“Seriously, I’m Okay With Criticism”: Assessing Participants Emotional Reactions During Participatory User Sessions via EEG Hyperscanning Analysis

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Abstract

We investigate using electroencephalography (EEG) devices to improve participatory user sessions, which are common in HCI research and practice. Using writing consultations as a critical example of such participatory user sessions, we evaluate six emotional reactions between a consultant and five patrons. EEG data was collected in consultant-patron dyads during each session and then analyzed concurrently. The analysis highlights the critical interaction effect between consultant and patron emotional levels, including stress levels, usually focused on criticism of the patron’s writing, and excitement centered on praising the patron’s writing. Findings point to the need to establish a positive relationship between the consultant and participants via eye contact and a welcoming environment. The findings imply that there is value in hyperscanning investigations to prepare HCI experts for qualitative user interviews, focus groups, and similar participatory user sessions and hint at the potential for neuroscience-informed practices in HCI processes.

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Keywords

EEG hyperscanning, brain connectivity, autonomic synchronization, user participation session, writing consultations

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1 Introduction

Many human-computer interaction (HCI) data collection processes involve HCI professionals collaborating with others to gather critical design insights, such as user interviews or user focus groups, which we refer to as *participatory user sessions* [7]. These HCI processes are critical for collecting data for research or design decisions, requiring HCI researchers to ensure these sessions are conducted effectively. This involves considering how communication shapes the social relationships, including levels of empathy [25] or stress [22]. In this pilot work, we use electroencephalography (EEG) sensors to evaluate these participatory user sessions and conduct such

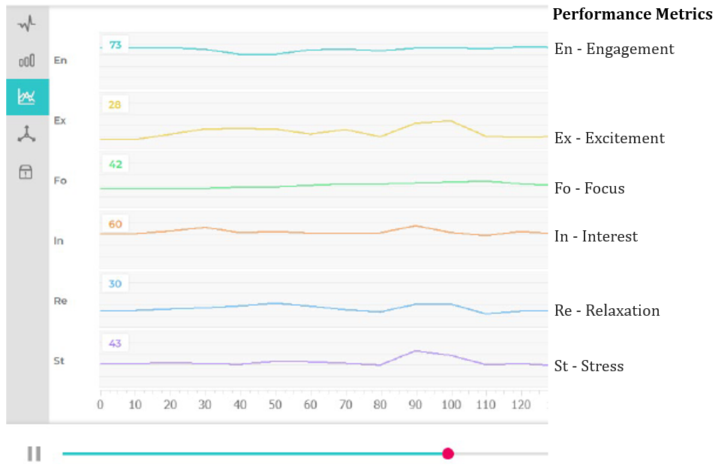


Figure 1: Image of an EEG sensor read out showing varying levels of six emotions from the EmotivPRO – Analyzer software package.

sessions more effectively. Our study is positioned between HCI and social neuroscience. Social neuroscience [3] examines the neural processes underlying interpersonal behavior. One key concept in social neuroscience is the *social brain* [8], a network of brain regions, including the medial prefrontal cortex and posterior superior temporal sulcus, underpining the neurophysiological foundations of interpersonal behavior and social cognition [24].

An EEG sensor [20] is a device that detects the brain's electrical activity by measuring the fluctuating signals generated by large groups of neurons near the brain's surface over time. EEG sensors detect small fluctuations in electrical current between the skin and the sensor electrode, amplify the signal, and apply bandpass filtering. EEG sensors have been applied to various contexts within the HCI [1, 2, 4, 9, 10, 12, 14, 15, 21, 23] and other domains [16, 26]. Peripheral autonomic parameters, alongside central electrophysiological activity, have been used to assess individuals' positive and negative emotional activation, arousal, and stress responses. As a result, they have proven valuable for evaluating cognitive-affective dimensions in social interactions [17]. See Figure 1 for a snapshot of an EEG readout. While there are other methodological approaches (e.g., interviews, surveys), they have inherent weaknesses if cognitive and affective communication processes are the research focus, given these methods are mediated by the person's language, cognitive processes, awareness, and observer bias.

The communication complexity arising in these user sessions can only be efficiently analyzed if data from all participants (i.e., researcher and patron) are collected [11]. For these reasons, *hyperscanning* (i.e., a technique that allows the simultaneous recording of brain activity of two or more participants) is a paradigm for investigating the interpersonal emotional reactions generated by social interaction [5]. Hyperscanning is the simultaneous recording of brain activity from two or more participants engaged in a task. Hyperscanning data captured using EEG informs about the functional connectivity among individuals' brains during social interactions. [13]. The effect of hyperscanning is a synchronization of responses in interacting dyads [6].

