Mind Over Matter: Multiperspective Findings on Brain-Computer Interfaces' Impact in Service and Technology Interactions

Von der Fakultät für Wirtschaftswissenschaften der
Rheinisch-Westfälischen Technischen Hochschule Aachen zur Erlangung
des akademischen Grades eines Doktors der Wirtschafts- und
Sozialwissenschaften genehmigte Dissertation

vorgelegt von

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Thinking Outside the Box – Literally

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A

Abstract

Human Enhancement Technologies (HET), heralded as the next frontier in service technology, hold the potential to revolutionize human capabilities to augment a person's physical, cognitive and emotional capabilities beyond their usual limits. Amidst this technological (r)evolution, Brain-Computer Interfaces (BCIs) stand out as a key technology in these developments. BCIs are wearable technology that establishes a direct communication link between users' brains and external devices by recording and decoding neural activity. As a result, users can turn on smart lights by thinking about it, query databases at the speed of thought or communicate their emotional state to another BCI user via brain-to-brain transmission. Clearly, this development holds important considerations for enhancing the capabilities of Frontline Employees (FLE) on service interactions, user intentions to adopt BCIs for technology interaction or changes in communication due to the extension of communication affordances. Although there is a substantial body of research on the technical aspects of BCI technology, there is a noticeable gap in the literature on the potential BCIs hold for services, user perceptions and communication. Therefore, the four essays of this dissertation offer a multi-perspective view on these critical areas.

The first paper finds that enhancing FLEs with BCIs for efficiency leads to the 'cyborg effect', where BCI enhancement has a negative impact on service evaluations, mediated by warmth and competence grounded in social cognition theory. We show that framing BCIs for personalization of encounters alleviates the cyborg effect and demonstrate that with increasing service complexity, personalized BCI-enhanced FLEs are perceived as warmer and more competent than their human counterparts. The second paper conceptualizes BCIs' impact on FLEs' well-being when the technology is worn as workplace technology. Depending on how BCIs are integrated, FLEs perceive the technology as a tech-resource (i.e. predominant positive impact) or tech-stressor (i.e. predominant negative impact). When FLEs see BCI as tech-resources, they perceive the technology as aiding in task completion, enhancing their motivation, and reducing stress. Conversely, when BCIs are perceived as tech-stressors, FLEs' perceive to be surveilled by technology, overwhelmed by its complexity that led to the view of BCIs as taxing or exceeding FLEs' available resources. The third paper aims to understand how regular users perceive this innovative method of controlling their devices, as it offers a more seamless and intuitive way of interacting with technology. Our findings reveal that users consider their self-perception as cyborgs and the device's functionality when deciding on their intention to interact with BCIs, depending on whether the BCI is used for individual or organizational interaction. The fourth paper explores how BCIs offer an unprecedented level of immersion and technological embodiment in the metaverse. This paper establishes a conceptual framework that details enhanced communication affordances using BCIs and discusses the ethical implications of mainstream market BCI technologies.

B

Zusammenfassung

Human Enhancement Technologies (HET), die als nächste Entwicklungsstufe der Servicetechnologien betrachtet werden, haben das Potenzial, menschliche physische, kognitive und emotionale Fähigkeiten über ihre natürlichen Grenzen hinaus zu erweitern. Im Zuge dieser technologischen Revolution ragen Brain-Computer Interfaces (BCIs) als Schlüsseltechnologie heraus. BCIs sind tragbare Systeme, die durch das Aufzeichnen und Entschlüsseln neuronaler Aktivität eine direkte Kommunikationsverbindung zwischen dem Gehirn des Nutzenden und externen Geräten ermöglichen. So können Nutzende beispielsweise smarte Lampen allein durch ihre Gedanken steuern, Datenbanken in Echtzeit abfragen oder ihren emotionalen Zustand über eine Brain-to-Brain-Übertragung mit einem anderen BCI-Nutzendem teilen. Diese Entwicklung wirft wichtige Fragen auf, wie etwa zur Verbesserung der Fähigkeiten von Frontline-Mitarbeitenden (FLE) in Serviceinteraktionen, zur Bereitschaft der Nutzenden, BCIs für die Technologieinteraktion einzusetzen, und zu den Veränderungen in der Kommunikation durch erweiterte Interaktionsmöglichkeiten. Trotz umfangreicher Forschung zu den technischen Aspekten der BCI-Technologie besteht in der Literatur eine deutliche Lücke in Bezug auf das bedeutende Potenzial von BCIs für Dienstleistungen, Nutzendenwahrnehmung und Kommunikation. Diese Dissertation zielt daher in einer multiperspektivischen Betrachtung darauf ab, diese Bereiche zu beleuchten.

