PsiNet: Toward Understanding the Design of Brain-to-Brain Interfaces for Augmenting Inter-Brain Synchrony

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ABSTRACT

Underlying humanity's social abilities is the brain's capacity to interpersonally synchronize. Experimental, lab-based neuropsychological studies have demonstrated that inter-brain synchrony can be technologically mediated. However, knowledge in deploying these technologies in-the-wild and studying their user experience, an area HCI excels in, is lacking. With advances in mobile brain sensing and stimulation, we identify an opportunity for HCI to investigate the in-the-wild augmentation of inter-brain synchrony. We designed "PsiNet," the first wearable brain-to-brain system aimed at augmenting inter-brain synchrony in-the-wild. Participant interviews illustrated three themes that describe the user experience of modulated inter-brain synchrony: hyper-awareness; relational interaction; and the dissolution of self. We contribute these three themes to assist HCI theorists' discussions of inter-brain synchrony experiences. We also present three practical design tactics for HCI practitioners designing inter-brain synchrony, and hope that our work guides a HCI future of brain-to-brain experiences which fosters human connection.

CCS CONCEPTS

• **Human-centered Computing**; • **Human-computer interaction (HCI)**; • **Interaction paradigms**;

KEYWORDS

Brain-to-Brain Interface, EEG, tES, Neural Synchrony, Inter-Brain Synchrony

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1 INTRODUCTION

Inter-brain synchrony describes the tendency for brain activity to synchronize between people when they interact [39, 45, 81, 90]. As large populations of neurons fire to allow the brain to signal between its substructures, rhythmic patterns of electrical activity emerge known as neural oscillations (or 'brain waves' to the layperson) [96]. These neural oscillations have been observed to synchronize between participants' brains during social interaction [39, 45, 81, 90] (figure 2). It has been argued that this synchronization is extremely beneficial to humanity's evolutionary development and success as a species, facilitates social behavior, and suggests that the boundaries of consciousness may go beyond the individual [10, 39, 45, 81, 90].

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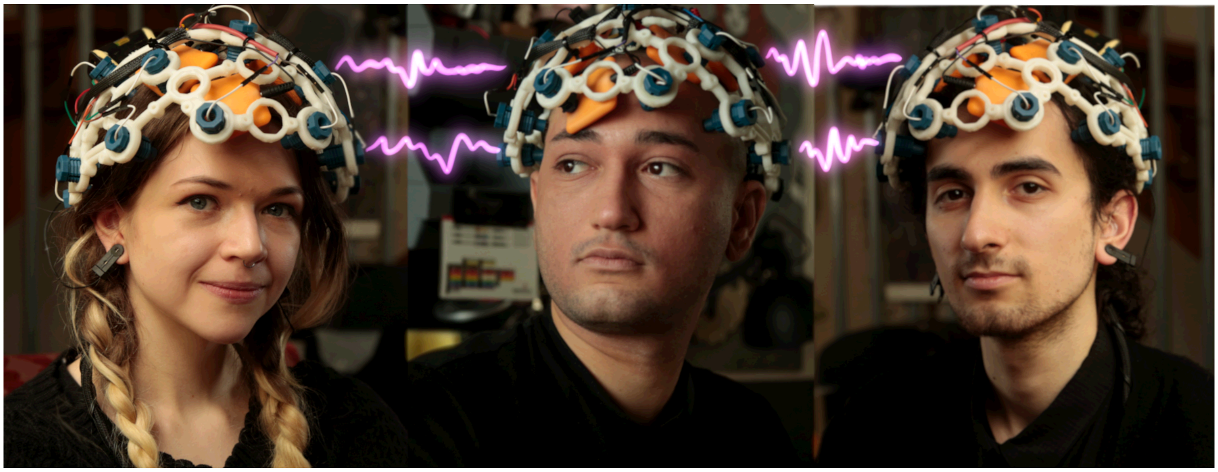

Figure 1: PsiNet is the first wearable brain-to-brain interface allowing us to study the experience of inter-brain synchrony in-the-wild

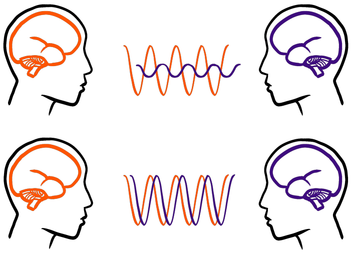

Figure 2: Two asynchronus brains (top) versus two synchronous brains (bottom). Note that neural oscillations can differ between people both in terms of phase (the length of the wave) and amplitude (the height of the wave).

The benefits of inter-brain synchrony are evident when considering the many behaviors and experiences it underlies. For example, romantic couples achieved higher degrees of inter-brain synchrony compared to strangers, which correlated to behavioral synchrony, suggesting that synchronization promotes interpersonal coordination and joint action [45]. Inter-brain synchrony has been found to predict group performance in economic tasks [74] and increases when people play music together [76], complete puzzles together [27], and play games cooperatively rather than competitively [7, 83], even in solving the prisoner's dilemma [26, 39]. Brain synchronisation has also been observed to increase when holding hands, and is associated with the resulting reduction in pain experienced [30]. Further human experiences that benefit from synchronization include positive affect [45], decision making [39], cohesion [11], agreeableness [101], and empathy [30]. These phenomena even translate to digital interactions, with inter-brain synchrony occurring between individuals in virtual environments [9, 32].

An argument could be made for exploring a new class of interactive systems that "augment" inter-brain synchrony. Such systems would artificially increase inter-brain synchrony, sustaining and evoking this pattern beyond what is generally achieved through coordinated human action alone. The addition of such interfaces to our technological toolkit would ultimately provide the foundation for designing technologies that strengthen interpersonal dynamics, empathy and coordination across many application domains, such as strengthening coordination in teams, assisting joint decision-making, heightening playful group experiences, and increasing empathetic communication through social technology. However, we find limited knowledge regarding the design of systems to augment inter-brain synchrony, possibly because inter-brain synchrony has only recently begun to be considered in HCI [9, 33, 61]. However, we find that the few related studies in inter-brain synchrony that do exist are not only conducted in controlled laboratory settings, but have also focused on the quantitative assessments of synchrony oscillations. This focus leaves the experiential aspects of inter-brain synchrony largely unexplored, which is unfortunate considering that such knowledge would be fundamental to understanding the user experience of inter-brain synchrony systems and useful in informing their design. As humans are largely social in all facets of life, it would make sense for these systems to be mobile, to facilitate access to the benefits of increased inter-brain synchrony throughout their day.

Thus, considering this apparent gap in the literature, the present study aims to understand the qualitative experience afforded by inter-brain synchrony systems in the wild. To achieve this aim, we ask the research question: "how do we design synchronising brain-to-brain interfaces to be experienced in-the-wild?" To serve as an artifactual probe in answering this research question, we designed "PsiNet". PsiNet is a novel networked wearable brain-to-brain system, designed to increase inter-brain synchrony within groups by sensing brain activity through electroencephalography (EEG) and by modulating brain activity through transcranial electrical stimulation (tES). We studied PsiNet "in-the-wild" [75], with a study design that was primarily focused on the collection of qualitative experiential data in order to address our aim of understanding the qualitative experience afforded by inter-brain synchrony systems in natural settings. Our primarily qualitative exploration was also supplemented by a smaller quantitative analysis of inter-brain synchrony by measuring the circular correlation coefficient of group EEG data before and after brain stimulation, to verify the system's potential in synchronizing brain activity interpersonally. Three themes emerged from the results of this work, and we have consolidated them to contribute to the parameterization of the user experience of brain-to-brain interfacing. We use this knowledge to articulate an initial framework for discussing brain-to-brain interface experiences which we hope will benefit HCI theorists of inter-brain synchrony-based experiences. Additionally, we present design tactics for HCI practitioners and designers interested in creating future systems. Our aim is to advance the HCI community's understanding of designing systems to promote inter-brain synchrony, and guide the design of brain-to-brain interfaces toward a technological future in which they foster human connection. We detail our contributions below:

- A novel wearable brain-to-brain interface system designed for inter-brain synchrony, capable of being deployed in-the-wild, and with scalable user group sizes.
- Results from a study of the user experience of brain-to-brain interfaces for inter-brain synchrony.
- An initial framework consisting of theoretical and practical insights on the design of BBIs for inter-brain synchrony, consisting of:
  - An elucidation of the major themes underlying the user experience of brain-to-brain interfaces in a naturalistic setting. These themes can be useful for researchers aiming to analyze the user experience of brain-to-brain interface systems systems.
  - Design tactics for the creation of future wearable inter-brain synchrony-focused BBI systems. These tactics can be useful for design practitioners aiming to create future BBI systems to foster human connection.

