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Examining User Perceptions of Brain-Computer Interfaces for Practical Applications: An Exploratory Study

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Short Paper

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Abstract

The idea of controlling technology with your thoughts only is becoming reality with the emergence of consumer-grade Brain-Computer Interfaces (BCI). Understanding how regular users perceive this innovative way of controlling their devices is crucial, as it offers a more seamless and intuitive method of interacting with technology. Despite the improving capabilities and smaller form factor of BCI, its potential usage by non-medical users remains largely unexplored. In this research, we address this gap in a mixed-methods approach. In (n=26) qualitative interviews we explore users' perception of BCI technology and identify its impact on users' attitudinal and behavioral outcomes. Our findings reveal that users consider their perception as a cyborg and the device's functionality when deciding on their intention to interact with BCI, dependent whether BCI used for individual or organizational interaction. We employ a pre-study (n=189) and multiple experimental studies to empirically triangulate and quantify findings from qualitative interviews.

Keywords: Brain-Computer interface, human-technology interaction, cyborg, mixed-methods

Introduction

Imagine controlling your computer or smartphone using only your thoughts. What once seemed like a far-fetched concept out of sci-fi novels or movies is becoming reality with rapidly evolving consumer-grade Brain-Computer Interfaces (BCI) (Vasiljevic & de Miranda, 2020). Recently, advancements in BCI technology have resulted in remarkable achievements such as Elon Musk's company Neuralink training monkeys to play Pong wirelessly through mind control. Meanwhile, NextMind, a startup that was acquired by Snapchat's parent company Snap in 2022, has developed a BCI headset that allows users to interact with their smart home or control their TV (Brown, 2021). Several companies are working on reducing the form factor of BCI devices, for example integrated in headphones, while simultaneously enhancing the detection of mental commands. These consumer-grade devices hold tremendous potential to enhance the user experience by providing a more intuitive and seamless way of interacting with technology. With a market value of $1.74 bn in 2022, it is projected to reach $6.18 bn by 2030 (Grand View Research, 2023). Based on these forecasts, it is evident that BCI technology will play a significant role in shaping and transforming how users interact with technology. For this study, BCI refers to an information technology that is placed on the outside of the brain that enables humans to interact with technology without any body movement, using only electrical signals generated in the brain to record activity (Nicolas-Alonso & Gomez-Gil, 2012).

Drawing on information systems (IS) and human-computer interaction (HCI) literature, BCI has primarily been researched to provide communication abilities to disabled or "locked-in" patients (Kawala-Sterniuk et al., 2021). With consumer-grade BCI devices moving more into mainstream applications, literature streams from IS and service marketing are relevant to comprehend regular users' adoption behavior. BCI has been found to enhance immersion and enable new forms of interactions with players in gaming and can be successfully utilized to control robots in hazardous environments (Liu et al., 2021; Vasiljevic & de Miranda, 2020). Additionally, it has been shown that BCI are able to operate IoT devices or used to navigate smart wheelchairs (Tang et al., 2018; Zhang et al., 2019). User acceptance of novel technologies is influenced by well-established constructs, such as the technology acceptance model (TAM) or the unified theory of acceptance and use of technology (UTAUT), where ease of use and usefulness impact users' intention and subsequent adoption behavior (Marangunić & Granić, 2015; Venkatesh et al., 2012). Furthermore, literature in service marketing suggests that new technologies also impact consumer perceptions, potentially altering their willingness to use it if their interaction data is at risk of being shared with companies, fearing to be controlled as a result. Therefore, users might feel different about interactions with BCI on an individual level, e.g. controlling their smart home devices, compared to interactions with organizations where they interact to purchase products or services with BCI (Smith, 2020).