Der erste Aufsatz zeigt, dass das BCI-gestützte Enhancement von FLEs zur Effizienzsteigerung einen „Cyborg-Effekt“ auslösen kann, bei dem das technologische Upgrade zu einer negativen Wahrnehmung der Dienstleistung bei Kund*innen führt. Dieser Effekt wird durch die Faktoren Wärme und Kompetenz, basierend auf der Theorie der sozialen Kognition, mediiert. Wir zeigen jedoch, dass der Einsatz von BCIs zur Personalisierung von Serviceinteraktionen diesen Cyborg-Effekt abschwächt. Zudem belegen wir, dass mit zunehmender Komplexität der Dienstleistungssituation personalisierte, BCI-unterstützte FLEs als wärmer und kompetenter wahrgenommen werden als ihre nicht BCI-gestützten Kolleg*innen. Der zweite Beitrag konzeptualisiert die Auswirkungen von BCIs auf das Well-being von FLEs, wenn sie als Arbeitsplatztechnologie eingesetzt werden. Je nach Integration der BCIs nehmen die FLEs die Technologie entweder als Tech-Ressource (mit überwiegend positiven Effekten) oder als Tech-Stressor (mit überwiegend negativen Effekten) wahr. Wenn BCIs als Tech-Ressource betrachtet werden, unterstützen sie die Mitarbeitenden bei der Aufgabenerledigung, steigern ihre Motivation und reduzieren Stress. Werden BCIs hingegen als Tech-Stressoren empfunden, fühlen sich die FLEs von der Technologie überwacht und von ihrer Komplexität überfordert, was dazu führt, dass sie die BCIs als Belastung ihrer Ressourcen wahrnehmen. Der dritte Beitrag untersucht, wie gewöhnliche Nutzende diese innovative Methode zur Steuerung ihrer Geräte durch BCIs wahrnehmen, da BCIs eine nahtlose und intuitivere Interaktion mit der Technologie ermöglichen. Unsere Ergebnisse zeigen, dass die Nutzenden bei der Entscheidung, ob sie mit BCIs interagieren möchten, sowohl ihre Selbstwahrnehmung als „Cyborgs“ als auch die Funktionalität des Geräts berücksichtigen. Dabei hängt ihre Entscheidung davon ab, ob das BCI für individuelle oder organisatorische Interaktionszwecke eingesetzt wird. Der vierte Beitrag untersucht, wie BCIs ein beispielloses Maß an Immersion und technologischer Verkörperung im Metaversum ermöglichen. Hier wird ein konzeptioneller Rahmen entwickelt, der die erweiterten Kommunikationsmöglichkeiten durch Neuroimaging- und Neurostimulations-BCIs detailliert beschreibt und die ethischen Implikationen des kommerziellen Einsatzes von BCI-Technologien erörtert.

C

Declaration on Essays

Reversing the Cyborg Effect: Enhancing the Service Quality of Frontline Employees with Brain-Computer Interfaces

Kies, Alexander (RWTH Aachen University); Hilken, Tim (Maastricht University); Heller, Jonas (Maastricht University); Paluch, Stefanie (RWTH Aachen University)

Received **Major Revision** Decision Post First-Round Reviews. Revision in Progress at *Journal of Service Research* (VHB-JOURQUAL3: A)

This paper was presented in various stages at *Winter AMA 2023*, *Frontiers in Service 2023*, *SERVSIG 2024* and *Frontiers in Service 2024*.

The candidate's contribution to each publication was made according to CRediT, which, according to Brand et al. (2015) , "is a high-level taxonomy, including 14 roles, that can be used to represent the roles typically played by contributors to scientific scholarly output. The roles describe each contributor's specific contribution to the scholarly output". Please find a detailed description of CRediT roles after the research essays. The candidate **conceptualized** the idea to investigate customers' perception on interactions with frontline employees. He conducted the **investigation** by performing qualitative interviews, preparing experimental data collection and supervising the laboratory experiments. Subsequently, he handled the development of **software** to integrate BCIs in the experimental context. Furthermore the candidate handled the **visualization**, **writing - original draft** and **writing - review and editing**.

Wired for Work: Brain-Computer Interfaces' Impact on Frontline Employees' Well-Being

Kies, Alexander (RWTH Aachen University); De Keyser, Arne (EDHEC Business School); Jaramillo, Susana (The University of Memphis); Li, Jiarui (Purdue University); Tang, Yihui (Elina) (Northern Illinois University); Ud Din, Ihtesham (Hasselt University)

Accepted for publication at *Journal of Service Management* (VHB-JOURQUAL3: B)

This paper was presented at *Frontiers in Service 2024*.

The candidate was leading the **conceptualization** of the framework and underlying structure of this research project. Furthermore, he handled the **visualization** of all figures and tables. Additionally, the candidate was in the lead for **writing - original draft** and also in the lead for **writing - review and editing** for this project.

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

Kies, Alexander (RWTH Aachen University); Paluch, Stefanie (RWTH Aachen University)

Published in 2023 *Proceedings of the International Conference on Information Systems (ICIS)* (VHB-JOURQUAL3: A)

This paper was presented at *ICIS 2023*.

The candidate **conceptualized** the idea to investigate users' perception about interacting with technology through BCIs. He conducted the **investigation** by performing and analyzing the qualitative interviews, as well as preparing and conducting the experimental data collection. Subsequently, he handled the **visualization**, **writing - original draft** and **writing - review and editing**.

Beyond Words: The Future of Metaverse Communication Through Brain-Computer Interfaces

Kies, Alexander (RWTH Aachen University); Paluch, Stefanie (RWTH Aachen University)

Manuscript is currently being prepared for submission to a special issue in *Internet Research* (7.9 5-year Impact Factor)

The candidate was leading the **conceptualization** of the framework and underlying structure of this research project. Furthermore, he handled the **visualization** of all figures and tables. Additionally, the candidate was in the lead for **writing - original draft** and also in the lead for **writing - review and editing** for this project.

CRediT Roles The roles from CRediT are comprised of:

Conceptualization Ideas; formulation or evolution of overarching research goals and aims.

Formal analysis Application of statistical, mathematical, computational, or other formal techniques to analyse or synthesize study data.

Funding acquisition Acquisition of the financial support for the project leading to this publication.

Investigation Conducting a research and investigation process, specifically performing the experiments, or data/evidence collection.

Methodology Development or design of methodology; creation of models.

Project administration Management and coordination responsibility for the research activity planning and execution.

Resources Provision of study materials, reagents, materials, patients, laboratory samples, animals, instrumentation, computing resources, or other analysis tools.

Software Programming, software development; designing computer programs; implementation of the computer code and supporting algorithms; testing of existing code components.

Supervision Oversight and leadership responsibility for the research activity planning and execution, including mentorship external to the core team.

Validation Verification, whether as a part of the activity or separate, of the overall replication/reproducibility of results/experiments and other research outputs.

Visualization Preparation, creation and/or presentation of the published work, specifically visualization/data presentation.

Writing – original draft Preparation, creation and/or presentation of the published work, specifically writing the initial draft (including substantive translation).

Writing – review & editing Preparation, creation and/or presentation of the published work by those from the original research group, specifically critical review, commentary or revision – including pre- or post-publication stages."