2 RELATED WORK

In order to answer the research question, we learned mostly from prior work on brain-to-brain interfaces, and brain-computer interfaces for inter-brain synchrony.

2.1 Learning from brain-to-brain interfaces

Brain-to-brain interfaces are neural interfaces that allow for signal transmission directly between brains by reading from one brain, processing that information, and then stimulating another. BBI's are relatively new. Their first incarnations demonstrated that tactile and motor information could be sent from encoder rats to decoder rats, who reproduced the encoder's behavioral choice to press the correct lever to receive a reward [68]. The information was extracted from microelectrodes implanted in the encoder rat's primary motor cortex, and then transmitted directly to a decoder rat's brain via microelectrodes in their primary motor cortex. Researchers also used transcranial focused ultrasound (FUS) to communicate information between a human and a rat [99]. Specifically, a human participant communicated intention by looking at a strobe light, producing changes to brain activity associated with vision, which was recorded by EEG. Detecting this recording triggered a FUS-induced excitation of an area of the rat's motor cortex, causing tail movement.

While these initial studies have shown BBI systems' capability to transmit sensory information between two organisms, translating BBIs towards human-to-human systems has been comparatively limited. One such human-to-human study involved internet-mediated brain-to-brain communication, in which an "emitter" participant's motor-imagery was detected by EEG, to communicate a '1' or '0', interpreted by the recipient as a magnetically induced phosphene (the visual illusion of a bright flash of light brought on by brain stimulation) [31]. While we acknowledge this work represents a leap forward as the first human-to-human BBI, we also argue that binary signaling does not offer much past proof-of-concept. While these prior works represent impressive technological feats, their lab-bound nature and specificity present contemporary brain-to-brain interfaces as over-engineered telegraphs, obfuscating how and why they might be used beyond the lab, More recent BBI systems have similarly used the restrictive, specific, low bandwidth modality of binary signaling through phosphenes. For example, BrainNet [41] used an EEG interface to send a decision to rotate or not rotate a block in a Tetris-like game from two senders, via the internet, to one receiver by inducing phosphenes through magnetic stimulation. While this system demonstrates the capability for BBI systems to be employed in group problem solving and in interactions of more than two participants, the limited means of information transmission and its lab-based setting fails to embrace the ambiguity, richness, and complexity of the human brain, all of which have been argued as important considerations when designing brain-based interactions [13, 14, 79]. Consequently, when these systems are removed from their lab setting and placed in the real world, we find that they become over-engineered telegraphs, missing out on the full potential of BBIs to share rich and detailed experiential information between individuals.

These limitations are unnecessary considering recent technological advances, including the miniaturization of brain sensing and brain stimulating technologies. These technologies could be used to develop wearable BBI's that could be studied in naturalistic settings. Wearable brain-computer interface (BCI) systems are becoming commonplace in HCI research, and there has been a recent increase in wearable neurostimulatory devices. In combining BCI and neurostimulation technologies, we have an opportunity to take brain-to-brain interfaces out of the lab, and into the wild, ushering in a new generation of wearable brain-to-brain interfaces for augmenting inter-brain synchrony. While prior research noted above exemplifies a growing move toward feasible brain-to-brain information exchange. However, rather than promoting inter-brain synchrony, the associated systems "task-ify" cognitive activities by using the conscious and purposeful acquisition of a predefined brain activity as a biological controller.In contrast, we propose that BBI systems should learn from contemporary "read-only" brain-computer interfaces, especially those contextualized within HCI research, as these have demonstrated potential for augmenting inter-brain synchrony, which we discuss in the next section.

2.2 Brain-computer interfaces for inter-brain synchrony

Several non-brain-to-brain BCI installations have explored inter-brain synchrony. However, these explorations have mostly been in artistic contexts [61], limiting the design knowledge for ubiquitously augmenting inter-brain synchrony. For example, "Hive Mind" is an installation in which two performers on a stage generate light pulses and sound in synchrony with the oscillations of their brains. This process creates a feedback loop where the performers' and the audience's brains enter synchronicity with the multi-modal presentation, cyclically modulating each other until participants reach and share an altered state of consciousness. "SocioPathways" [24] demonstrates how to apply inter-brain synchrony to game design. Players are represented as dots on a screen and their dots become closer to other players' as they become more synchronous with each another. This process continues until the brains of the group converge on a singular synchronous oscillation and all the dots move into a singular large clump. "NeuralDrum" [67] is an inter-brain synchrony-focused drumming game where the goal of the player is to hit objects in time with a musical rhythm. By situating the experience within extended reality and employing players' EEG activity, the game expands traditional drumming games by adding visual and audio distortion as players become more synchronous. Through this mechanism, the game becomes easier while players are out of sync, and harder as they became more synchronous. However, participants reported that it was difficult to interpret synchrony, and we anticipate that combining added difficulty with higher synchrony might punish and discourage, rather than facilitate, inter-brain synchrony.

While more examples of inter-brain synchrony-based art installations exist (see "Brain Art" for an exhaustive list [61]), we find that most are similar in that they use some sensory modality such as sounds or visualisations to represent synchrony to audiences. While these works demonstrate how brains can interact with each other through technology, we contend that our work goes further by offering a more direct channel between brains. Furthermore, in these prior works, the systems require the participants to be situated in some form of installation, be it a stage or a large display they share. Moving forward, we instead extend this knowledge toward the design of wearable systems such that users may benefit from augmented inter-brain synchrony in-the-wild.

2.3 Opportunity for inter-brain synchrony brain-to-brain interfaces

While the prior research hereto discussed has demonstrated proof of concepts for the viability of brain-to-brain interfaces and the promotion of inter-brain synchrony through social BCI systems, we have found no prior works of these concepts in concert. More specifically, there appears to be an absence of research focused on designing for experiences of brain-to-brain interfaces for inter-brain synchrony. We argue that there is an opportunity to further our understanding of inter-brain synchrony brain-to-brain interfaces. Considering the benefits that come with inter-brain synchrony, and the wide variety of situations in which synchronization can take place, this knowledge is important because it has the potential to allow groups to benefit in their day-to-day living. With these opportunities in mind, this paper addresses the research question: "how do we design synchronising BBI's to be experienced in-the-wild?"

3 PSINET

In order to begin answering the question above, we designed PsiNet. PsiNet is composed of three wearable units and an offsite server hosting a reinforcement learning agent that supervises the system. While inter-brain synchrony is observed when humans participate in coordinated activities [45, 90], PsiNet explores how to design technologies that augment inter-brain synchrony, specifically through perturbing brain frequency dynamic toward the underlying neural activity seen during inter-brain synchrony, sustaining and evoking this pattern beyond what is naturally possible through coordinated human action alone. The following sections describe the design of PsiNet and provide an overview of the system architecture and a description of the algorithm aimed to support inter-brain synchrony.

3.1 System architecture

Each wearable unit consists of an OpenBCI 16 channel Cyton EEG board, mounted onto an OpenBCI Ultracortex Mark IV headset, which houses 16 Ag/AgCI dry EEG electrodes (figure 3). Electrodes were configured following the international 10-20 electrode configuration (figure 4). Each headset was modified to house an additional four 5cm x 5cm sponge tES electrodes situated at the positions of F2, F3, F4, and C3, stimulated by an onboard "foc.us V3" tES device. The Foc.us V3 was chosen as PsiNet's tES module due to its very small size (approximately the size of a matchbox) allowing it to be wearable, contrasting to the desktop form factor of other tES systems we considered. Furthermore, the foc.us V3 is capable of producing both tDCS and tACS stimulation, allowing us to implement the full range of tES stimulation types we identified to be useful to our design based on our review of tES literature, which will be further discussed in section 3.5 (see table 2). To facilitate the collocation of EEG and tES electrodes on the same 10-20 positions, a hole was cut in the top corner of each tES sponge holder, and the ultracortex prong holding the EEG electrode was passed through the hole. A moat of epoxy resin was moulded around the EEG electrode at the contact point with the tES electrode sponge holder to both fasten the EEG electrode in place while also serving to isolate the EEG electrode from the tES electrical output. Participants were also fitted with a small carry bag that contained a battery-powered Raspberry Pi 4, connected to the headset via Bluetooth, with a tether from the Pi to the headset to power tES stimulation. The Raspberry Pi was also connected through participants' home Wi-Fi to a server hosted by the researchers where de-identified data was saved securely.

The headset sensed the electrical activity of each participant's brain and sent data to their Raspberry Pi for processing. This processing resulted in the classification of the participant's brain activity as interpreted by our algorithm. Data was sent in 10-second epochs since the system requires a window of time on which to base its classification of the user's state. Ten seconds was chosen as it allows classification to be robust to noise, movement, and eye-blink artifacts, while being short enough to respond quickly to changes in the user's brain activity [48].