Our research aims to determine whether using EEG sensors in hyperscanning mode can deliver the intended benefits and modifications to participatory user sessions. This includes investigating the usability of the EEG sensor when operating within actual conditions while referencing the impressions of the patrons and consultants (consultant refers to the person conducting the consultation). Using a writing consultation as a critical example, we identify the ability of EEG technology to improve writing consultations by detecting cognition and stress levels. As such, we propose the following research questions (RQs).

RQ1: *How does the consultant's delivery during the session impact participants' experiences and comfort levels as indicated by EEG sensor readings?*

RQ2: *How do the participant survey results align with the EEG sensor readings, and what insights can be drawn from this comparison?*

RQ3: *What improvements can be made to create a more comfortable and engaging environment for optimal consultation success?*

We evaluate the consultant's and participants' emotional variation to understand EEG's effectiveness in assessing writing consultation sessions. Specifically, we incorporate the *EmotivPRO+* EEG sensor in the current study to help determine factors that influence the experience of the patrons as well as obtain information that will lead to an improvement in session quality. Our methodological approach involves close observation of the participants along with EEG monitoring, taking notes, and questionnaires. The insights from the findings present information that can inform the fine-tuning of participant user sessions.

2 Method

2.1 Participants

The participants for this pilot evaluation were one professional writing consultant and five patrons actively seeking assistance with writing consultations. So, six participants, one consultant, and five patrons participated in the study. Patrons were recruited based on their interest in receiving guidance from the writing consultant and their willingness to undergo an EEG-monitored consultation; inclusion criteria required patrons to be proficient in English and actively seeking writing feedback. Participants were divided into five dyads of one consultant and one patron. These dyads were actual writing consultation sessions with patrons seeking assistance and real advice from an actual writing consultation. Patrons varied in age from nineteen to sixty-four, with twenty-four being the median. Three of the patrons were males. Concerning education, four had a bachelor's degree, and one had a graduate degree. None had ever attended a writing consultation session before.

Before the execution of the session, participants filled out a survey that asked about their familiarity with EEG sensors and their writing activities. According to the results, four participants were aware of EEG devices. The ones familiar with it had previously used it in projects or research. As for their consultation expectations, the same ratio of participants were looking to proofread and improve their resumes. They all hoped for professional and effective feedback. Most participants stated that they participate in academic writing the most. Personal, creative, and professional types were used at 20-40 percent.

2.2 Procedure and Data Collection

A detailed script was prepared to provide formal introductions to participants in the study that clearly stated all study procedures. Participants sign an informed consent form and complete a short pre-session survey before the session begins. For the data collection, dual-EEG sensors in a hyperscanning paradigm were designed, and both the consultation and the patron were fitted with EEG sensors. We had two EMOTIV EPOC+ brain-wear devices (see Figure 2) and two laptops each for the participant and consultant. The EEG sensor was placed on the patrons in the study as per the EMOTIV instruction manual; the nodes were thoroughly moistened with saline solution and then placed gently on the participant's scalps. The nodes were re-positioned to achieve near 100 percent contact quality of the device, which was shown in the EmotivPRO+ application on the laptop's display. The recordings were collected from the EmotivPRO application as CSV files. This data was used to compare the participant's and the consultant's EEG readouts. The results helped compare how the participants answered the survey with their EEG readings. The metric were calculated using a Python script for the following emotions: attention, engagement, interest, relaxation, stress, and excitement. EEG data is prone to noise from muscle movements and environmental interference; raw signals were processed using a bandpass filter within the software to ensure accuracy.

After the set-up was ensured to be complete and successful, both the consultant and participant performed a 30-second baseline recording at the same time. The EEG sensor readings began when the baseline recording was complete, and then the writing consultation session proceeded as usual. Interpretations of participants' facial expressions, tone, and verbal responses during moments where constructive criticism and feedback were given were noted by the research team. While this session was ongoing, one moderator remained in the room to monitor the EEG readings and take physical notes of the participants' behaviors. Each session was about 30-45 minutes, depending on the type of consultation the participants needed. At the end of the session, one of the moderators then removed the devices, and the consultant was given a 15-minute break between the sessions. Participants completed a survey about their experience with the EEG sensor and the consultation, their overall satisfaction, and demographics. Every participant received a gift for volunteering in the study.