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Brand, A., Allen, L., Altman, M., Hlava, M., & Scott, J. (2015). Beyond authorship: Attribution, contribution, collaboration, and credit. Learned Publishing, 28(2).

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Glossary

AR - Augmented Reality: Technology that overlays digital information on the real world.

BCI - Brain-Computer Interface: A system that enables direct communication between the brain and external devices.

B2B - Brain-to-Brain Interfaces: A system allowing direct exchange of information between two brains.

ECoG - Electrocorticography: A technique to measure electrical activity from the cerebral cortex.

EEG - Electroencephalography: A method to record electrical activity of the brain using electrodes on the scalp.

fMRI - Functional Magnetic Resonance Imaging: Imaging technique to measure brain activity by detecting changes in blood flow.

fNIRS - Functional Near-Infrared Spectroscopy: A technique for measuring brain activity by monitoring blood oxygenation.

FLE - Frontline Employee: Employees who directly interact with customers in a service setting.

HCI - Human-Computer Interaction: The study and design of how people interact with computers.

HET - Human Enhancement Technologies: Technologies designed to enhance human physical, emotional and cognitive abilities.

MEG - Magnetoencephalography: A technique for mapping brain activity by recording magnetic fields.

tDCS - Transcranial Direct Current Stimulation: A non-invasive brain stimulation technique using a constant, low electrical current.

tES - Transcranial Electrical Stimulation: A group of techniques for brain stimulation using electrical currents.

VNS - Vagus Nerve Stimulation is a technique that uses small electrical pulses to stimulate the vagus nerve (helps control important body functions like heart rate, digestion, and relaxation) potentially affecting mood, inflammation, and neurological function.

VR - Virtual Reality: An immersive technology that creates a simulated, three-dimensional environment.

01

Introduction

"It feels almost like living in outer space. It's hard to grasp that a [Brain-Computer Interface] can read my thoughts and process them. I think that's really cool, but it's also a bit spooky." (C9, l. 44)

01.1
Background and Context

The next wave of technological service innovation is aimed at human enhancement. By leveraging cutting-edge technologies to augment physical, cognitive, and emotional capabilities beyond their usual limits, these advancements propel us toward superintelligence and optimal well-being (Lima and Belk, 2022; Marinova et al., 2017). While fitness and health trackers and other smart devices are already commonplace, so-called brain-computer interfaces (BCIs) are heralded as the next key technology in these developments (Garry and Harwood, 2019). Coined as the technology of the year 2023 (Nature Electronics, 2023), BCIs create a direct interface between users' brains and external devices by capturing and interpreting neural signals (Nicolas-Alonso and Gomez-Gil, 2012). These devices have the dual capability to decode individuals' mental states or translate thoughts to mental commands, allowing users to control and manage technology with unprecedented efficiency and precision (Aricò et al., 2018; Hilken et al., 2022). For example, Wenco, a Canadian company specializing in technology solutions for the mining industry, introduced SmartCap, a wearable BCI integrated into headwear that measures drivers' brain activity to detect real-time fatigue. When fatigue levels reach critical thresholds, the system provides immediate alerts to drivers and fleet managers, prompting corrective actions. This not only enhances road safety by reducing accidents caused by drowsiness, but also improves operational efficiency by managing fatigue-related risks proactively (Wenco, 2021). Another example is NextMind, a startup that developed a wireless BCI headset capable of translating neural activity to control smart home devices, such as changing the music, adjusting the color of smart lights, or switching TV channels. This marks a significant shift towards a more seamless and natural way of engaging with digital environments (Hilken et al., 2022). The company was later acquired by Snapchat, which aims to integrate this BCI technology into its hardware offerings (Heater, 2022).

Affordances gained through BCIs can be utilized by both frontline employees (FLEs) and consumers interacting with technology. As the primary point of contact between firms and customers, FLEs perform essential boundary-spanning functions (Lages and Piercy, 2012). Service providers are beginning to explore the use of BCIs to enhance the capabilities of FLEs in an effort to improve the quality of service interactions (Grewal et al., 2020). For example, BCIs could allow FLEs to deliver high-quality service at the speed of thought, while staying focused on building personal rapport. As a result, FLEs could interact more seamlessly with customers by minimizing distractions that divert attention from the customer, such as looking up product information on a laptop or tablet. Additionally, workplace BCIs can analyze FLEs' cognitive and affective states, including emotion, relaxation, and cognitive workload levels (Saha et al., 2021). By tracking brain activity, BCIs provide FLEs with feedback on their mental states, allowing for real-time analysis and long-term logging to gain detailed insights over time (Zander and Kothe, 2011). Adjusting workplaces and tasks based on these insights are being put forth as one promising solution to help FLEs function better in today's rapidly changing and highly taxing workplace environments (Grewal et al., 2020). For use by customers, BCIs offer a more intuitive way of interacting with technology, allowing users to control smart home devices or increase immersion and engagement when used to control games (Vasiljevic and de Miranda, 2020). Furthermore, by granting users the ability to gain insights into their mental state, directly manipulate reality-enhanced environments, or receive communication seamlessly without the need for peripheral technology, the ability to communicate with individuals and technology through thought is becoming a reality (Semertzidis et al., 2023). This development holds the potential to foster deeper social connections and shared experiences, thus enhancing individuals' well-being.

Indeed, BCIs are no longer solely a vision for a distant future, as major steps already have been taken to move the technology out of labs and into practical applications (Drew, 2023). For example, Neurable manufactures headphones with integrated BCIs that can suggest brain breaks for users when focus wanes and detect early signs of burnout and suggest timely interventions to mitigate its onset (Takahashi, 2024). Similarly, the Emotiv BCI headset enables reliable detection of mental commands, which enables FLEs to navigate software or allows customers to play a first-person shooter game using their thoughts, leading to significantly increased engagement as reported by users (Vasiljevic and de Miranda, 2020). Furthermore, OpenBCI offers a VR headset integrated with BCI technology, which notably controlled a drone flying over the audience of a TED talk (Houser, 2024). A notable indicator of their potential for mainstream rollout is Apple's patent application, proposing the integration of BCI sensors into their popular AirPods headphones (Purcher, 2023). First strides have been made to enable brain-to-brain communication with consumer-grade technology in a research device, enabling new forms of communication and gameplay. With a market size of $1.74 billion in 2022, projections suggest that this figure will reach $6.18 billion by 2030 (Grand View Research, 2023), indicating the wider adoption of BCIs across different usage settings.