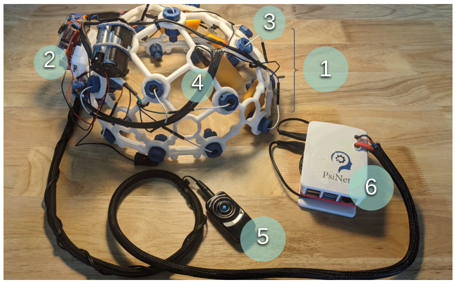

Figure 3: The components of PsiNet: 1 - Ultracortex, 2 - OpenBCI Cyton Board, 3 - EEG Electrodes (blue bolts), 4 - tES Electrodes (orange squares), 5 - tES Device, 6 - Raspberry Pi

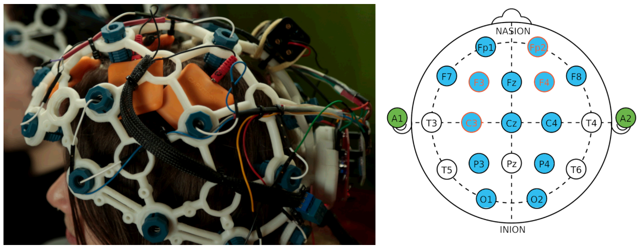

Figure 4: The left shows a closeup of PsiNet fitted to the head of a user. Note the orange sponges for tES stimulation. The right illustrates PsiNet's electrode configuration mapped on to the internation 10 - 20 EEG electrode positions. Positions in blue indicate the positions of EEG electrodes, and orange outlines indicate a tES sponge electrode also fitted in that position. Green indicates the positions of the ground and reference EEG electrodes.

In describing the flow of information through PsiNet at a high level, the pipeline (see figure 5) underlying PsiNet can be described as having four major components. First is the EEG pre-processing and subsequent classification of the brain activity of each member in the group through measuring individual event-related desynchronization/synchronization. Second is a weight matrix, which considers what brain state each user is in, and then uses this information to decide who in the group receives stimulation, and what stimulation they will receive, with the aim of increasing inter-brain synchrony. Third is the tES stimulation itself. Finally, fourth is the calculation of the inter-brain synchrony of the group before and after being stimulated, with the result of this calculation being used to reinforce the weight matrix such that it better learns how to increase inter-brain synchrony in the next stimulation.

3.2 Preprocessing and noise reduction

Before interpreting the brain activity, PsiNet first employs a series of processes to filter the EEG signal, removing noise, and extracting relevant features. To do this, raw EEG data is received in real-time and passed, in 10-second windows, through a fourth order Bessel bandpass filter between 0.5-48Hz; the standard relevant frequency range in EEG signal processing [35, 93]. To correct for noise, including ambient signal, eye blinks, and muscle artifacts, we applied a wavelet-based denoising filter called 'coif3' that efficiently improves signal-to-noise ratios compared to other wavelet-based filters [4, 44]. A mean smoothing filter was also applied [8] in addition to the wavelet denoising filter, adjusting for large shifts in window variance that might be brought on by blinks and muscle artefact . Finally, we calculated Welch Power Spectrum values using a Blackman-Harris window for alpha (8-12.5Hz), beta (12.5-30Hz), theta (4-8Hz), and mu (9-11Hz) bands [47].

3.3 Classifying brain activity

PsiNet classifies seven different brain activity states: concentration, focus, stress, excitement, relaxation, boredom, and motor activity/imagery. Table 1 provides the theoretical basis underlying the classification of each state of brain activity, as well as the methodological details of its execution. The rationale for this classification is to accommodate a variety of different states that may arise during an average user's daily routine. While future BCI's may be able to capture a more broader range and nuance of the subjective human experience, we are currently constrained by both our computational and neuroscientific knowledge. Consequently, we have attempted to approximate this range through the selection of broad yet common brain states that have each been verified as reliable [6, 28, 36, 53, 57].

3.3.1 *Event related desynchronization/synchronization.*

To interpret brain activity, PsiNet employs an "event-related desynchronization/synchronization" (ERD) approach [6, 23, 43, 51]. We note that ERDs are distinct from inter-brain synchrony in that ERDs consider synchronization within the brain of a single individual, rather than between individuals. For instance, it is understood that short-lasting amplitude changes of neural oscillatory rhythms within a predefined feature space in an EEG's spectra corresponds to cortical activity [70]. Combining knowledge of where this cortical activity is taking place with the observation of an increase or decrease of amplitude in that specific feature space, we are able to deduce the underlying brain activity responsible for that shift in spectral amplitude [23, 43, 51]. Therefore, if we have the foreknowledge of which EEG channels and spectral power density bands are associated with a specific state of brain activity, we can classify brain activity as being in that given state by observing changes in those features. In practice, classification of a user being in a given state was discrete binary judgement made in real time by PsiNets algorithm, triggered by a either an increase or decrease in EDR bandpower in bands and channels channels relevant to the mental state relative to the participants fixed baseline, based on the specific criteria identified for each mental state described in table 1 in the column "classification conditions". These classifications were not logged for later analysis but rather calculated, consumed and destroyed in real time to facilitate the functioning of the system. Table 1 provides more details for each individual classification.

We acknowledge that other approaches to interpreting brain states through EEG could have been adopted. Specifically, machine learning (ML) has become almost standard [55]. Whilst we adopt a reinforcement learning system for guiding the distribution of stimulation across participants (later described in 3.4), we opted

Brain State	Theoretical Basis	Classification Conditions
Concentrate	Increased theta band power over the frontal mid-line associated with high cognitive load[57]. Decreased alpha band power over parietal and occipital regions associated with high cognitive load [6].	Negative theta and alpha ERD% (equation 1) in F1, F2, F3, F4, F7, F8. Positive theta and alpha ERD% in O1, O2, P3, P4.
Focused	Increased beta and theta band power in Fp1 and Fp2 associated with higher concentration. [53]. Significant decreases in beta and theta band power found over C3, C4, and O2.	Negative Beta and theta ERD% in F1, F2. Positive beta and theta ERD% in C3, C4, O2.
Motor Activity	Decreased mu band power in electrodes over the motor cortex when moving, imagining, or watching motor movement [28, 36].	Positive mu ERD% in C3, C4, Cz.
Stressed	Asymmetry of frontal alpha-beta activity between brain hemispheres correlate with valance [2, 12, 46]. Increase in the alpha/beta ratio on the mid-frontal cortex correlate with arousal [2, 46, 73].	Positive Log2 of alpha/beta ratio ERD% in Fz. Negative difference between alpha/beta ratio ERD% in F4 and alpha/beta ratio in F3.
Excited	As above.	Positive Log2 of alpha/beta ratio ERD% in Fz. Positive Difference between alpha/beta ratio ERD% in F4 and alpha/beta ratio in F3.
Relaxed	As above.	Negative Log2 of alpha/beta ratio ERD% in Fz. Positive difference between alpha/beta ratio ERD% in F4 and alpha/beta ratio in F3.
Bored	As above.	Negative Log2 of alpha/beta ratio ERD% in Fz. Negative difference between alpha/beta ratio ERD% in F4 and alpha/beta ratio in F3.

Table 1: Brain states measured by our algorithm, the theoretical basis for making that classification, and the conditions that must be met for that state's classification.

to classify brain states using a rule-based system rather than a ML system. Using a rule-based approach (ERD) we are able to make inferences of the user's brain states based on differences between their current EEG activity and values derived from a resting baseline, with the baseline accounting for unique biometric properties of the user at rest. When compared to building a machine learning model, a baseline of averages would require significantly shorter time to establish (seconds) as demonstrated in past studies [20, 22, 66, 71, 78, 80, 86, 87]. This is in contrast to personalised machine learning models, which for tasks involving the detection of cognitive states often require hours per participants and unique training tasks and sessions dedicated to training the classification of the different classification classes of interest, which may even necessitate multiple sessions over multiple days before the participant can begin to use the system [3, 55, 63].

We also acknowledge that our approach of interpreting brain activity from EEG as "states" embeds our work in a larger ongoing contention regarding the interpretation of biodata as stateful [38, 84, 85]. For example, some have warned that the entanglement of psychology and computer science has led to the "calculability of human subjectivity," quantizing the individual into information for psychographic models through which individuals can be digitally categorized [84, 85]. Furthermore, some have argued that rather than designing for discretely classified presentations of physiological or psychological activity, designers should instead consider ambiguous displays that allow for the user to form their own meaning [38]. We nonetheless maintain our stance in applying a stateful approach to the interpretation of EEG, grounding our system in neuroscience's paradigmatic conceptualization of brain activity as dynamically stateful [29, 58, 77, 92]. The functional neuroanatomical representations of brain states like affect are robust, generalizable, and produce predictable reactions in response to corresponding stimuli [18]. Also, considering PsiNet employs neurostimulation, the safety of employing non-categorical tES stimulation is relatively unknown, as we find that neurostimulation research to date has been focused on discrete simulations for categorical brain functions.