2.3 EEG Analysis

To interpret EEG fluctuations with participant and consultant responses, we adopted a triangular approach that combined EEG readings with real-time behavioral observations between Python-processed EEG data and post-session survey data. Moderator notes were taken on all participant reactions (e.g., facial expressions, body language, and verbal responses) at moments corresponding to EEG fluctuations. EEG data was processed using Python scripts to compute key statistical measures of mean, median, mode, and standard deviation for the emotions: attention, engagement, interest, relaxation, stress, and excitement.

The mean (μ) of the EEG readings for each emotional state was computed using the formula:

$$\mu = \frac{1}{N} \sum_{i=1}^{n} Xi$$

, where Xi represents individual EEG readings, and N is the total number of recorded values in a session.

To standardize EEG values, we applied variance normalization, calculated as:

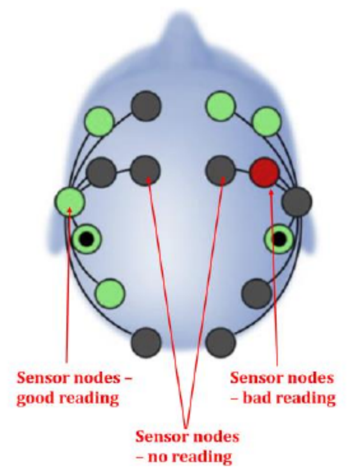
$$\mathrm{X}' = \frac{X - \mu}{\sigma}$$

, where X' is the normalized EEG value, X is the raw EEG reading, μ is the mean, and σ sigma is the standard deviation of EEG values. The EEG exports from EmotivPRO were further processed to fine-tune trend analysis to validate EEG fluctuations over time, using MATLAB and Pandas (Python library). EEG signals were subjected to bandpass filtering (0.1Hz–45Hz) to remove various artifacts caused by muscle movement and electrical interference. Other steps included artifact rejection by the EmotivPRO software's built-in filters and visual inspection to remove anomalies unrelated to their reactions.

Qualitative observations were coded using thematic analysis. Session moderators categorized participant behaviors into themes: 'Positive Engagement' (smiling, nodding, active questioning), 'Discomfort' (avoidance, defensive body language, prolonged silence), and 'Neutral' (passive listening, minimal response). These categories were then mapped against EEG readings. For example, 'Discomfort' was analyzed in relation to stress peaks in response to criticism, and 'Positive Engagement' was compared against increased engagement/excitement metrics.

The EEG data was cleaned and structured in Python by identifying the missing values and contending with outliers. In such an approach, peak detection techniques marked the moments of heightened stress during critical feedback and engagement peaks while the participant was active. Additionally, survey responses were analyzed to identify patterns in participants' self-reported experiences, which were then compared to both EEG trends and qualitative observations. The hybrid technique of using built-in

(a) EmotivPro+ EEG Sensor



(b) Image of EEG sensors nodes

Figure 2: The EEG Sensor, (a) showing the EmotivPro+ EEG Sensor, and (b) showing a reading of the EEG sensor nodes during set-up.

processing of EmotivPRO and statistical validation in Python provides a thorough validation of the emotional states deduced from the EEG.

3 Results

3.1 RQ1: How Does the Consultant's Delivery During the Session Impact Participants' Experiences and Comfort Levels as Indicated by EEG Sensor Readings?

Table 1 presents the descriptive statistics of the Attention, Engagement, Excitement, Stress, Relaxation, and Interest emotions of the session participants as recorded by the EEG sensor. *The key statistic is the Scaled value (column 2), which is the Raw value scaled to fit on a 0 to 1 scale, with the scaling based on successive approximation of the mean and variance for each recording repeatedly calculated during the session.* Higher is the more intense emotion.

The outcome of the EEG sensor recordings and physical notes of the study's moderator reflected how the participants responded to certain stimuli and different tones during their communication with the consultant. All participants had scheduled their consultation sessions to help them improve their resumes. However, a common theme between all the sessions was that once either person was speaking about something that resonated with them, whether it was a personal anecdote or a story they were telling, their engagement level went up. The participant's excitement, as well as interest, increased proportionally.