Clearly, the way users perceive BCI in individual and organizational interaction is relevant in determining their future intention to use such devices. However, despite the abundance of literature on the technical aspects of BCI, research on regular users' perceptions outcomes is limited but much needed (De Keyser et al., 2021). Recognizing this research gap, our study is directed towards addressing an overarching research question accompanied by sub-research questions that align with each of the (to be) conducted studies.:

Main RQ: How do users perceive interactions with consumer-grade BCI technology?
Sub-RQ1: What are the key drivers and barriers that influence users' interactions with BCI?
Sub-RQ2: How does the interaction setting impact user-evaluations of BCI technology?
Sub-RQ3: To what extent does the level of BCI functionality shape user perceptions?
Sub-RQ4: How does the BCI context influence the self-perception as cyborgs?

By answering these research questions, our study contributes to literature in both information systems and service research, ultimately promoting interdisciplinary collaboration and knowledge exchange: (1) Our research is among the first to analyze the drivers and barriers of user' acceptance of BCI technology. (2) We investigate the determinants and psychological processes for users' intentions to use BCI for technology interaction through our qualitative and experimental studies. (3) Our study explores the relationship between the use of BCI technology by users in individual and organizational settings, and sheds light on the differences that affect its usefulness and the intention to use it.

Background Literature

Our investigation of the adoption of BCI for user control of devices draws upon a diverse range of research streams from the fields of information systems, service management, marketing, and psychology. Most existing research on BCI has primarily focused on extracting features from brain waves or developing medical applications to assist users with brain injuries or locked-in states to communicate or control robotic extensions (Kawala-Sterniuk et al., 2021). Despite these efforts, there has been a lack of research both within and outside the IS literature on the acceptance of BCI for individual and organizational technology interaction (De Keyser et al., 2021; Kögel et al., 2019; Vasiljevic & de Miranda, 2020).

Limited studies have begun to investigate the implications of consumer-grade BCI for users in applications such as gaming, IoT control, robot control and inferring user intentions from brain waves. In gaming, letting users interact with games with BCI devices has demonstrated to increase engagement and enable novel forms of interaction as a passive or active controller, thereby enhancing the gaming experience (Vasiljevic & de Miranda, 2020). Improved signal detection and the ability to distinguish it from noise has shown to make it feasible to utilize BCI technology to control IoT devices, including in smart home settings (Zhang et al., 2019). Another recent study explored the potential of utilizing BCI for robotic commands to operate construction robots from a distance. The research demonstrated that BCI could be effectively used to control construction robots in hazardous operations, such as underwater or space constructions, in situations where a worker's capacity to physically guide the robot is restricted (Liu et al., 2021). Utilizing BCI technology, it is possible to infer the intentions of drivers and determine whether users plan to switch lanes, allowing semi-autonomous vehicles to make the necessary adjustments autonomously (Xing et al., 2019). Despite the possibilities BCI enable, their use also has a dark side as sensitive neural data is handled. Even though data can be analyzed without compromising privacy, malicious actors could exploit real-time emotional or intention data, potentially enabling constant surveillance. Thus, responsible data management is paramount as the technology evolves (Bonaci et al., 2014; Dignum, 2019). In recent years, the development of non-invasive BCI technology has significantly improved, shifting away from wired brain-caps with wet electrodes to more user-friendly methods such as headbands, headphones, and headset-like devices with integrated dry electrodes. Several companies have entered this market and provided consumer-grade devices that allow users to gain insight into their mental state of concentration, focus, or meditation, while others enable control of devices such as smartphones or in-game controls (Kögel et al., 2019). Currently available consumer-grade BCI devices are listed in Table 1.