3.3.2 *Establishing a baseline for calculating ERD's.*

To calculate ERD's, we require an individualized baseline recording for each participant, which quantitatively describes their brain in a normal resting state. Since EEG signals can differ between individuals due to age, head shape, hair density, and so on, comparing absolute powers of frequency bands is not advisable [6]. Instead, we calculated ERD's as a percentage divided by the baseline [6].

$$ERD\% = 100 \times \frac{baselinebandpower - presentbandpower}{baselinebandpower} \tag{1}$$

Each day of system use, the first 10 seconds were considered for calculating baseline values for ERD classifications (again, we stress that this is separate to the calculation of inter-brain synchrony). Our choice of a 10 second baseline was informed by previous studies also employing ERD BCI paradigms. We found that previous works employed baselines ranging from less than 1 second to 10 seconds. Specifically, we found studies to report adopting ERD baselines of:

0.1 second [78], 1.5 seconds [22], 3 seconds [20, 66, 87], 4 seconds [71], and 10 seconds [80, 86]. Considering this, we decided to implement a baseline of 10 seconds to err on the side of caution finding it was a conservative time window. Participants were informed that the first 10 seconds of use would form a baseline that would be important for the system to function correctly. Participants were instructed to get into a comfortable and unoccupied state, only turning the system on when they felt they were ready.

3.4 Weight matrix calculations

Once the concurrent brain activity of each user was classified, classifications were sent to the central server. The server hosts a reinforcement learning agent (a weight matrix) that decides which group member receives what kind of neurostimulation based on the brain activity of other members of the group, with the agent motivated to ultimately increase the group's inter-brain synchrony. After classifications were made, a binary state vector was generated for each group member, in which a "1" signifies that the user met the conditions for that state, and a "0" indicates they did not. Concatenating these into one state matrix *S*, we get, for instance:

$$S = \begin{bmatrix} [l] & \text{Con} & \text{Foc} & \text{MI} & \text{Str} & \text{Exc} & \text{Rlx} & \text{Brd} \\ \text{P1} & 1 & 0 & 1 & 0 & 1 & 0 & 0 \\ \text{P2} & 1 & 1 & 0 & 1 & 0 & 0 & 0 \\ \text{P3} & 0 & 1 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \tag{2}$$

The state matrix is then multiplied by a weight matrix $\mathrm{W}_{\mathrm{i,j}}$, where entry (*i,j*) represents the probability that a user's state *i* will trigger stimulation *j* in the rest of the group. The weightings themselves were initially set to favor intuitive outcomes while remaining close to chance value. The system was reinforced by changes in the group and weightings were updated according to favorable pairings. The exact initial starting values of the matrix were made as a design decision based on trial-and-error experienced gained through prototyping the system. The initial $\mathrm{W}_{\mathrm{i,j}}$ matrix was:

$$W_{i,j} = \begin{bmatrix} & motor & concentrate & relax & phosphene \\ concentrating & 0.5 & 0.6 & 0.5 & 0.5 \\ focused & 0.5 & 0.6 & 0.5 & 0.5 \\ motor-imagery & 0.62 & 0.5 & 0.5 & 0.5 \\ stressed & 0.5 & 0.5 & 0.5 & 0.59 \\ excited & 0.5 & 0.5 & 0.5 & 0.5 \\ relaxed & 0.5 & 0.5 & 0.5 & 0.5 \\ bored & 0.5 & 0.5 & 0.5 & 0.5 \end{bmatrix} \tag{3}$$

We then multiply these matrices:

$$S{*}W_{i,j} = \begin{bmatrix} & motor & concentrate & relax & phosphene \\ participant1 & 1.62 & 1.6 & 1.5 & 1.5 \\ participant2 & 1.5 & 1.7 & 1.5 & 1.59 \\ participant3 & 1 & 1.1 & 1 & 1 \end{bmatrix} \tag{4}$$

Each person then receives the stimulation type with the highest magnitude, which does not belong to their row. In this case, we get:

$$\begin{bmatrix} & candidateoutputstimulation & receivedstimulation \\ participant1 & motor & concentrate \\ participant2 & concentrate & motor \\ participant3 & concentrate & motor \end{bmatrix} \tag{5}$$

If group neural synchrony increases, the system rewards each *i,j* weighting that was not zeroed by the S matrix from the corresponding column in the $\mathrm{W}_{\mathrm{i,j}}$ matrix by 0.05, or reduces it by 0.05 if synchrony did not increase. In the above example, if the "motor" synchrony stimulation from participant 1 was run on the other participants and an increased inter-brain synchrony is observed within the group, the "concentrating", "motor-imagery" and "excited" entries under the "motor" column of $\mathrm{W}_{\mathrm{i,j}}$ would each increase by 0.05, increasing the likelihood that these pairings result in motor stimulation in the future, where this new $\mathrm{W}_{\mathrm{i,j}}$ will function.

3.5 tES stimulation

After the weight matrix decides who to stimulate and which type of stimulation to use, PsiNet then delivers said stimulation through the use of transcranial electrical stimulation (tES). The decision to use tES was multifaceted. Our primary motivation was due to the technology's portability, with the model that we used being under 5 cm cubed, battery-powered, and Bluetooth compatible.

3.5.1 tES with EEG. We acknowledge that tES produces electrical activity and introduces exogenous current to the brain. Hence, there is the potential for the stimulation to introduce noise to EEG readings. In anticipation of this, we designed the system such that the EEG of a given participant would not be read whilst they were being stimulated. This absence in the data stream did not interfere with assessing inter-brain synchrony, as measures of inter-brain synchrony were taken just before stimulation and 30 seconds after stimulation. Thus, EEG data during stimulation was not needed for the calculation of post-stimulation change in inter-brain synchrony. Furthermore, as classifications could not be made during stimulations due to the absence of data, this simply meant that participants could not stimulate others while they themselves were being stimulated.

3.5.2 Stimulations and electrode positions. The electrode positions chosen for tES stimulation are described in Table 2 and expressed using anatomical features and international standard 10-20 electrode positioning, based on their validity from past research [72, 89]. We considered these choices of stimulation types to be acceptable because they appear consistently across tES reviews, and their efficacy is validated as producing consistent results [72, 89]. We note that we employed the lower limit of the recommended time for each stimulation to prevent over-stimulation [62, 98] (table 2).

3.5.3 Classification-stimulation pairings and the experience of stimulation. We found that our chosen tES stimulations could coincidentally be easily paired with the EEG classifications we employed, with all EEG classifications having a thematically corresponding stimulation. To further understand how these classifications and stimulations relate to each other, four researchers trialed the stimulation on themselves and individually took notes describing their

Stimulation Name	Stimulation Locations	Parameters	Duration
Motor	Between C3 and rSupraOrbital	tDCS; 1.5mA; anodal [89]	2 minutes
Relaxation	Between F3 and F4	tDCS; 2mA; anodal [89]	2 minutes
Cognition	Between F3 and rSupraOrbital	tDCS; 2mA; anodal [89]	5 minutes
Phosphene	Between F3 and F4	tACS; 1.5mA; 12Hz; bipolar [72]	10 seconds

Table 2: tES stimulation names, electrode locations, parameters, and duration of each stimulation type

experience as soon as the simulation was complete. Each researcher then compared notes and coded each experience. Experiences with common codings across each researcher were then described generally by the first author and compared to descriptions in the literature. A summary of descriptions is provided in table 3.

3.5.4 Safety features. We followed safety recommendations from the device's user guide and the literature. With respect to use of tES stimulation in a non-clinical setting, we tailored our stimulation to be below the safe maximum [62, 98]. Considering the sources in table 2, we implemented a number of steps to ensure that parameters were below that of what is recommended. This included long "cooldown" periods between simulations to allow for endogenous neural activity to return to normal before a sequential stimulation and amperage limits that did not exceed 2mA. We also maintained an exclusion criteria during recruitment to avoid populations that might be at risk of harm when using PsiNet. This included the following conditions: a history of brain surgery, head trauma, and/or cognitive deficit; a history of tumor, stroke, seizures, epilepsy, or other intracranial diseases; the implantation of intracranial metal; the wearing of a pacemaker; and pregnancy.