There was some variation in the participants' responses to constructive criticism. While some had their attention increased, others had stress peaking at high levels with very low excitement levels. Raw emotions that are displayed, like laughter, confusion, or bonding, were displayed through an increase in engagement and relaxation emotions. Any technical issues (e.g., computer login or access issues) faced during the session rapidly increased the consultant's stress levels. In contrast, the participant's emotions would be neutral or low in attention and engagement. Some participants did not take suggestions and feedback in the best way, as reflected by their disproportionate stress and relaxation.

The general flow of conversation between the participants was smooth, with minimal awkwardness for all participants. The main emotions being altered were always stress, engagement, and attention. Any external stimuli, such as the opening of the session room door, the websites shown during the session facing issues, and noise from objects dropping outside the session room, would create an influx of stress for both participants.

Interestingly, one patron with a long work experience had a much longer and more detailed resume than the others. This caused the consultant to show signs of slight panic and anxiety. In this participant session, the consultant had the highest stress levels.

3.1.1 *Participants' Experiences.*

During the EEG-monitored writing consultations, five participants, referred to as Participants A, B, C, D, and E, engaged in the consultations to enhance their writing, namely their resumes. The EEG sensor data captured emotional states such as stress, engagement, concentration, and relaxation throughout the sessions, revealing insights into the emotional dynamics experienced by the participants and the consultant. In the following, we summarize the experience of each participant.

Participant A: The main goal of Participant A's consultation session was to edit their resume to make it more concise and applicable to job applications. At the beginning of the session, Participant A exhibited increased enthusiasm and stress compared to the consultant. However, as the session proceeded, Participant A's attention increased as Participant A's stress levels went down—especially when there was shared laughter between the consultant and participant. Receiving positive feedback and personal anecdotes from the consultant made the participant more relaxed as opposed to

Table 1: Descriptive Statistics of Attention, Engagement, Excitement, Stress, Relaxation, and Interest Readings. Means above 0.5 are bolded.

Attention					Engagement				
Metric	Scaled	Raw	Maximum	Minimum	Metric	Scaled	Raw	Maximum	Minimum
Mean	0.467	-9.033	-14.5	-2.78	Mean	0.648	-0.305	-1.15	0.191
Mode	0.432	-10.99	-21.05	-5.56	Mode	0.625	-1.099	-1.52	-0.284
StDev	0.069	0.761	1.76	2.42	StDev	0.103	0.181	0.13	0.234
Median	0.461	-9.045	-14.1	-3.60	Median	0.653	-0.279	-1.14	0.239
Excitement					Stress				
Metric	Scaled	Raw	Maximum	Minimum	Metric	Scaled	Raw	Maximum	Minimum
Mean	0.587	9.098	5.05	11.9	Mean	0.552	198.22	-117.20	449
Mode	0.613	2.95	4.91	13.5	Mode	0.170	21.51	-785	136
StDev	0.252	3.32	1.74	2.58	StDev	0.194	146	147	205
Median	0.584	8.70	4.88	12.01	Median	0.498	163	-57.7	436
Relaxation					Interest				
Metric	Scaled	Raw	Maximum	Minimum	Metric	Scaled	Raw	Maximum	Minimum
Mean	0.469	0.271	0.0986	0.361	Mean	0.539	10.5	-29.7	49.1
Mode	0.697	0.234	0.0965	0.273	Mode	0.414	2.72	-218	18.79
StDev	0.169	0.131	0.0387	0.0652	StDev	0.120	5.090	49.4	55.1
Median	0.465	0.235	-0.104	0.345	Median	0.505	9.77	-9.47	28.5

[a] For further descriptions of values, see EmotivPRO v3.0 Managing Your EEG Data Recordings https://emotiv.gitbook.io/emotivpro-v3/managing-your-eeg-data-recordings/exporting-an-eeg-data-recording/csv-files

receiving critical resume feedback, which made their stress levels peak.

Participant B: The main goal of Participant B's session was to improve the substance and length of their resume. The session was quite exciting as Participant B first discussed their progressive experience. However, as the consultant gave input on the technical details, such as the color scheme of the resume, the participant's stress level significantly increased. Despite this, there was consistent involvement when discussing extracurricular activities, suggesting a shared interest. When Participant B saw examples of professionally formatted resumes, their enthusiasm increased, highlighting the benefits of using visual aids in consultations.