Despite the promise of BCIs, there is a looming threat from other emerging service technologies, which have faced intense user resistance (Keeling et al., 2019; Mani and Chouk, 2018). This resistance is particularly pronounced for technologies that blur the boundaries between humans and machines, such as service robots (Uysal et al., 2022). BCIs pose the distinct challenge that they might make their user appear less human and more robotlike, essentially turning them into 'cyborgs' (Grewal et al., 2020). Indeed, prior research indicates that people who utilize enhancement technologies such as an augmented reality device are negatively perceived as less human (Castelo et al., 2019). Furthermore, employees may fear that their neural data could be misused to monitor their mental states, raising concerns about increased surveillance and reduced autonomy (Yuste et al., 2017). Extant research shows that these concerns can lead to employees rejecting BCIs, potentially even sabotaging their use (Ball, 2010). Additionally, literature suggests that new technologies can affect consumer perceptions, reducing their willingness to use them if sensitive interaction data might be shared with companies, leading to fears of control (Ayyagari et al., 2011).

01.2
Objectives and Essay Summary

Despite the importance of BCI adoption's implications for users and its expected massive impact on many service providers' work environments, customers' ways to interact with technology and communication, scant extant research on this topic exists in the service marketing and service management field (Grewal et al., 2020; Hilken et al., 2022). As this statement from the beginning of this chapter suggests, customers and FLEs can view the technology as both fascinating and unsettling, and this dissertation aims to clarify the factors that shape these divergent evaluations. To help guide practitioners with the implementation and adoption of BCIs in the foreseeable future, service scholars need to address this challenge early on proactively. As illustrated in Figure 01.1, the four essays in this dissertation collectively address different aspects of the research gap, each offering distinct contributions and perspectives. Essay 1 focuses on the left side of Figure 01.1, where FLEs are using BCIs in interactions with customers. The aim of this project is to investigate customers' perceptions of BCI-enhanced 'frontline-cyborgs' in service interactions. Essay 2 seeks to conceptualize BCIs' impact on FLEs' well-being when the technology is used in workplaces. Essay 3 focuses on the right side of Figure 01.1, where customers' perception of using BCIs to interact with (service) technologies or service firms is delineated. Outside the center of Figure 01.1 is the scope of Essay 4, which conceptualizes BCIs' impact on communication by integrating overarching roles of FLEs and customers