3.6 Measuring inter-brain neural synchrony

Once the system administered neurostimulation, the system calculated whether that round of stimulations increased the group's inter-brain synchrony. If the system was successful in increasing inter-brain synchrony, the agent was rewarded, strengthening the connections between inputs and outputs that lead to that result. In related works, measures of inter-brain synchrony are most often measured using Phase Lock Value (PLV) and Phase Lock Index (PLI) [9]. However, Burgess et al. [17] found that PLV and PLI can result in spurious hyper-connections when study conditions are not well-controlled. Considering this, we chose the circular correlation coefficient (CCorr) [40] as our measure of neural synchrony, as it has been shown to be more robust [17].

CCorr is defined as:

$$CCorr_{\phi,\psi} = \frac{\sum_i sin(\phi - \overline{\phi}) sin(\psi - \overline{\psi})}{\sqrt{\sum_i sin^2(\phi - \overline{\phi}) sin^2(\psi - \overline{\psi})}} [17] \tag{6}$$

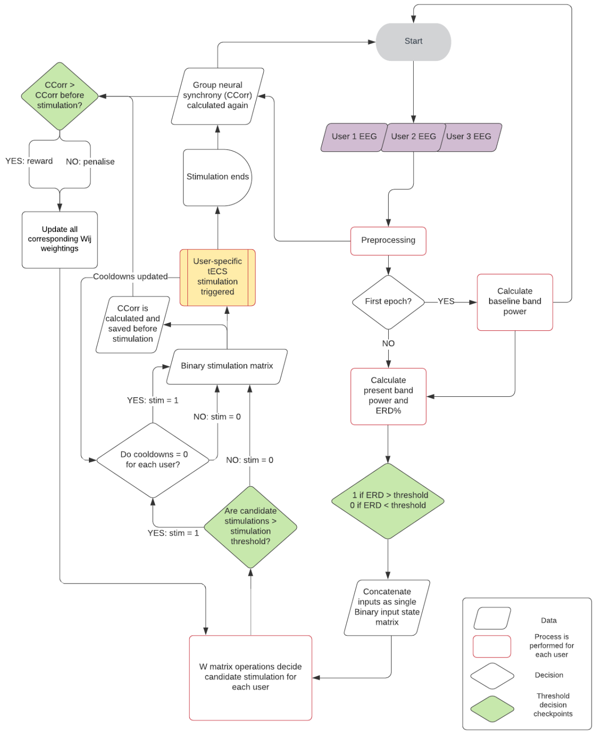

Figure 5: Pictorial depiction of the algorithm behind PsiNet. Where ϕ is one user's phase angle at time i, ψ is another user's phase angle at time i, and $\bar{\phi}$ and $\bar{\psi}$ are the mean phase angles over that epoch. High covariance and CCorr values closer to 1 indicate synchrony, while low covariance and CCorr values closer to 0 indicate little synchrony [37].

Pairwise CCorr values for all participants were calculated, and transformed to Fisher's z; letting CCorr equal r:

$$z = \frac{1}{2} \log_e \left(\frac{1+r}{1-r}\right) \tag{7}$$

These z values were averaged over, and this average was then transformed using the inverse of (7). These transforms were done to circumvent the bias introduced from averaging over multiple correlation coefficients [82]. In regard to how and when group inter-brain synchrony was measured, we assessed group inter-brain synchrony though taking readings of CCorr just before each stimulation, and 30 seconds after each stimulation.

3.7 Preventing trivial observations of inter-brain neural synchrony

To measure changes in inter-brain synchrony resulting from the presented stimulation, we made comparisons between CCorr just before the initiation of stimulation and 30 seconds after stimulation was completed. This time window was chosen to mitigate the chances that readings of increased synchrony were due to participants cognitively attenuating toward the sensations associated with the stimulation, rather than the neuronal activity resulting

Stimulation Name	Literature Description	Our Experience
Motor	Experiences of heightened reflexes and reaction times, a heightened desire to move, and a predisposition toward thinking about moving [89].	Feelings of restlessness and strong mental imagery of performing movements such as “hoisting a flag” while our eyes were closed.
Relaxation	Drops in physiological activity indicative of arousal, such as a decrease in heart rate and with reported experiences also indicating a lowering of self-perceived arousal [89].	Mild feelings of heaviness.
Cognition	Experiences of heightened mental acuity, including improvements in focus and concentration and improvements in the performance of tasks designed for testing cognitive abilities such as recall and cognitive load [89].	Feelings of heightened arousal, with intensity ranging between a feeling of increased energy, to feeling agitated or hyper-vigilant.
Phosphene	Perceptions of flashing lights in the periphery of the visual field, which blink at the speed of the simulation’s frequency (e.g., a stimulation at 12Hz will result in seeing twelve blinks per second) [72].	Our own experiences corroborated this experience.

Table 3: Comparisons of experiences of tES stimulation documented in the literature with our own documented experiences.

from the stimulation, by providing a time window for their brain activity to normalize and habituate to the introduction and subsequent removal of the sensation of stimulation. We believe this time window was short enough to prevent measures of change in synchrony that might have resulted from participant activities or interpersonal interaction. Therefore, any increase identified after stimulation was most likely due to the tES stimulation itself and not caused by situational factors or other stimuli. Finally, the system rewards the relevant weights in Wi,j if this final value is greater than the CCorr value measured just before stimulation occurred.

4 METHOD

The following sections detail the methods we used to study the user experience of PsiNet.

4.1 Participants

Nine participants were recruited for our study, four males and five females, with no participants identifying as non-binary or self-described. There was a mean age of 35 years (SD = 14.34). Participants were recruited as groups of three. This included families, housemates, and close friends. Participants were recruited from a healthy, non-clinical population. To gather our sample, we advertised our study via our lab’s mailing list and social media pages. Participants were given no compensation for participation. They were seemingly participating in the study out of genuine interest. As the study was conducted toward the beginning of the pandemic wherein many people were at home but not working, participants often stated they were excited to participate because they "wanted something to do".

The choice of focusing on participant groups from a shared household was multifaceted. Firstly, the study was conducted during a Covid-19 lockdown. Consequently, we were unable to conduct a study in which participants from other households could congregate and use the system together. Furthermore, the sharing of a single IP address between participants was greatly beneficial in ensuring a stable connection between headsets during use sessions, as all headsets were connected on the same local network. Co-location also had the added benefit that all participants were more likely to be available at similar times, maximizing the time they could spend using the system together. Participants completed a medical questionnaire to ensure they did not exhibit any conditions listed in the exclusion criteria. Participants provided informed consent before beginning their participation in the study.

4.2 Procedure

Our study of PsiNet employed an "in-the-wild" approach, which can be described as a research design that centers on studies taking place outside the lab and situated within naturalistic settings such as homes and communities for extended periods, with the intention that researchers develop an understanding of the impacts and affordances given technologies have on "real-world" day-to-day life [16]. We intended this study to be an exploration of the themes and factors underlying the design and associated user experiences of inter-brain synchrony interfaces. The in-the-wild approach allowed us to uncover naturally occurring experiential themes that emerged through interacting with PsiNet, highlighting them for more directed future studies using controlled experimental designs with specific hypotheses. With this in mind, we opted not to constrain participant use of the system to facilitate an exploration of potential naturalistic use cases and contexts, wanting to observe how participants explored how this technology could fit into their lives.

Following ethics board approval, groups were given PsiNet headsets. Each group was to use PsiNet at their own discretion over three days. Participants were free to go about their daily activities while wearing PsiNet. Participants were instructed to try and use the system for at least 15 hours total during their time with PsiNet (i.e. not 15 consecutive hours but rather spread over the time they had the system). Participant reports of system use illustrated that the system was only used on average 3.81 hours per participant. This may have been due to the system being uncomfortable to wear for extended periods, which will be future discussed in the qualitative results.

Before receiving their PsiNet headsets, participants provided measurements of the circumference of their heads to ensure a good fit, connection to the scalp, and correct electrode placement. Three sizes were available to each participant: small (40-50cm), medium (48-58cm), and large (58-65cm), and each size could be adjusted by loosening and tightening screws supporting the headset's electrodes.

4.2.1 System use. Participant groups were sent their PsiNet headset in the mail. Participants were instructed to wear the system whenever possible. Each group consisted of three group members within a single household who were required to wear their headsets concurrently during each use session (the system did not provide stimulation unless all group members wore their PsiNet headset).

For each groups' first session, participants were guided on setting up the system through a teleconference meeting, in which the researchers ensured that PsiNet was properly fitted and that the system was running correctly. The researchers were able to remotely monitor the data, ensuring that the system was interfacing with the brain correctly and that the data being passed through the system was of good quality (e.g., if the electrodes were exhibiting good impedance and producing clean signal). During each session, participants notified the researchers when they were about to begin using the system via a call or text, allowing the researchers to monitor the data stream to again ensure proper operation of the system, and good quality data, while also enabling troubleshooting of problems and to provide support. This support was necessary for all groups, as there were house-specific startup issues when participants used the system for the first time.