Device	Functionality	Technology	Price
Emotiv Epox X	Raw EEG Headset, Mental Commands, Emotion and Facial Expression Detection	14-channel EEG	$849
Galea (OpenBCI)	Integration for VR headset, multiple biometrical data sources (brain, eyes, heart, skin), attention, stress and cognitive load detection	EMG, EEG, EOG, EDA, PPG	$25,000
Muse S	Headband to detect brain activity and heart rate for meditation and stress reduction	7-channel EEG	$399
Neurable Enten	Headphones detect focus and distraction, adjust music or noise cancellation levels, control smartphone (e.g. skip song)	16-channel EEG	$400
Nextmind	Headband to detect brain activity of visual cortex allowing control of devices with visual attention. Available as a developer kit.	9-channel EEG	$399

Table 1. Examples of Consumer-Grade BCIs

In recent years, NeuroIS research gained traction in understanding users' emotions, stress and factors related to technology acceptance while interacting with information or communication systems (Dimoka et al., 2012; Riedl et al., 2020). This advancement is comparable to neuromarketing research, which employs brain activity monitoring to anticipate advertising effectiveness or gain insights into consumers' preferences without their explicit verbalization (Lee et al., 2007). Although much of this research does not focus on BCI device interaction and mostly involves observing users in those contexts, it can yield valuable findings. For example, two studies demonstrated that EEG-based BCIs were capable of detecting users' choices before they made them (Hibbeln et al., 2017; Xing et al., 2019). This could potentially pave the way for an enhanced user experience, where consumer-grade devices go beyond direct control intention and become capable of predicting user intentions or emotions.

Research in the field of service marketing has begun to pay attention to human enhancement technologies (HET) and their implications for consumers (Garry & Harwood, 2019; Grewal et al., 2020). As part of HET, BCI are a central technology which could allow more advanced approaches to merge its users with AI. This, in turn, could reshape the service experience, improving the well-being of customers and enhance their overall experience (Lima & Belk, 2022). However, there may also be drawbacks, such as financial inequality or ethical concerns related to the technology. Grewal et al. (2020) have conceptualized the impact of HET on front-line employees, who may be perceived as robotic cyborgs, leading to potential dehumanization and negative perceptions of warmth and competence during service encounters. In this context, cyborgs are users who interact with BCI technology to augment their abilities. Additionally, Castelo et al. (2019) found that consumers who enhance their abilities through technology are more likely to be perceived as less human than individuals who use HET to restore lost abilities.

Research Design and Methodology

Due to the novelty of consumer-grade BCI technology in user engagement and limited existing research, we adopted a two-step exploratory design. First, a qualitative study examined users' perceptions and opinions on BCI adoption. This study identified crucial usage aspects, factors, and boundary conditions affecting user responses. Our research design and methodology, following Sarker et al. (2013) recommendations, are comprehensively outlined.

As a first part of our mixed-method design, ***qualitative problem-centered interviews*** were conducted as a way to capture rich and nuanced insights from participants, shedding light on their experiences, attitudes, and beliefs towards this emerging technology (Patton, 2014). Our personal interviews featured insights from 26 interviewees. Given the potential broad integration of BCIs for individual or organizational interactions with technology, impacting diverse consumer groups, we opted for heterogeneous interviewee selection. The age of our interviewees varied between 21 and 50 years (M_{age} =28.54, SD=6.45; 10 female, 16 male). In a purposive sampling approach individuals had to fulfill two criteria (Patton, 2014). First, interviewees should be primary consumers in their household. Secondly, we assessed individuals' experience levels with novel HCI technologies like augmented or virtual reality (high or low) during the interview invitation process, ensuring a balanced distribution across participants. The interviewees were recruited through personal contacts and the interviews ranged from 32 to 67 minutes in duration.

We designed an interview guide to provide structure and guidance during interviews, ensuring consistency. The interview guide comprised four main sections and 28 open-ended questions: (1) General knowledge and think-aloud protocol of consumer-grade BCI devices. Due to the BCI technology's novelty and participants' lack of prior experience, we introduced explanatory videos and images showcasing consumer-grade BCI use. We encouraged interviewees to vocalize their thoughts and emotions while viewing the content, similar to the think-aloud technique (Solomon, 1995). We chose this design to enable us to directly observe the individual reactions of users when they imagine interacting with a BCI. (2) The perceived influence on interactions with technology mediated through BCI, (3) willingness to use BCI for interactions for individual use or organizational interactions, (4) Privacy and data safety concerns of individuals.