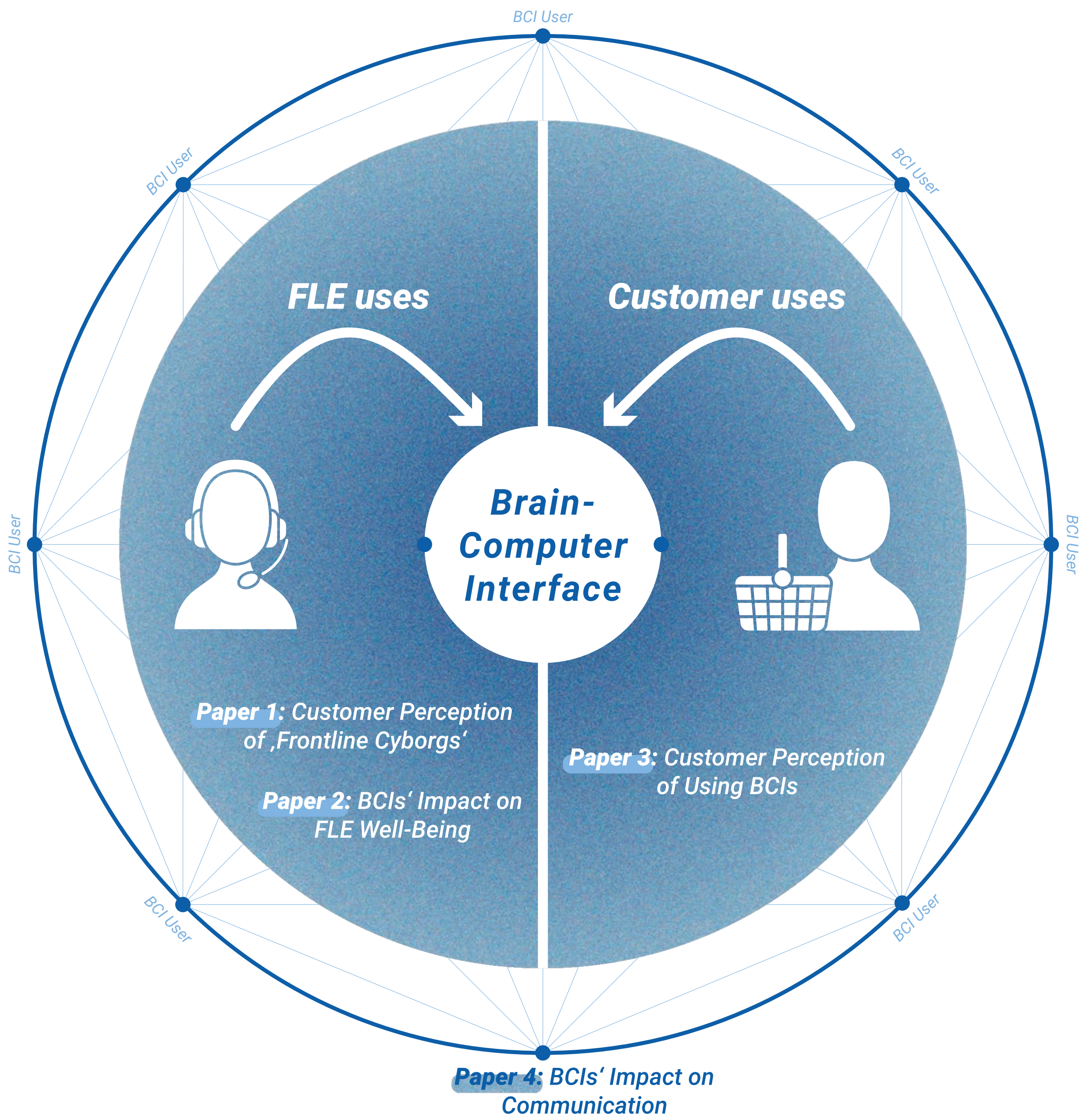

Figure 01.1: Overview of this Dissertation. Source: The figure was created by the author.

as BCI users in reality-enhanced settings of the metaverse.

Therefore, the following sections will delineate the objectives of the essays in this dissertation and explain their intended contributions.

Essay 1 (RQ: *How do customers perceive their interactions with BCI-enhanced frontline employees, and what factors influence these perceptions in service encounters?*): Despite advancements in understanding the impact of fully robotic service providers and extensive knowledge on human interaction, little is known about the integration of humans and technology through BCIs (van Doorn et al., 2017; Jörling et al., 2019; Wirtz et al., 2018).

Therefore, it is crucial to gain a comprehensive understanding of how customers perceive BCI-enhanced FLEs and how these perceptions might influence the evaluation of service interactions. We can learn from early conceptual works about 'frontline cyborgs' (Garry and Harwood, 2019; Grewal et al., 2020) and the adjacent field of service robots, which emphasize the challenge of achieving a social connection between humans and machines in terms of warmth and competence (Belanche et al., 2021). On this basis, we investigate customers' perceptions of interactions with FLEs wearing BCIs and seek to make three contributions with our research. First, we address the notable lack of empirical evidence on customer and FLE perceptions of BCI-enhanced service interactions by providing insights from two qualitative inquiries, revealing both the bright and dark sides of BCI adoption at the frontline. Second, building on these qualitative insights, we conceptualize and empirically demonstrate the 'cyborg effect' using actual BCI technology in service encounters. Our findings reveal that when customers interact with a BCI-enhanced FLE, it negatively impacts perceived service quality. In doing so, we extend the application of social cognition theory (Fiske et al., 2002) from robotics (van Doorn et al., 2017) to cyborg contexts, demonstrating that the negative cyborg effect is explained by reduced perceptions of FLE warmth and competence. Third, we identify two remedies to counteract the cyborg effect and mitigate negative customer perceptions of warmth, competence, and service quality: (1) the framing of the type of BCI enhancement (efficiency vs. personalization), and (2) the use of BCIs in more (vs. less) complex service contexts. In sum, our study represents one of the first empirical investigations into the consequences associated with the use of BCIs by FLEs and the impact on service encounters.

Essay 2 (RQ: *What are the implications of BCIs as workplace technology for FLEs' well-being?*): FLEs' roles are undergoing significant transformation. Today's increasing labor shortages, continuous adaptation to emerging technologies, and heightened customer expectations have intensified the risk of cognitive overload and emotional exhaustion (Chen et al., 2019; Day et al., 2010). This growing pressure poses adverse consequences for FLEs' well-being, which is defined as the comprehensive evaluation of one's life satisfaction and the extent to which FLEs experience "optimal psychological functioning" (Ryan and Deci, 2001, p. 142). Left unchecked, these strains can culminate and lead to burnout, diminished job performance, and increased turnover, all of which threaten not only FLEs' well-being, but also the firm's long-term success and profitability (Chen et al., 2019). BCIs are being put forth as one promising solution to help FLEs function better in today's rapidly changing and highly taxing workplace environments (Grewal et al., 2020). Workplace BCIs can analyze FLEs' cognitive and affective states, including emotion, relaxation, fatigue, and cognitive workload levels (Saha et al., 2021). By tracking brain activity, BCIs provide users with feedback on their mental states, allowing for real-time analysis and long-term logging to gain detailed insights over time (Zander and Kothe, 2011). For example, air traffic controllers' workplaces can be adjusted based on their current stress levels, such as reduction of visual load by displaying fewer aircraft on the screen or minimizing auditory alerts to prevent distractions from noncritical notifications. This adaptation has been demonstrated to reduce employees' stress levels while increasing operational safety and efficiency (Aricò et al., 2016). Despite the importance of BCI adoption's implications for FLEs and its expected massive impact on many service providers' work environments, scant extant research on this topic exists in the service marketing and service management field. To this end, this essay seeks to (1) conceptualize what BCIs entail, (2) introduce a framework to understand BCIs' impact on FLEs' well-being, and (3) put forth a future research agenda that may inspire future BCI-related work in the service space.

Essay 3 (RQ: *How do users perceive interactions with consumer-grade BCI technology?*): Drawing on information systems (IS) and human-computer interaction (HCI) literature, BCIs have primarily been researched to provide communication abilities to disabled or "locked-in" patients (Saha et al., 2021). With consumer-grade BCI devices moving more into mainstream applications, literature streams from IS and service marketing are relevant to understanding regular users' adoption behavior. User acceptance of novel technologies is influenced by well-established constructs such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), where ease of use and usefulness impact users' intention and subsequent adoption behavior (Marangunić and 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 them if their interaction data is at risk of being shared with companies, leading to fears of being controlled as a result. Therefore, users might feel differently about interactions with BCIs on an individual level, such as controlling their smart home devices, compared to interactions with organizations where they purchase products or services using BCIs (Smith, 2020). Clearly, the way users perceive BCIs in individual and organizational interactions is relevant in determining their future intention to use such devices. However, despite the abundance of literature on the technical aspects of BCIs, research on regular users' perception outcomes is limited but much needed (De Keyser et al., 2021; Hilken et al., 2022). 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 users' acceptance of BCI technology. (2) We investigate the determinants and psychological processes for users' intentions to use BCIs for technology interaction through our qualitative and experimental studies. (3) Additionally, our study explores the relationship between the use of BCI technology by users in individual and organizational settings, shedding light on the differences that affect its usefulness and the intention to use it.