How PsiNet worked specifically was omitted, allowing participants to establish their own understanding. Specifically, we explained to participants that there is a natural tendency for human brains to synchronise during the performance of social activities. We then stated that we designed a system that attempts to artificially induce synchronous brain activity through brain stimulation. Finally, we explained to participants that we were interested in exploring what kind of experiences such a technology would create, and what kind of uses people might find for it in day-to-day life. However, the first group contacted us requesting more information about the stimulations and therefore knew the four different stimulation types. Participants were informed that "there is no predefined task for [them] to complete with PsiNet. Rather, we [encouraged them] to use PsiNet at will in [their] day-to-day life to explore the system's affordances and experiment with it by trying different activities, reflecting on subsequent experiences". During this three-day period, participants kept an electronic diary to document any noteworthy thoughts or experiences they had with the system.

Participants reported completing a variety of activities with the system, which included: working (writing, programming, completing assignments, and administrative work), playing games (card games and videogames), watching television, cooking, eating, and housework. All participants were working from home and thus were able to participate in the study while working.

Figure 6: Users wearing PsiNet while playing a videogame. Groups playing games together while using PsiNet was a common behavior exhibited by participants in our study.

4.2.2 Debriefing phase. On returning the system, participants were involved in a semi-structured interview, focusing on their experiences of the system and how it facilitated experiences of inter-brain synchrony. These interviews—lasting an average of thirty minutes per participant—were conducted individually, using a videoconference, and they were recorded.

5 RESULTS

In this section, we present both the qualitative and quantitative results of the present study. Note that as the contribution yielded through our study is primarily concerned with the understanding of user experiences afforded by inter-brain synchrony BBI's in-the-wild, our results and analyses are primarily qualitative in nature (section 5.1). Nonetheless, we also provide a complimentary quantitative analysis in section 5.2 in which EEG activity is analyzed to verify whether the system significantly increased group inter-brain synchrony through the circular correlation coefficient (CCorr) metric.

5.1 Quantitative analysis of inter-brain synchrony

To evaluate whether the group's inter-brain synchrony increased after stimulation, we measured group inter-brain synchrony before and after each stimulation, as given by the metrics $\text{CCorr}_{\text{before}}$, and $\text{CCorr}_{\text{after}}$, respectively. As discussed in 3.6, we transform these values using Fisher's z-transform (equation 4), since z becomes normal with increased sample size and can thus be used to conduct tests of significance and calculate confidence intervals [60]. Hereafter, references to CCorr values are to their z-transformed values.

On average, the system was used for 3.81 hours per group total, with each use session lasting for an average of 1.27 hours. During each use session, participants received on average 5.56 stimulations, with an average stimulation frequency of 4.38 stimulations per hour. The total number of inter-brain synchrony change measurements across all groups and participants given by CCorr was 48.

We removed two outliers where the $\text{CCorr}_{\text{before}}$ value was 0.035, likely due to signal artifacts like movement or sensor interruption.

Descriptive statistics for the remaining data are summarised in Table 4.

	$\text{CCorr}_{\text{before}}$	$\text{CCorr}_{\text{after}}$
Valid cases	48	48
Mean	0.88	0.92
Standard deviation	0.16	0.14
Minimum	0.68	0.63
Maximum	1.34	1.26

Table 4: Descriptive statistics for z-transformed circular correlation values before and after stimulation.

The difference in $\text{CCorr}_{\text{after}}$ and $\text{CCorr}_{\text{before}}$ was evaluated, with this value ranging from -23.26%, and 38.92%, with an average of 3.78% and standard deviation of 10.74%. Thus, on average, group inter-brain synchrony increased after stimulations, as given by the metric CCorr.

A Shapiro-Wilk test found evidence that $\text{CCorr}_{\text{before}}$ was not normally distributed ($p < .001$) and no evidence that $\text{CCorr}_{\text{after}}$ was not normally distributed ($p = 0.54$). Thus, to investigate whether the increase in group inter-brain synchrony after stimulation was statistically significant, we performed a two-tailed, paired-samples, Wilcoxon signed-rank test. We found that $\text{CCorr}_{\text{after}}$ is significantly greater than $\text{CCorr}_{\text{before}}$, with $Z = 794.00$, $p = 0.035$, indicating that the increase in group inter-brain synchrony was of statistical significance. This result had an effect size, calculated by the matched rank bi-serial correlation, of 0.35. These results will be discussed in 6.1.

5.2 Qualitative analysis of user experience

In analyzing the interviews and participant diaries, three major themes were revealed. Participant diaries were integrated with interview data in that each participant's diary was appended to the end of their respective transcript Analysis of the collected data was performed inductively through thematic analysis [9] in which six researchers independently reviewed transcripts and participant diaries and coded the data. Each unit of data represents a completed sentence from the data. Codes were iteratively clustered into high level groupings agreed upon between researchers until they were consolidated into three final themes emerging from the data. The following sections investigate these results further by articulating three themes: dissolution of self, hyper-awareness, and relational interaction.

5.2.1 Theme 1: Dissolution of Self. This theme describes 40 units of data in which participant recounts implied a blending between the subjective selves of those using the system. Eight participants described feelings of uncertainty regarding what stimulation they were receiving, and from whom they were receiving it. This was compounded by the observation that participants often did not directly interact with the system but often allowed it to operate passively, noting that at times they were unaware of whether a stimulation was taking place. Five participants noted that it was difficult to appraise whether their feelings, affects and behaviors were purely endogenous, or under exogenous influence. In the pursuit of trying to understand the source of the stimulation, participants

Theme	**Group**	**Quote**
Dissolution of Self: A blending between the subjective selves of those using the system	1	"I'd associate a flashing light to something high energy. Maybe if someone was quite agitated, that might explain why our housemate got a phosphene" (P2).
	2	"Your kind of don't know why you are doing things or to what degree you're influencing each other. You don't really know where [stimulations] are coming from" (P6).
	3	"We felt connection and being able to affect each other without having to act. It was like a phone picking up on your emotions and brain states and sending a message for you" (P8).
Hyper-awareness: The system promoted a heightened level of awareness toward their own feelings and those of the group.	1	"We were all working separately and there was the stimulation. I noticed I started to feel like I had a coffee. And then I think my partner got stimulation as well, and then a housemate in the other room messaged us saying that they got a phosphene" (P1).
	2	"I heard the [stimulation] while I was in the flow of my work. I knew everybody else was doing work, I was wondering if everyone else was also in their own flows and it made me feel connected to them" (P5).
	3	I would have a look at the others and think "What are they doing? Are they talking about [the stimulation]? Are they talking about the sensation?"
Relational Interaction: Participant experience of the system was influenced by the relations between elements within its context of use	1	We were just hanging out and being silly, trying to influence each other ['s brain activity]" (P1)
	2	"I almost forgot entirely about the study [while on my own]" (P5).
	3	[I though], hmm, maybe I'll sit down and watch Netflix and see how [the groups stimulations] differ" (P8).

Table 5:

found themselves empathizing with their group. Six participants stated that their thoughts contributed equally to the function of the system, believing they controlled the system together. When the interviewer asked participants where they felt the power lay in directing the flow of information across the system and its users, most participants described feelings of an equal distribution of agency over the system and the others in their group. Other participants described feeling little control over the system, feeling stimulations were random and without pattern.

5.2.2 Theme 2: Hyper-Awareness. This theme describes 48 units about participants' descriptions of how the system promoted a heightened level of awareness individually and as a group, labeled *"hyper-awareness."*. Seven participants discussed the way their body was feeling when they were receiving stimulations and how it made them reflect on what they were doing at the time when the stimulation occurred. While attention was usually directed toward external bodily sensations, participants also discussed being mindful of how they felt internally. Participants described how their state of bodily awareness was brought to the fore by the unintended audio design feature of the headset, specifically the clicking sound made by the relays when stimulation began. Participants experimented with different activities while using PsiNet in order to understand how the system reacted. As participants began experiencing the stimulation and discussed the resulting sensations, they became more aware of their shared experience. For example, more than half of the participants played games while using PsiNet. As a result of their experimentation, participants reported experiences of increased team cohesiveness, with five participants reporting feelings of connectedness and feelings of closeness even when in separate rooms, describing how the physical sensation of the stimulation made them reflect on how they and their group was feeling. Participants discussed their group having a similar state of consciousness, describing how they were not certain if the shared sensations put them in a flow state but nonetheless chose to "*believe*" this was the case.

