamma band and total number of correct answers, i.e., the greater the number of significant connection observed between the participants' brains in Gamma band, the better performance (RW = 0.73, VR = 0.68). Gamma is measured between 30 and 44 Hz and is the only frequency band found in every part of the brain. The subjective feeling states for gamma bands are thinking and integrated thoughts, high-level information processing and binding (Kaiser and Lutzenberger, 2003). It's also associated with information-rich task processing which was a part of this study.

4.2.6 Theta band

Theta activity is classified as “slow” (4–7 Hz) and is associated with creativity, intuition, daydreaming, and fantasizing. It also serves as a storage area for memories and emotions, sensations (Carson, 2010; Bekkedal et al., 2011). We observed a strong correlation between the number of correct answers and the number of significant brain connections in Theta band in both RW and VR environments (RW = 0.73, VR = 0.67).

4.2.7 All bands results

Our statistical analysis reveals an improvement in the number of correct answers (Figure 11) and faster response time (Figure 12) when the total number of significant brain connections across all bands is increased. Correlation tests showed a meaningful

correlation between total number of strong connections and correct answers in the VR and RW conditions as well as response time in both environments (Table 4).

4.3 Subjective data analysis

Statistical analysis of the subjective data using a correlation test and the Wilcoxon signed-rank test demonstrated that there appeared to be no correlation between how the participants felt and the proportion of correct answers, or time on task. The rating scores from the subjective questionnaire results also demonstrated no significant differences ($p > 0.05$) between the RW and VR conditions for any of the questions (Table 5). This is an indicator that participants did not appear to differentiate significantly between the two environments, or how they felt it affected their sense of presence and interaction with their partners. This result bodes well as it demonstrates that VR is capable of eliciting similar responses to the RW in terms of presence and interactions with another person inhabiting the same environment.

4.3.1 Mediation analysis

We also conducted a mediation analysis to test whether the path “task performance → neural synchrony → subjective experience” holds, or to discuss why subjective ratings and neural synchrony don't always match—maybe because high ratings (close to 7) – create a ceiling effect that hides small differences. In both Real-World (RW) and Virtual Reality (VR), the results showed a clear pattern: doing well on the task (faster time and more correct answers) boosted neural synchrony (RW: $a = 0.45$, $p = 0.03$; VR: $a = 0.42$, $p = 0.035$), and this synchrony made people have better subjective experience (RW: $b = 0.38$, $p = 0.04$; VR: $b = 0.37$, $p = 0.042$). Without synchrony in the model, task performance did not directly affect feelings (RW: $c' = 0.12$, $p = 0.22$; VR: $c' = 0.10$, $p = 0.28$), and the indirect effect was significant (bootstrap excluded zero). So, neural synchrony fully links performance to subjective experience in both settings. Still, the ceiling effect in ratings suggests we need better ways to measure subjective experience to catch tiny changes.

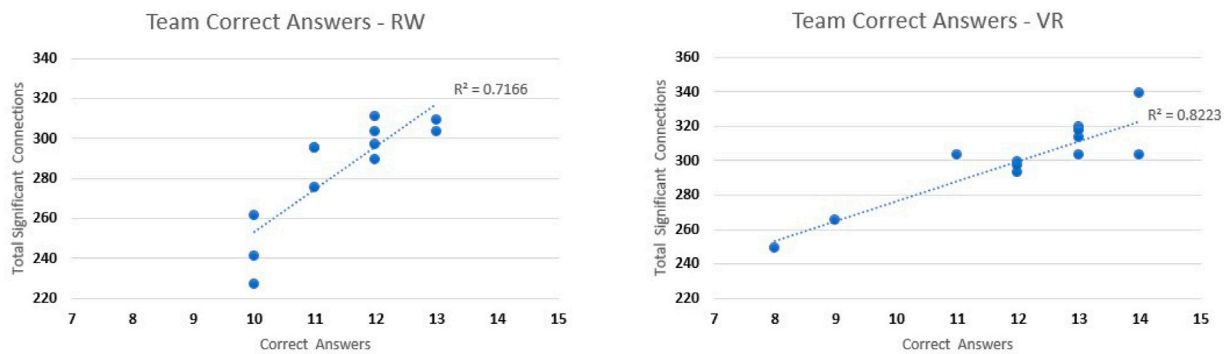


FIGURE 11
Correct answers and total number of significant connections across all bands.