Participant C: The consultation with Participant C centered on enhancing their resume's design and organization. While both the participant and the consultant were relaxed at the beginning of the session, participant C's stress levels varied greatly when they were given helpful criticism. For instance, enthusiasm grew when the participant knew the consultant was equally engaged, like when the consultant offered formatting suggestions and showed interest in the visual organization. However, stress spiked when Participant C was told to remove pointless material. Talking about accomplishments increased both Participant C's and the consultant's levels of engagement, and times of agreement led to greater excitement and relaxation for both.

Participant D: The session focused on improving D's resume content and organization. The participant and consultant showed moderate involvement initially, but as the session continued, especially when talking about job applications, Participant D's emotions changed. Stress levels increased when the consultant commented on the resume's use of action-oriented verbs. However, once the two agreed on the most important changes, engagement and relaxation improved for both.

Participant E: The meeting with Participant E was centered on editing a lengthy resume (more than 70 pages). Participant E was excited to talk about their career achievements right away, whereas the consultant appeared more stressed, given the large document to help organize. Excitement for Participant E rose when discussing proud moments in the resume, and engagement remained high during these discussions. Still, when Participant E received helpful criticism-particularly when it came to the recommendations to cut down on content or write in the first-person, their stress levels increased. When there was agreement or laughter, the consultant and participant showed high levels of involvement; nevertheless, tension rose when discussing sensitive subjects like incorporating images.

General Observations: In every session, participants' stress levels fluctuated when receiving constructive criticism, while engagement and excitement increased when given personalized feedback or when discussing topics of mutual interest. For the participants and the consultant, humor and personal stories were useful in lowering stress, increasing relaxation, and improving the formal environment. According to the EEG sensor data, emotional reactions like stress, relaxation, and engagement are crucial and integral to the success of the consultation sessions, suggesting that managing emotional dynamics is important for the consultation experience.

3.2 RQ2: How Do the Participant Survey Results Align with the EEG Sensor Readings, and What Insights Can Be Drawn from This Comparison?

Comparison of the EEG findings with the survey results provides insight into participants' experiences during consultations. Conspicuous spikes in stress levels during sessions were recorded when participants experienced technical problems or constructive criticism, thus showing that participants were in discomfort. This can be seen mirrored in the data from the survey as well, where two (40%) of the five participants reported discomfort, and one (205) even reported pain after a more prolonged use of the EEG sensor. Most participants reported that the sensor was easy and the consultation sessions were valuable; one participant reported it was not helpful.

The EEG showed variation in both engagement and attention during the sessions. Again, on themes that participants were passionate about, there was a high degree of engagement, while attention tended to drift on and off according to the flow of the session. This brings us back to the survey data, where most (80%, n=4) responses indicated that the sessions had been helpful and that they would recommend them. Another example is the interest in improving one's resume. According to the surveys, most participants were interested in this part, which corresponds to higher levels of engagement, as witnessed in the EEG data during these discussions.

The EEG measurements represented the emotional response and showed a higher level of excitement when subjects found the discussion most relatable, as well as increased stress during critical feedback or technical disruption periods. This corresponds to the responses from the survey, in which the four participants who were delighted with the consultations found the input clear and helpful. In contrast, the one who did not find it helpful had lower excitement and higher stress levels in the EEG measurements. This was also influenced by demographics and habits related to writing. Those familiar with the technology of EEG expressed fewer complaints but more interest, which was consistent with their EEG data indicating less stress and more engagement.

Integrating EEG data in this holistic way with survey response data underlines the need to consider objective measurements and subjective feedback to enhance the overall effectiveness and comfort of writing consultations.

3.3 RQ3: What Improvements Can Be Made to Create a More Comfortable and Engaging Environment for Optimal Consultation Success?

The participants' emotional reactions were also influenced by their physical surroundings. According to the post-survey results, eighty percent (n=4) of the participants reported that the consultation room was pleasant, raising their level of relaxation. This is reflected by the EEG results, which show that participants were generally able to relax during the sessions, with an average relaxation level of 0.469, as seen in Table 1. Although not frequent, outside disturbances like noise or technical problems with the EEG sensor also raised stress levels. Additionally, an observer was present throughout the consultation to monitor the EEG sensors and ensure the quality of the data. This presence may have made the participant feel uncomfortable and self-conscious, contributing to increased stress during the session. This highlights the necessity of creating a peaceful, pleasant, and private environment for in-person consultations. This quality is more challenging to control in other consultation methods (e.g., online consultations). For the EEG experience, two (40%) participants found the sensor uncomfortable, while the rest (n=3, 605) felt no discomfort. No technical issues were faced in fitting the EEG sensor except for one respondent who stated that having it on for a long time caused them some pain. All participants rated the usage of the sensor as very easy.