Essay 4 (RQ: *How do BCIs and neurostimulation alter the communication affordances for users in the metaverse?*): While initially created to assist individuals with physical disabilities in communicating through spellers and controlling electronic wheelchairs (Kawala-Sterniuk et al., 2021), the advent of consumer-grade devices marks a shift towards enhancing interpersonal communication and engagement in the metaverse. These BCIs extend the communication affordances of users by providing insights into mental states, the capability to communicate with technology through thoughts, and the ability to receive communication from others (Drew, 2024; Hilken et al., 2022). A novel medium for communication emerges, enhancing well-being by allowing individuals to share emotional experiences and enabling of effortless and rapid exchange of communications, deepening connections and mutual understanding (Zander et al., 2010). This is particularly relevant in the metaverse, where the blending of physical and virtual worlds demands greater technological embodiment (Rubo et al., 2021). As BCIs gain popularity among consumers, it becomes imperative for communication and marketing scholars to understand their potential and ethical implications. Therefore, this paper seeks to investigate how BCIs change the communication affordances of users in the metaverse and details how these changes affect the well-being of individuals. Thus, the contribution of this paper is to: (1) synthesize the existing literature on BCIs and provide a definition and overview of BCI as communication technology, detailing the functionality of neuroimaging and neurostimulation uses. (2) develop a conceptual framework for BCI-enhanced communication along four dimensions, discussing the impact of BCI-enhanced interaction for self-communication, BCI-to-BCI, BCI to the metaverse, and one-sided BCI communication. Building on this basis, we highlight the (3) ethical implications arising from the use of BCI-enhanced communication, emphasizing their possible adverse effects on individual well-being. Furthermore, we propose a research agenda that aligns with the dimensions outlined in our conceptual framework, aiming to investigate these critical issues further.

01.3

Structure of This Dissertation

This dissertation is structured as outlined in Figure 01.2, providing an overview of the key chapters and their content.

First, the next chapter provides the conceptual background, outlining key characteristics of BCI technology. This includes an introduction to BCIs as interfacing technology, detailing their various uses and characteristics to provide a solid understanding of the technological background. Additionally, an overview of consumer-grade devices is presented, along with a review of relevant literature on BCIs and adjacent fields in service research. This review also encompasses the enhancement of BCI functionality through neurostimulation, which enables brain-to-brain or machine-to-brain communication pathways, extending beyond merely reading and interpreting neural signals. In a second step, based on the literature review, research gaps are identified, and research questions are established. Third, a summary of each of the four essays is provided. Finally, an integrated discussion highlights contributions to theory and practice, addresses limitations, and suggests directions for future research. All four research papers are included in full length in the appendix.

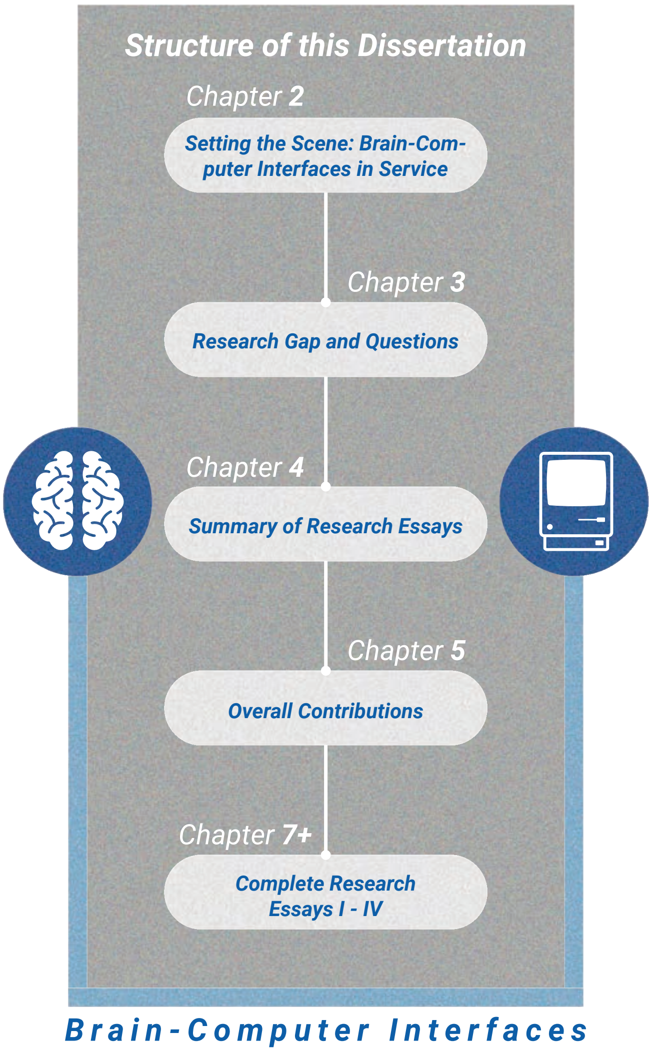

Figure 01.2: Structure of This Dissertation. Source: The figure was created by the author.

02

Setting the Scene: Brain-Computer Interfaces in Services

This chapter sets the theoretical background for the four research essays in this dissertation, which focus on the impact of BCIs on services research, helping the reader contextualize the different studies. The first section introduces the definition of BCIs and provides an overview of the technology, including its technological background and boundaries of investigation in this work. The subsequent chapter then presents an overview on BCIs' boundary extension when integrated with neurostimulation technology, which, for example, enables direct brain-to-brain communication. Finally, the last section details the impact of BCI technology on users and the role of BCI-enhanced FLEs in service encounters.