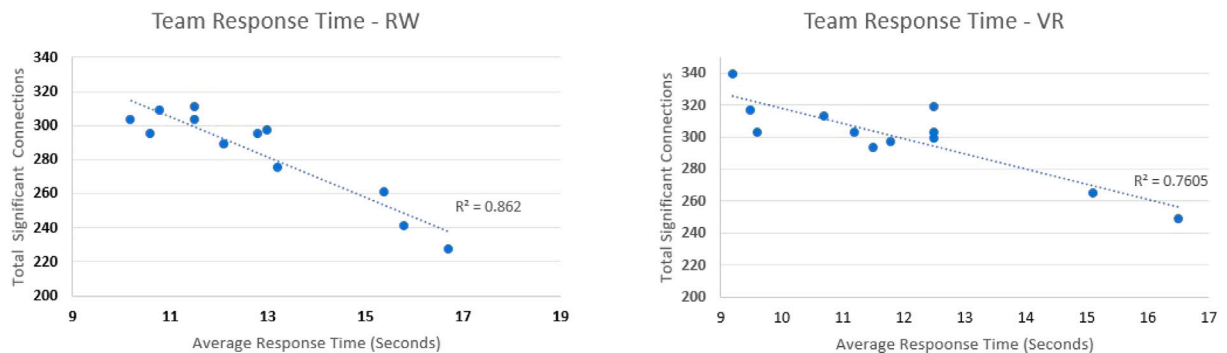


FIGURE 12
Average response time and total number of significant connections across all bands.

TABLE 5 Subjective data analysis result (average and SD in Likert scale rating for RW and VR).

Question	Average (RW)	SD (RW)	Average (VR)	SD (VR)
I felt connected with my partner	6.63	0.74	6.46	0.58
I felt I was present with my partner	6.63	0.77	6.25	1.10
My partner was able to sense my presence	6.63	0.38	6.54	0.62
I enjoyed the experience	6.46	0.72	6.79	0.33
I was able to focus on the task activity	6.67	0.39	6.83	0.33
I am confident that we completed the task well	6.58	0.36	6.33	0.49
My partner and I worked together well	6.71	0.40	6.63	0.38

4.3.2 Participants' VR experience effect

Our study included one group new to VR, four with a single VR-experienced member, and seven where both teammates were VR-familiar. To address the potential confounding effect of participants' VR experience and the limitations of our final sample size ($n = 24$), we conducted an ANCOVA with total significant inter-brain connections as the dependent variable, VR experience as a categorical factor (novices vs. experienced users), and average response time per question (Time) as a covariate. The analysis revealed a significant main effect of VR

experience on Total scores, $F(2, 9) = 5.78$, $p = 0.028$, indicating that VR familiarity influences performance independently of response time, which was controlled to disentangle its potential confounding role such as preventing inflated effects if experienced users responded more slowly. While our sample meets the G*Power minimum ($n = 24$, power = 0.85), we recognize that high inter-individual EEG variability and the complexity of team collaboration may increase Type II error risk, particularly for non-significant findings like the theta-band VR-RW difference (Section 4.2.6).

5 Discussion

The research study detailed in this paper set out to explore the neural correlates of cooperation in VR versus the RW using the hyperscanning technique for a joint attention task. We chose an existing real world visual search task that had previously been found to produce brain synchronization (Szymanski et al., 2017). This was replicated in the RW and in VR to study the similarities and/or differences in the inter-brain connectivity of the pairs undertaking the task. Task completion times and a subjective measures of presence and cooperation were recorded in order to evaluate their correlation with inter-brain connectivity measures.