In preparation for the data analysis, all taped interviews were transcribed, which yielded 363 pages of data. The transcribed interviews were analyzed with atlas.ti, an established qualitative data analysis software (Hwang, 2008). Our approach involved employing the thematic analysis (Braun & Clarke, 2006) method to analyze and interpret our data. We screened the text sentence by sentence to familiarize ourselves with the material and to perform an initial coding by identifying recurring and interesting features in the data. The coding system was established inductively by two independent researchers performing an in-depth textual analysis. New codes were created by iteratively moving through the data in multiple cycles to capture the meaning of our initial code groups and were organized hierarchically in a coding tree (Thomas & Harden, 2008). By iterative cycling through the coding tree the data was further managed, filtered, highlighted, and focused on the salient features of the qualitative dataset. The two members of the research team then independently formed the main categories. Engaging in discussions regarding content and labels, we iterated through several rounds of deliberation to arrive at a conclusive set of themes.

In a next step, we will conduct one pre-study (completed) and three additional ***experimental studies*** (completed until Fall 2023) to triangulate the findings from the qualitative study. The objectives of these studies will be to empirically test and quantify the proposed relationships between users' cyborg perception and BCI functionality for individual or organizational use settings on the behavioral intention measure. Moreover, we plan to explore identified moderating effects from the qualitative study.

To prepare for our experimental studies, we conducted a **pre-study** to test the manipulations we plan to use. Our goal was to identify reliable and accurate categories that clearly distinguish between individual and organizational *interaction settings*, as well as between low and high *BCI functionality*, which are important for Study 1 and 2. In the vignettes, low BCI functionality was manipulated to participants by explaining that the BCI technology enables similar functions to common interaction devices like mouses or keyboards. On the other hand, high BCI functionality was presented as a more sophisticated interaction, which takes into account factors such as reading emotions or mood and performing actions in a more congruent way (e.g. adjust music to mood). Interaction setting was manipulated with the BCI user interacting in a smart home setting vs. booking vacations online. To achieve this, we presented four scenarios to n=200 participants from the United States, United Kingdom, Ireland, Australia and New Zealand, recruited from Prolific Academic (Peer et al., 2017). However, 11 participants who did not complete the full study, failed two or more attention checks, or indicated, without impacting their compensation, not reading all instructions and material carefully, were excluded from analysis (Oppenheimer et al., 2009). Our final sample included 189 participants (M_{age} =39.78, SD=13.43, 51.3% female). Participants were randomly assigned to a vignette, receiving a BCI interaction description. As a manipulation check, participants indicated the extent to which the BCI technology had limited vs. advanced capabilities and were either used for a business vs. leisure setting.

In **experimental study 1**, we will be conducting real user interactions with a BCI and a computer using an Emotiv Epoc X headset. The interaction is programmed using "Emotiv BCI" and a Python script to enable real-time control of the computer based on the user's neural signals. We will manipulate the *interaction setting* in a 2 (individual vs. organizational interaction) x 1 between-subjects experiment. To prepare for the user interaction with the headset in our study, participants will be undergoing a training session lasting between 15 and 30 minutes, which is necessary to allow the device to accurately recognize individual mental commands from each participant. To ensure a positive user experience, the training will be designed to not induce fatigue or annoyance with BCI technology and there will be frequent breaks in between training sessions. We will select the task for the BCI interaction based on the results of our pre-study. Participants will be asked to fill out part of the survey before the technology interaction and part after.