02.1 Brain-Computer Interface Definition

Unlike traditional mouse and keyboard or touchscreen-based interfaces, BCIs allow users to interact with devices solely through their brain activity, eliminating the need for any muscular movement (Wu et al., 2022). Building on extant studies (Kawala-Sterniuk et al., 2021, Nicolas-Alonso and Gomez-Gil, 2012), BCIs have been defined as a technology that *establishes a direct communication link between users' brains and external devices by recording and decoding neural activity*. This definition emphasizes that unlike other (mostly wearable) technologies that measure physiological signals (e.g., smartwatches), BCIs establish a distinct communication channel for unique interaction with devices that is not possible with other wearables (Paluch and Tuzovic, 2019; Vasiljevic and de Miranda, 2020). This marks a significant shift towards a more seamless and natural engagement with the digital environment (Hilken et al., 2022; Vasiljevic and de Miranda, 2020). Figure 02.1 presents a selection of consumer-grade BCIs that can be purchased and used by both customers and FLEs.

BCIs, as artificial intelligence systems, recognize patterns in brain signals through a sequential four-stage process (Nicolas-Alonso and Gomez-Gil, 2012; Saha et al., 2021), depicted in Figure 02.2. First, during the signal acquisition stage, brain signals are captured, amplified, and preprocessed to reduce noise and artifacts in the data. Next, during the feature extraction stage, the digital sig-

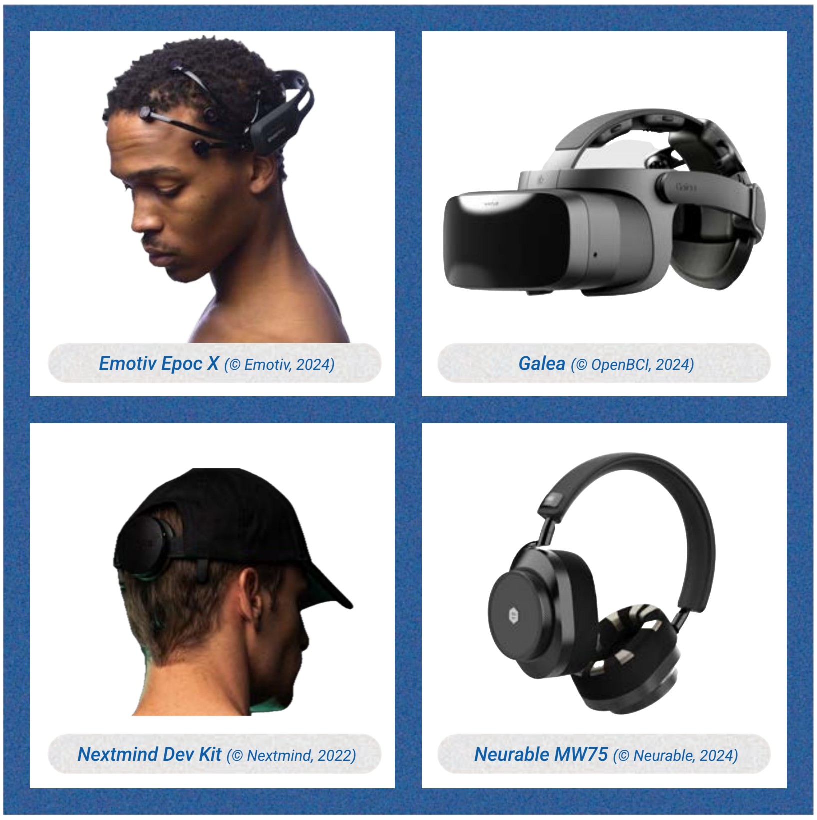

Figure 02.1: Overview of Consumer-grade BCI Devices. Source: The figure was created by the author.

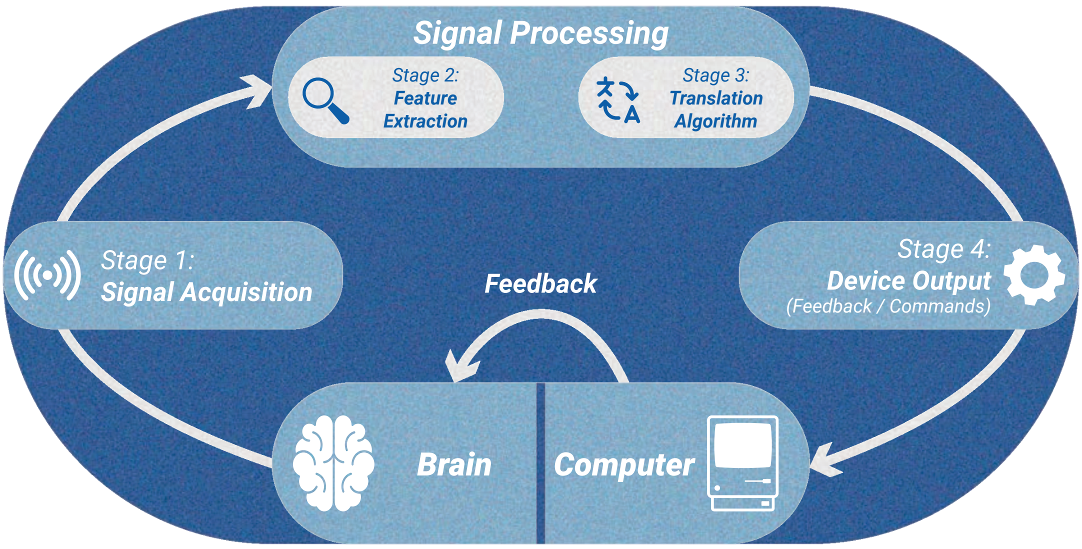

Figure 02.2: Brain-Computer Interface System Architecture. Adapted from Kawala-Sterniuk et al. (2021)

nal is analyzed to distinguish relevant characteristics, such as the user's intent or affective state, from extraneous context. Subsequently, during the feature translation stage, signal features are processed through a translation algorithm that converts the data into readable information for the output device. Finally, during the device output stage, commands from the feature translation algorithm operate the external device or display users' affective state, completing the communication loop.