For both the VR and real world conditions, statistical analysis revealed that dyads with a higher number of significant inter-brain connections performed better at the collaborative visual search tasks than dyads with a lower number of significant inter-brain connections. It also appears that teams with a higher number of inter-brain connections within the three bands (beta, gamma and theta) performed significantly better at the task than dyads that had less number of connections within those bands. Interestingly, studies have shown that alterations in theta band activities in occipital and frontal brain areas can significantly impact memory processing and performance (Takase et al., 2019). Additionally, enhancements in frontal theta and beta oscillatory synchronizations have been linked to improved executive abilities, attention control, and memory maintenance during working memory tasks, showcasing the importance of different frequency band oscillations in cognitive processes (Tian et al., 2021). While there appears to be few studies in VR looking at inter-brain synchrony, the results obtained here appear to suggest that a large amount of inter-brain connectivity within a certain set of bands can be a predictor of outcomes in a joint attention collaborative task.

Our results in this study demonstrate that there appears to be a meaningful correlation of inter-brain connectivity within certain bands and the number of correct answers and time of doing the requested visual search task. It also demonstrates effective collaboration between individuals when they display a certain level of inter-brain connectivity across a range of bands. These results indicate that there is potential to evoke activity in those bands among collaborating individuals which shows some correlation in the number of significant connections and collaboration efficiency without considering the causality. This, in turn, could aid in measuring or monitoring the quality of collaboration between individuals and result in improved task completion times, as based on this study results, there's a correlation and brain synchrony in VR comparable to the same task in the real world.

So, in terms of the three hypotheses, we did indeed see an increase in brain synchronization from individual to team conditions in the real world, reproducing the previous results of Szymanski et al. (2017), so hypothesis H1 was supported. We also observed brain synchronization in the visual search task in VR for most of the EEG bands, so hypothesis H2 was supported. However, there was no significant increase in brain synchronization in the VR condition, compared to the real world condition in task completion time ($t(11) = 2.2$, $p = 0.073$) and number of correct answers ($t(11) = 2.2$, $p = 0.026$), so hypothesis H3 was not supported.

While these results are promising, it must be noted that there is still an element of uncertainty to the research detailed in this paper. Hyperscanning is an emerging technique that has found usage in a number of fields that explore the different facets of collaboration, both in real and virtual environments. A major factor determining the validity of the results obtained via Hyperscanning are the analysis methods. In its current state, there exist several methods for processing data that have stirred a considerable debate within the community with regards to their validity and ability to reliably measure and represent inter-brain synchrony. However, notwithstanding these methods, Hyperscanning has shown itself to be a useful technique to capture neural data from two or more individuals interacting simultaneously both in the real and virtual environments.

6 Limitations of the research

Although these results are very interesting, there are a number of limitations with the study that will have to be addressed in future work. We tried to reproduce the results of a similar real world study Szymanski et al. (2017) and compare it to running the study in a VR environment. So the task employed for this study was very simple and the results obtained may not be generalizable to a wider range of VR activities. In the future we would like to explore a range of different joint activity tasks in VR, such as object matching, tracking, and text comprehension, among others. The task simplicity meant that there was only a small range in the number of correct answers, which may have limited amount of data points for the correlation measures. In the future we will look for tasks that can produce a wider range of performance measures. The participants were all university students or staff which may limit the applicability of the results. For example, elderly may exhibit different behaviours. In the future we plan to test with a wider range of subjects.

Another important limitation was lack of a standard data analysis method or tool in EEG hyperscanning studies to identify synced brain signals, so we had to work on different techniques and prepare custom scripts for data analysis to get reliable results. Automatic visualizing tools for such studies are also not yet available to draw different understandable brain figures and connections. There is a great opportunity for developers to work on such tools to be used in future hyperscanning studies.

In addition to this, it is also important to note that another limitation is the lack of directionality analysis in our PLV results. PLV measures phase synchronization but does not distinguish the direction of information flow, such as whether a “leader-follower” neurodynamic pattern exists, potentially involving enhanced parietal-to-frontal information flow in VR. This could provide insights into hierarchical collaboration dynamics, as parietal regions are associated with spatial attention and frontal regions with executive control. The absence of analyses like Granger causality or Phase Lag Index limits our ability to explore these patterns, which was not feasible in the current study due to time and resource constraints. Future work should address this by incorporating directionality measures to better understand the neural mechanisms of VR-based collaboration.