5.2.3 Theme 3: Relational Interaction. This theme describes 36 units about participants' descriptions of how the system was influenced by the relations between elements within its context of use. Participants experimented with different social activities while using PsiNet, such as playing cards (P4, P6), playing video-games (P1, P2, P3, P6), and watching TV (P8). Some participants reported feeling as though PsiNet improved the group's performance in the tasks they were jointly engaged in. Five participants described their attitudes toward PsiNet positively using words like, *"curious," "excited," and "new"*. Such curiosity drove participants to play and explore with PsiNet. They consciously strove to adjust their brain activity or the task they were doing to see what kind of social interaction could be triggered by PsiNet. In the context of group activities, participants reported more *"playful"* experiences (P1). The presence of PsiNet in these group activities also contributed toward a feeling of combined enhancement of ability in the activity they were engaged in. Participants also believed that the system might have changed how their group interacted as they used the system, and believed that it could *"amplify"* (P8) how someone was feeling by stimulating the others in the group. Some participants noted that they were able to get into solid workflow states while doing work individually, reporting they could *"concentrate intensely"* (P8) and felt *"the time is passing really quick"* (P7). Participants also suggested that they felt *"a silent motivation"* (P3) when working by themselves because they still felt connected to others in the group through PsiNet.

6 DISCUSSION

In this section, we discuss our study's quantitative and qualitative results.

6.1 Discussion of quantitative results

Our results showed that neural synchrony increased in the period after stimulation, compared to the period just before stimulation. While this result could indicate that PsiNet was able to increase neural synchrony in the group, as was intended, we proceed cautiously in drawing such a conclusion. We acknowledge that results may depend on the epoch length analysed, and little research exists to guide appropriate epoch lengths for measuring neurostimulation-triggered increases in inter-brain synchrony [95]. Furthermore, it is difficult to infer exactly how the stimulations may have increased group neural synchrony. Considering how conscious experiences can be considered as integrated [88], it would be impossible to separate what contribution the stimulations were having to the individual's conscious experience from other causal factors. This uncertainty is consistent with participant's experiences, with P2 stating that *"...it was very difficult to tell what stimulation you were getting and… [any] change in your mental state"*, and P3 similarly stating, *"there was no way to tell...which stimulation you were getting and… hard to correlate that with what people were doing"*. Nonetheless, the significant effect measured in our quantitative analysis of CCorr suggests that brain-to-brain interface use was associated with increased inter-brain synchrony, validating participants' experiences and beliefs that the system was influencing them and their group. This result also illustrates the strong potential for future iterations of brain-to-brain interfaces to be powerful tools in the amplification of inter-brain synchrony, which will no doubt become more effective and efficient as technology improves. We therefore believe our research frames the future development of BBI's as an important technological instrument in the design of systems for strengthening interpersonal relationships and group dynamics.

6.2 Discussion of qualitative results

Here we discuss the themes from section 5.2 in the broader context of the literature.

Regarding the theme, *dissolution of self*, participants reported feelings of ambiguity as to whether their conscious experience resulted from endogenous or exogenous causes, from their "selves" or from the system. We acknowledge that users experienced some ambiguity over what the system's feedback meant. This ambiguity seems to be endemic to systems that interact with users without requiring conscious attention [69]. Systems that modulate the user's physiological processes influence users in ways that may be difficult to articulate or be consciously accessed by the user [69]. Our results suggest this promotes feelings of a sense of ownership [54, 59] over the physiological activity invoked by the system's output and a sense that agency over the system is equally distributed across users in the network. Furthermore, this could suggest that as humans integrate with technology, we may trend towards the experience of a seamless blend of the self with technology, and thus the dissolution of the old self into something "other". This notion speaks to recent human-computer integration research and theory. In their "bodily integration framework", Mueller et al. [54] describe the user experience of bodily integration systems—systems in which the human body and computational machinery are tightly coupled in a way that allows for bidirectional actuation—and acknowledge that both human and machine can possess agency and enact on each other. This human-machine relationship allows for the system to be experienced as something that modulates or extends the human body. The authors describe bodily integration using two axes comprised of psychological concepts: "bodily agency," (the feeling that the user has control over their body or the machinery acting upon it); and "sense of ownership," (the degree to which the user feels they are the owner of their body, or that the system is part of their body). In the case of PsiNet, the ambiguity of the system's stimulation and its ability to modulate the user's brain activity without their attenuation ultimately allowed the output of other brains to be experienced with a high sense of ownership, meaning these individuals felt their modified cognitive experience to be their own. Users can find it difficult to separate their own unique cognitions from the collective cognitions of the group, suggesting that they can at times experience exogenous feelings, which come from the stimulation of the system, as their own naturally occurring endogenous feelings. This high sense of ownership is complimented by the notion that participants felt that agency within the system was homogeneously distributed across all users. This allowed PsiNet to facilitate experiences of collective agency, characterized by the feeling of "we did that" rather than "I did that." Thus, we can say that the PsiNet users experienced the output of other brains with a high sense of ownership and agency, ultimately extending the theory of bodily integration by demonstrating that bodily integration can also take place between human and human, rather than just between human and machine.

In our second theme, *Hyper Awareness*, users initially experienced increased bodily awareness while adjusting to the headset. But as participants habituated to the sensation of wearing the headset, their increased awareness arose from anticipating the next stimulation and observing other group members having similar experiences. As a result, participants reported experiences of increased team cohesiveness, connectedness, and feelings of closeness even over a distance. This increased awareness is consistent with the findings of Andres et al. [5]. In relation to their theme, "The User Experience of Peripheral Awareness as a Mechanism for Integration," participants recalled actively attempting to reach higher levels of peripheral awareness because their context was one in which they interacted with the system. With respect to the theme "Internal Bodily Signals Observed by Users," participants reported feeling greater awareness of their internal states as a result. Since we understand that PsiNet could alter participants' conscious experiences by changing how they interact with their environment, we reason that it may lead to participants feeling greater awareness of their internal or external states. This does not mean that PsiNet stimulations directly cause this heightened awareness. It is possible that simply knowing that the system could lead to changes in awareness may have caused users to act in accordance with this knowledge and fulfill a kind of placebo effect. In interviews, participants reported that, while using PsiNet, they discussed how they were feeling more than they usually would. It may be that simply knowing that other users were sharing a similar experience and exhibiting heightened awareness may have produced a feedback loop in which all users felt drawn to participate in this heightened awareness.

The theme of *relational interaction* is similar to the theme "Passivity and Self-Exploration" from Inter-Dream [71], which involved projecting brain-waves onto walls in addition to streaming them to a VR headset. Participants reported alternating between feelings of passivity and playful exploration. In a similar way, participants who used PsiNet reported feeling sometimes as though the system operated passively in the background, particularly when the participant was alone or focusing on a particular task. In contrast, participants also reported experiencing feelings of engagement, play, and silliness, particularly when operating PsiNet in proximity with other users. Clearly, context impacted how participants experienced PsiNet, whether it was a context appropriate for play, for social interaction, for solitude, or for work. In each context, PsiNet served different purposes, which include but are not limited to: helping to improve group performance in shared tasks; promoting individuals to be mindful of the presence of others when interacting in a group; or providing a feeling of connectedness with others even when alone.

6.3 Design tactics

After reflecting upon the discussion of our results, we translated the knowledge contributed by each theme into actionable advice. Specifically, each theme yielded a corresponding design tactic, with themes and tactics being presented in the same order. We contribute these design tactics to HCI practitioners, developers of wearable BBI systems, and designers of inter-brain synchrony experiences to better guide their own forays into research. We also acknowledge that these preliminary tactics represent only an initial attempt to guide developers interested in the design of wearable BBI systems for inter-brain synchrony, serving as a place to start. As such, these are not the only possible design tactics and future research on this topic will likely yield additional design tactics, providing further guidance.

6.3.1 Tactic 1. Consider designing technologies favoring implicit interactions for inter-brain synchrony. We recommend that designers consider designing brain-to-brain interfaces that avoid direct human input and instead favor implicit interactions [59, 100]. This could involve ensuring that systems do not require users' direct attention or cognitive capacities. For example, our system did not require responses to notifications. Instead, our system acted autonomously; automatically taking in electrical activity as input and adapting to the users through reinforcement learning. This tactic is congruent with the idea of "mindless computing" [1], referencing technologies that do not require explicit user attention. Studies found that such technologies can still result in subtle changes in behavior, of which the user is unaware, while potentially overcoming the limitations of technologies that require their users to divide cognitive capacities and attention through controlling the system [21]. For PsiNet-like systems, we specifically suggest passive BCI input paradigms (e.g. state classifications and observations of Synchronisation/Desynchronisation related potentials), rather than active (e.g. motor imagery) and reactive (e.g. steady-state evoked potentials) based BCI paradigms. One example would be using synchronisation/desynchronisation related potentials indicative of sleep onset as an input signal, which triggers slow-wave tACS oscillations as an output in another user.