In **experimental study 2** the laboratory study will be slightly modified and extended. In addition to the *interaction setting* we will manipulate *BCI functionality* in a 2 (individual vs. organizational interaction) x 2 (low vs. high BCI functionality) between subjects design, to investigate the impact of ease of use and usefulness on behavioral intention to use BCI. The BCI functionality will be varied by presenting different scenarios based on the pre-tested low and high functionality assessments regarding the ease of use and usefulness of the BCI system. In **study 3** another scenario-based experiment will be conducted to investigate the impact of *cyborg perception* on behavioral intentions of users. With a 2 (enjoyment vs. productivity) x 2 (individual vs. organizational interaction) design we investigate the driving forces for cyborg perception in contexts where the BCI device is used for enjoyment (e.g. gaming) versus productivity (e.g. monitor cognitive functions).

In all studies, participants will be requested to complete a survey that comprises validated multi-item scales to measure the dependent variables consistently. We will pre-register all studies with aspredicted.org and analyze the data with multi-factor ANOVA using R. The studies are scheduled to be conducted in Fall 2023.

Results of the Qualitative Study

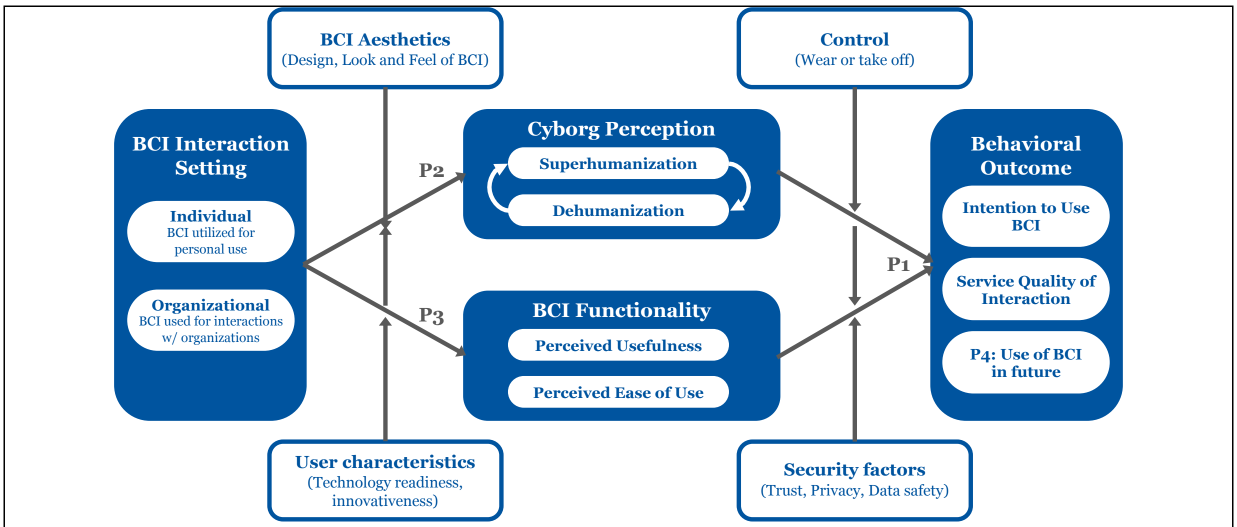

Figure 1. Proposed Research Model

In our proposed research model, we present the outcomes of an extensive qualitative study comprising 26 in-depth interviews. Employing a rigorous iterative process through thematic analysis, we diligently analyzed these interviews, leading to the emergence of distinct thematic categories. The formulation and positioning of these categories within our model were influenced, in part, by the well-established frameworks of TAM and UTAUT (Marangunić & Granić, 2015; Venkatesh et al., 2012).

Interaction Setting

The interaction setting category refers to how BCI are utilized by users to interact with devices, either for individual use, such as controlling smart home devices or for organizational use, such as purchasing a product or service. For individual usage settings, participants were mostly open to the implementation of BCI technology, as they believed it would enhance their interaction with technology and make it more congruent with the way they intended to interact with it.