4 Discussion

The current study focused on writing consultation as an example of shared social interaction in the HCI participatory user sessions. The research investigated the value of using EEG sensors in a hyperscanning set-up for insights into the interpersonal reactions of the consultant and patrons. Data analysis highlighted the consultant's influence on the patrons' emotional reaction and, perhaps surprisingly, the reverse. Overall, the study with EEG sensors offers significant insights into gauging the effectiveness of this user session, particularly in how the emotional states, like stress, engagement, relaxation, attention, excitement, and interest, influence the overall session experience. The combination of EEG data, qualitative observations, and post-survey data provided a detailed view of how participants responded to different stimuli during their consultations.

The variety of emotional responses from the consultant and patrons suggests the cognitive demands required by such a complex interaction. Social exchanges during user sessions encompass a rich array of verbal and non-verbal communication channels within these dyadic interactions, which EEG data analysis helps to uncover. Multiple social cues in these user sessions increase processing effort, which HCI researchers must consider when conducting such sessions. Not only for the participants in such sessions but also for the HCI consultant, as prior research in other domains reports some brain activities were synchronized in dyads engaged in joint actions [18].

The EEG analysis results in this study indicated that participants showed more engagement and excitement when there were moments of shared humor, good eye contact (from observations), individualized feedback, and visual aids. As shown in Table 1, the average engagement score is 0.648, which highlights the consultant's and the participants' active participation. These findings support the idea that humanized interaction is essential to the effectiveness of these user sessions. Real-time, personalized feedback needs to be modified in response to the participant's immediate response to increase engagement and lower stress. For instance, the average excitement score in Table 1 of 0.587 indicates that the participants were typically enthusiastic and open to criticism, particularly when the consultant spoke upbeat and sympathetic. These moments of personal connection are essential in sessions where the consultant must assess and react to the participant's emotional condition.

While EEG warrants valuable insight into engagement and emotional states during participative user sessions, considering the contexts when it is advantageous is also essential. Thus, EEG could be useful in real-time research settings where one seeks objective measures of user reactions. For example, EEG can be employed in usability tests, focus groups, and HCI studies to detect unconscious cognitive and emotional responses that would not easily come forth in verbal feedback alone. That said, EEG is not always necessary. If self-reported feedback and behavioral observations are good enough, EEG will be an unnecessary complication in data acquisition and interpretation. Besides that, within the broader scope of environmental variables-influenced responses are external noise, participants' motions, and discomfort caused by the use of equipment; thus, variability of EEG reading occurs, affecting the reliability. Future studies will combine EEG with complementary measures using eye tracking and/or heart rate monitoring to arrive at a concurrent assessment of emotional states in participatory work.

A potential weakness in the study is that an observer was present during the consultation process. While it was essential to maintain the integrity of the data collection and ensure the EEG sensors were fitted properly, some participants might have felt uncomfortable, adding to their stress levels, especially if they felt like they were being watched when they received critical feedback. This possible cause of discomfort could be reduced in other research by not having an obvious presence of observers or by using more covert monitoring techniques, allowing for a more natural consultation experience. The next step is to replicate the study with an increased sample size and include participants in diverse user sessions to provide a thorough understanding of the consultant-patron interplay in such sessions, including controlled shifts in the consultant interactions. However, this would cause the sessions to lose some natural interaction. Future research could investigate alternative technologies, including large language models [19], in conjunction with EEG sensors, such as facial recognition, to capture emotional responses.

5 Conclusions

This study explored applying neuroscience methods in participatory user sessions of writing consultation. Given the value of these and similar user sessions, these forms of person-to-person interaction typically elicit high levels of cognitive resources and engagement for the HCI researcher and the user. Findings highlight the value of hyperscanning investigations as a methodology to explore the quality of these user sessions. The next step is a full study with larger samples in other user-type sessions. Findings from these neuroscience investigations allow consultants to modify their approach based on the participant's instant emotions and develop a stronger emotional connection via increased engagement and excitement. This study highlights that encouraging personalized constructive feedback can result in positive changes without overwhelming the participant.

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