Technical problems and limitations were also considerable in this study. Placing VR displays on EEG caps added some pressure on a few electrodes and in some cases caused electrode movements and signal weakness. To overcome this issue and have reliable EEG signals, we had to reset the electrodes placements and EEG setup after each condition which increased the study time and led to EEG gel dryness. So we needed to reapply gel on the head to prevent signal loss and enable capture of constant signals. In the future VR HMDs such as the OpenBCI Galea³ will become available which has EEG sensors into the HMD, reducing this problem.

Moreover, the possibility of EEG signal interference caused by the VR head-mounted displays was another limitation of this study. To control or reduce the interference, the participants were asked to avoid unnecessary movements to minimize the electrical noise from the device, movement-related artifacts, or changes in electrode placement when wearing the headset. To address this, future studies could use VR headsets with built-in EEG sensors, which may improve signal stability and reduce motion-related noise. Additionally, multiple signal processing techniques were used to help separate brain signals from unwanted interference. However, we note that other processing methods such as surrogate analysis or machine learning-based noise removal methods can be employed for upcoming studies in the future to enhance the signal quality.

Finally, another limitation was that the study participants were mainly university students, which may not represent the general population. Students often have similar experiences, education levels, and familiarity with technology, which could influence the results. Future research should include a wider range of participants, such as people of different ages, backgrounds, and professional experiences. This would make the findings more applicable to real world settings. Increasing the number of participants and including individuals with different levels of VR experience could also provide insights into how familiarity with VR affects brain synchrony and collaboration quality.

7 Conclusion and future work

In this paper we presented results from one of the first brain synchronization studies using a joint attention task in VR. We observed inter-brain synchrony occurred in the VR environment similar to the real world as well as increased phase synchronization between the brains.

The results confirm that brain synchronization can occur in a joint attention task in VR and produces similar results to those seen in the real-world. This implies that collaborative VR environments could be used as a means to elicit, promote and increase inter-brain synchrony among individuals. VR could be also used to perform more controlled experiments that might help better understanding brain synchronization in the real world, exploring more about the social neuroscience of communication, and creating guidelines for developing better collaborative VR experiences.

There are many directions that this research could go in the future. In the limitations section we outlined some work that could be done to address some of the shortcomings of this study. In addition to this, we would like to explore what features could be added to VR experiences to increase the amount of brain synchronization. For example, in VR it is possible for both people in the real world to have the same viewpoint and share the same virtual body. This shared perception may increase the amount of brain synchronization (Gumilar et al., 2022). Another interesting area of research would be to see if other physiological cues also synchronize in collaborative tasks. For instance, VR HMDs may have integrated eye tracking, heart rate sensors and EEG sensors⁴. Using these, it would be interesting to see if pupil dilation and heart rate demonstrate the kind of synchronization between participants that we have observed with neural activity. Finally, we would like to explore brain synchronization in large group settings in VR, and see if this could be used as a potential team performance enhancement tool in the future.

This research is just the beginning of various work that can be done to explore the potential of VR for social neuroscience studies. We hope that the study detailed in this paper will inspire others to continue research in this area.

Data availability statement

The datasets presented in this article are not readily available because the IP of the data belongs to the University of South Australia and collected data could not be shared. Requests to access the datasets should be directed to unisa.edu.au.

Ethics statement

The studies involving humans were approved by Ms Tess Penglis, Manager of Research Ethics Committee - University of South Australia. The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. Written informed consent was obtained from the individual(s) for the publication of any potentially identifiable images or data included in this article.

Author contributions

AFH: Writing – original draft, Writing – review and editing, Formal Analysis, Investigation, Methodology, Project administration, Resources, Software, Visualization. AB: Writing – review and editing. IG: Software, Writing – review and editing. AM: Software, Writing – review and editing. GL: Writing – review and editing. AC: Supervision, Writing – review and editing. MB: Supervision, Writing – review and editing.

³ <https://shop.openbci.com/products/galea>

⁴ <https://openbci.com/community/introducing-galea-bci-hmd-biosensing/>

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