"Like in smart homes, the interaction will be a lot more direct than it is currently. Now, the least I have to do is to grab my smartphone and go into an app, browse through the app a lot to get to the button that opens a window [...] and still it's inconvenient." (I. 23)

Although some participants expressed skepticism towards BCI in general, they still recognized the benefits of using BCI to interact with technology in an individual setting at home. On the other hand, when it came to using BCI in an organizational setting, participants' perceptions were more divided. While some still recognized the advantages of using BCI technology for improved interaction and the potential to save time and effort, others were hesitant or even mentioned to avoid using BCI due to concerns about trust. This suggests that trust plays a significant role in determining people's willingness to use BCI technology, particularly in interactions with organizations.

"Actually, it makes my tasks easier and, yes, I'm faster, [...] no disadvantages, only advantages, therefore, why not use it?" (I. 9)
"Actually, I don't want that at all, I don't want them to have all my thoughts somewhere." (I.12)

Our text data suggests an impact of the interaction setting on users' evaluation of BCI implementation. Individuals mentioned to be more open to engaging with BCI technology in an individual setting. Insights on using BCI for organizational interaction are divided. Therefore, we propose:

Proposition 1 (P1): Individuals are more willing to use BCI in individual usage settings compared to organizational usage settings.

Cyborg Perception

A recurring topic in the interviews was the respondents' self-perception as a cyborg while using BCI to interact with other devices. Our study revealed that users held contrasting views on using BCI technology. Some participants felt that using BCI made them feel like superhumans due to their perceived enhanced abilities compared to non-users. Participants believed using BCI for interaction would boost their self-perceived competence and capability compared to non-users.

"In a way, yes, because you can do something that no one else [...] or people can't do by nature." (I. 5)
"Yes, because, I can control it all with my thoughts and he can't." (I. 13)

In contrast, other participants expressed concerns that using BCI could dehumanize them, and that their self-perception as a cyborg might diminish their sense of humanness. This was true even for participants wo were initially intrigued by controlling technology with their thoughts only. Individuals mentioned that using BCI could cause them to lose their distinguishing human features, such as feelings or physical movement ability.

"A lot of things that you no longer have to do manually, you just think about them mindlessly, and when you think, you don't really need a lot of feelings or anything." (I. 3)
"People might start to lose some physical functionality from being human, people will be dependent on these things [...] simple physical interactions activity might not work anymore." (I.21)

We argue that users' self-perception as cyborgs when interacting with BCI technology is a key factor that shapes their behavioral intentions to use it for interaction. Depending on the individual user's characteristics, either superhumanization or dehumanization may influence their decision to use BCI. Against this background, we propose:

Proposition 2 (P2): Individuals perceiving the technology as enhancing/reducing human abilities will react favorably/negatively to using BCI for technology interaction.

BCI Functionality

Our results show that the level of functionality of BCI devices has an impact on the formation of usage intentions. Functionality, which encompasses the capabilities of the BCI device, is closely related to the concepts of perceived usefulness and ease of use that have been widely established in IS research. As BCI technology involves a novel concept and unique interaction style, our participants mentioned high expectations of the devices in terms of capability and ease of use.

"But, if you bring something like this to the market, it should work perfectly and error-free." (I. 4)

“It's really just a few clicks, whether I do it with my mind or type it twice, it doesn't help me much.” (I.12)

Even hesitant participants expressed a willingness to adopt BCI technology as its functionality increases. They viewed BCI as offering a more convenient and efficient way of interacting with their daily devices, including smartphones. They considered the technology as providing a faster and more congruent interaction, which saves time and enhances usefulness.

“It's really useful. It's also really creative. I have to say. These actually break the traditional model of how we interact with another device. It's pioneering technology.” (I. 21)
“So much easier to use such a device [...], everything would be much easier, much faster, if it really works, much safer.” (I.13)

Based on our findings, individuals suggest that BCI devices must exceed the current level of usefulness provided by existing ways of interacting with technology, which is in line with existing IS research (Venkatesh et al., 2012). The perceived functionality of BCI devices was closely related to their ability to accurately recognize the complexity of thoughts and translating them to commands on other devices. Based on the qualitative insights and empirical confirmation in previous IS research, we therefore propose:

Proposition 3 (P3): Higher functionality of BCI devices for user-device interactions have a positive impact on behavioral intention.