6.3.2 *Tactic 2: Consider developing seamless bodily integration for unobtrusive operation.*

For those motivated to design wearable inter-brain synchrony BBI's, we recommend improving the comfort and portability of wearable technologies so that they might be used in more contexts and for longer periods of time. This design tactic will also improve the temporal resolution of data for researchers and industry. Previous studies [52] suggested that unobtrusive systems—those that can be operated without the user's attention and employed when the user is not focused on the interactive device—can facilitate experiences of inter-brain synchrony. Applying this design approach to brain-to-brain interfaces, it can be argued that inter-brain synchrony promoted by an unobtrusive interface may allow users to experience their contribution to group synchrony as something generated by themselves, not something mediated through technology. This experience would ultimately allow for an empowering experience of user agency, where amplified inter-brain synchrony may be perceived as a natural process of their body [59]. In practice, this idea taken to its logical conclusion would be to favour radically bodily integrative designs such as brain implants. However, we acknowledge that currently, it is not desirable, nor economically and socially possible for the majority to access brain implants for non-clinical applications, and instead consider how seamless bodily integration can be achieved non-invasively. Electronic tattoos represent an opportunity for bringing the system much closer to the human body by limiting much of the system's factor to the user's skin. Alternatively, another approach could be to consider headwear that may be congruent with the application domain or context the system is being used in (e.g., embedding a PsiNet-like system into gaming headphones for an e-sports team).

6.3.3 *Tactic 3. Consider designing user-controllable system adaptability for transparency and consent.*

We saw that PsiNet provided different uses in different contexts, including facilitating play and stimulating curiosity, enabling connectedness with others, increasing awareness of self and the environment, and possibly assisting work. However, P1 stated that they felt the system could be intrusive when they were trying to concentrate and *"you're not really open to disruptive inputs."* Indeed, trying to force a playful experience within a work context seems inappropriate. It may, therefore, be beneficial to provide users with options that allow them to tailor the system for appropriate use in different contexts such as play, social interaction, and work. For example, this could mean allowing users performing a similar activity to set agreed-upon stimulation settings in accordance with what they think may be appropriate (e.g., disabling stimulations that may hinder someone's ability to concentrate while they are working). Another suggestion would be allowing users to set times in the day when they are open to receiving stimulations (and times when they are not). This capacity to limit is important as it gives users the power to consent to the experience (or not), including defining what consent means for them in different contexts and them having the discretion to change that.

7 LIMITATIONS AND FUTURE WORK

We believe our work could be complemented by further studies that include more controlled experimental approaches focusing on statistical power and efficacy, contrasting our longitudinal and experientially focused approach. Due to the in-the-wild study design adopted, the presence of experimental control or a placebo group was sacrificed to allow for real-world, naturalistic, and authentic interactions between the participants and PsiNet. We do this following a well-established HCI research methodology employed in many similar studies, in which human interactions with technologies, and the experiences they afford, are qualitatively analysed in their naturalistic setting [15, 19, 34, 49, 50, 56, 64, 65]. While this approach imposed a limitation on how precisely we could evaluate PsiNet's efficacy in promoting inter-brain synchrony, we gained access to detailed first-person accounts and insights into the user experience of brain-to-brain interfaces, specifically those focused on inter-brain synchrony, which has helped to understand this emerging technology from a subjective experiential perspective. We acknowledge that our study may have been impacted by experimenter bias through the use of autoethnographic exploration of tES stimulation to inform the system's design, and subsequent evaluation of participant experiences, and future studies may wish to utilise double-blind study designs in future evaluations of the effects of neuromodulation in brain-to-brain interfaces. We argue the use of autoethnography was a necessary step in the design of the system, due to the extreme novelty of designing an interactive experience through brain stimulation. It would have been difficult and possibly even counterproductive to design a system so distinct from contemporary interaction paradigms and metaphors without ourselves having a first person experience and understanding to serve as a starting point. Nonetheless, in all research it is difficult for researchers to separate their own expectations (from their own experiences or informed by past research) of an experience, from the ones studied in their participants. However, such biases can be addressed in part through more rigorous double-blind experimental studies, which is beyond the scope of our present study considering its in the wild nature. That said, future studies may benefit from a more experimentally controlled exploration of the user experience of systems such as PsiNet, including researchers naive to the experience of tES stimulation, or with studies including a double-blind procedure.

In addition, future studies could consider how the situational context or activities being performed by participants might alter measures of inter-brain synchrony. While our study was designed to mitigate the effect of situational context and activity on readings of inter-brain synchrony, additional work could investigate differences in neural synchrony in different contexts. For example, studies could compare groups of individuals when they are together and when they are apart, or whether shifts in inter-brain synchrony are different across groups participating in the same activities (for example, where all participants engage in a team sport together) versus groups participating in different activities.

Given that our study group members were either family members or close roommates, it would also be interesting to investigate users who are not familiar with each other. An additional direction for future work would be the consideration of alternative tES stimulations. While much of the stimulation in this study was tDCS, there has been many recent developments in the use of tACS stimulations to induce neural entrainment [94]. While less researched than tDCS, neural entrainment from tACS can allow for generating more varied and pronounced neurodynamic effects, such as the induction of slow-wave oscillations associated with sleep and meditative states of consciousness [97]. Furthermore, tACS could also be used non-categorically if a stimulation paradigm were adopted in which stimulatory oscillation in one user matched endogenous brain oscillations in another, hypothetically allowing for dynamic brainwave synchronization without needing to preemptively categorize mental states for classification. In the same vein, it would also be beneficial for future lab-controlled studies to assess and compare the individual efficacy of each stimulation type in relation to its contribution toward inter-brain synchrony. In addition, while the circular correlation coefficient was the metric chosen for measuring inter-brain synchrony in the present study, future studies may consider alternative measures of inter-brain synchrony, for example, phase lock value, which has also been used to measure inter-brain synchrony in the past [17]. The cross-validation of synchrony scores with the user experience of inter-brain synchrony was also not performed in our study, and would be of value to future studies, to establish the validity of circular correlation or other synchrony metrics as measures of inter-brain synchrony. This could be done through evaluating the consistency between synchrony scores and a metric of experienced inter-brain synchrony as reported by participants. However, quantitative metrics of experiential inter-brain synchrony have not been well-explored, though are likely associated with social factors like group affinity [25], identification [91] or interactions [42] found in various scales and questionnaires.

Finally, we note that all participants mentioned that the OpenBCI headset was uncomfortable to wear, describing it as heavy, and the dry EEG electrodes as spikey. Many participants described how while they found the experience to be mostly positive, they were relieved to take the system off at the end of their session as they began to feel fatigued from the stain generated by the pain of the dry EEG electrodes and the weight of the system overall. This may have been the biggest factor driving the discrepancy between the amount of time we hoped the participants would wear the system (15 hours), and the amount of time they actually wore it on average (3.8 hours). With that said, we suggest that future BBI studies in-the-wild would do well to spend significant effort in reducing the system's form factor and increasing wearability. One way to do this would be to employ conductive silicone dry electrodes, which while relatively new, we believe will become more common for BCI systems as their signal quality meets that of traditional gold cup paste-based electrodes. Furthermore, we also suggest embedding the system into headwear that is typically worn for extended periods (e.g. a beanie) rather than the OpenBCI 3D printed Ultracortex frame, in order to reduce form factor and weight.

8 CONCLUSION

In this paper, we argue that brain-to-brain interfaces present an opportunity for the ubiquitous augmentation of inter-brain synchrony in-the-wild. Informed by related work on brain-to-brain interfaces and inter-brain synchrony-based systems, we designed PsiNet. PsiNet is the first networked system of wearable brain-to-brain interfaces designed to increase inter-brain synchrony between individuals through sensing and actuating brain activity. We studied PsiNet in-the-wild, deploying the system to households of participant groups who engaged in unrestricted, open-ended use of the system. Through this work, we contribute an understanding of the experience of inter-brain synchrony BBI systems in-the-wild in the form of three themes (dissolution of self, hyper-awarness, and relational interaction), which will help HCI theorists to articulate brain-to-brain interface experiences. Additionally, we propose three design tactics gained through our craft knowledge and experience gained through developing PsiNet and reflection on the results of the present study, to guide designers of future brain-to-brain interfaces with actionable recommendations. We also contribute PsiNet itself as a case example of how to design a brain-to-brain interface for promoting inter-brain synchrony that can be deployed in-the-wild with scalable user group sizes. Ultimately, it is our aim that this work advances HCI's understanding of designing for inter-brain synchrony and guides the design of brain-to-brain interfaces toward a technological future where BBI's are a medium for fostering human connection.

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