Behavioral Intention

Behavioral intention refers to participants' intention to use BCI technology, assuming they have access to it. This category is therefore closely related to the concepts of intention to use in IS research (Venkatesh et al., 2012). In general, participants expressed openness to trying the technology, as it only required wearing a headband or headset to communicate with other devices. Some participants were enthusiastic and amazed that such technology exists, as they previously only encountered it in science fiction.

“The attraction is simply there, then also to actually [perform] some things from the room by thought transmission.” (I. 11)
“First of all, I am somehow a bit excited [...] very interesting and would like to try it out for myself.” (I. 6)

It is worth noting that most participants showed a positive attitude towards trying BCI technology. However, a few participants expressed their reluctance in their intention to use it for various reasons. Some individuals mentioned the lack of benefits offered by the technology as a reason for rejecting it, while others disliked the idea of wearing head-mounted devices or believed that using BCI would take away the fun from leisure activities.

“You are only sitting and staring at the monitor. I can tell that playing the game is boring. [...] The most relaxing thing in the game is while moving [mouse and keyboard], the reflex and so on.” (I. 24)
“I think even if it was weightless or something or you could only see it slightly, I still probably wouldn't do it for purely aesthetic reasons.” (I. 8)

One participant expressed their neutrality towards BCI technology, stating that they have not yet been persuaded to use it.

“I'm still neutral about the whole thing, so it hasn't blown me away yet, but I'm not saying it's totally bad either” (I.3)

Overall. We summarize that the behavioral intention to use BCI are essential for actual use of consumer-grade BCI. Therefore, we propose:

Proposition 4 (P4): Positive disposition of behavioral intention to use BCI devices translate to higher actual use of BCI in the future.

Results of Pre-study 1, Expected Contributions and Outlook

Our pre-study findings reveal participants' accurate distinction between individual and organizational BCI interaction. Consequently, our planned quantitative studies can confidently incorporate these examples. However, functionality manipulation proved highly significant only for individual interaction, contrasting the non-significant result in organizational interaction (p=0.13). Ease of use control measures indicate that manipulated BCI functionality in organizational contexts is perceived as easier to use, though not significantly distinct in functionality. Based on these findings, we will rerun the pre-test for organizational BCI interactions, exploring alternative descriptions.

We expect this study to offer two major contributions. First, this study will advance the limited research on regular user interactions with technology through a BCI. By addressing a gap in the literature, which primarily investigated *observing* users while interacting with technology in neuroIS and neuromarketing fields, this research takes a pioneering step towards understanding how individuals perceive *interacting* with technology through BCI (Dimoka et al., 2012; Grewal et al., 2020; Lee et al., 2007). We thus contribute to the research of HCI and provide an additional perspective exploring the utilization of BCI by users in both individual and organizational interactions. As a second contribution, we investigate the determinants and underlying psychological processes driving users' perceptions and attitudes toward the application of BCIs, employing a combination of qualitative and quantitative (experimental) studies. Our proposed research model from our interview study makes a clear conceptual contribution, as it shows distinctive factors driving and hinder the adoption of BCI technology (i.e. cyborg perception, manipulation concerns), thus shaping users' intentions to embrace or reject its application. Prior research providing such a comprehensive and structured overview is currently lacking. On the basis of these identified criteria, our objective is to validate and refine the research model through three experimental studies, among which one involves actual users interacting with technology via a BCI. This approach is designed to offer a thorough comprehension of the dynamics inherent to this pioneering method of technology interaction.

Our upcoming steps include re-running the pre-study to establish manipulations, followed by verifying Emotiv Epoc X functionality for our laboratory experiment with faculty members. Beginning with the lab experiment and preregistering our hypotheses, we will subsequently conduct two online experiments through Prolific Academic.

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