The history of BCIs dates to the 1970s when Vidal (1973) theoretically established and demonstrated cursor movement using electroencephalography (EEG) technology (Vidal, 1977). Since then, the primary motivation for BCI research has been to enable individuals with motor disabilities, such as paralysis, to communicate and interact with their environment (Kawala-Sterniuk et al., 2021). The field draws on interdisciplinary knowledge from neuroscience, computer science, medicine, and engineering, making significant strides from basic communication programs to more sophisticated applications that are now increasingly transitioning out of laboratories and onto the heads of users (Abiri et al., 2019; Nicolas-Alonso and Gomez-Gil, 2012; Saha et al., 2021; Shih et al., 2012).

02.2

Characterization of BCI Systems

A 2x2 matrix has been developed to categorize different BCI technologies for FLE use (Figure 02.3). This matrix outlines two key dimensions that categorize different BCI devices, illustrating how these technologies could soon be integrated into service frontlines. The first dimension focuses on the categorization of BCIs, describing how the device captures and processes brain activity either for passive and active use (Kawala-Sterniuk et al., 2021). Notably, active and passive BCIs are distinguished by how collected neural data are processed, as one BCI can be used in either an active, passive, or integrated manner. The second dimension focuses on signal acquisition modality, distinguishing between non-invasive (i.e., wearable) and invasive (i.e., implantable) techniques (Nicolas-Alonso and Gomez-Gil, 2012).

Quadrant 1 represents passive, non-invasive BCIs, which are most prevalent in the market and closest to mainstream adoption. Passive BCIs analyze brain signals generated without conscious effort from the user, thereby not requiring intentional thought to operate (Aricò et al., 2018). These brain signals typically reflect the user's cognitive and affective states, such as emotion, relaxation, fatigue, and cognitive workload levels (Saha et al., 2021). Non-invasive BCIs capture neural information directly from electrodes placed on the scalp, making them the dominant choice in BCI technology due to their sufficient accuracy in detecting and translating brain signals into actionable insights (Aricò et al., 2018). Most companies offering consumer-grade BCI headsets in this quadrant integrate dry EEG sensors into aesthetically appealing devices (Drew, 2023). For example, Neurable incorporates dry EEG sensors into headphones (Takahashi, 2024), while Muse (Hunkin et al., 2021) produces a headband with inte-

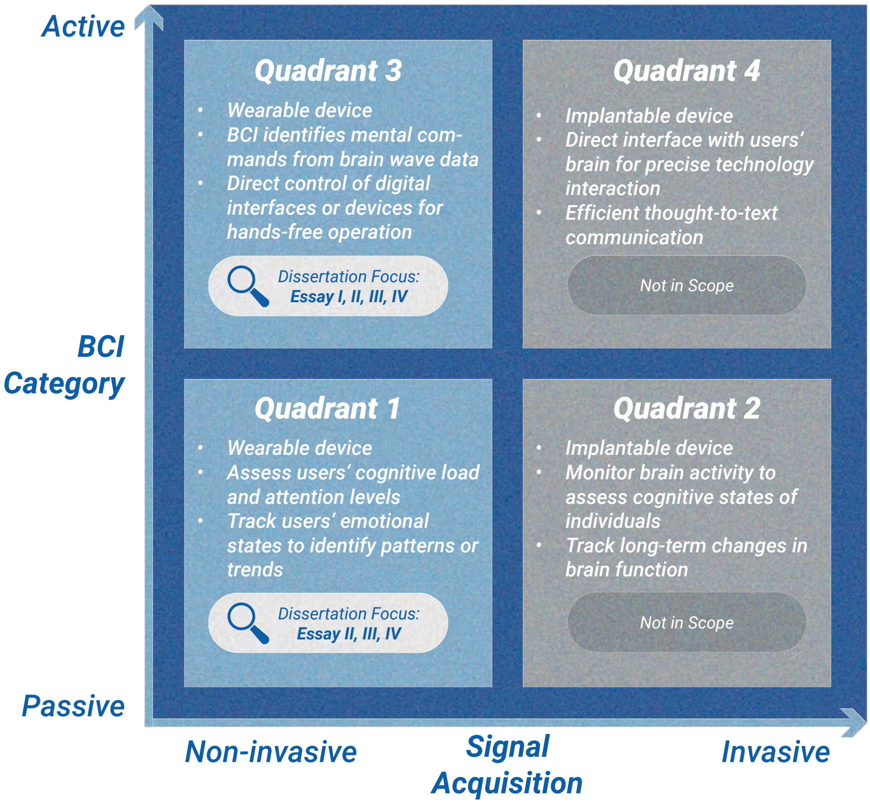

Figure 02.3: Brain-Computer Interface Typology. Source: The figure was created by the author.

grated BCI sensors, both at affordable price points. Other non-invasive technologies include functional near-infrared spectroscopy (fNIRS), magnetoencephalography (MEG), and functional magnetic resonance imaging (fMRI) (Aricò et al., 2018; Saha et al., 2021). When deployed as workplace technology, the ActiCap, a passive non-invasive BCI, can assess cognitive workload and adapt employee tasks accordingly. In learning contexts, for example, adjusting tasks based on analyzed cognitive load has been shown to significantly improve learning outcomes and overall task efficiency (Walter et al., 2017; Wascher et al., 2023). In consumer settings, this type of BCI can dynamically adjust game difficulty based on the user's emotional and cognitive state or enhance self-communication by facilitating deeper mindfulness meditation (Hunkin et al., 2021; Vasiljevic and de Miranda, 2020). *Devices from this quadrant are in focus of Essay 2, 3 and 4.*

Quadrant 2 encompasses BCIs that are passive and invasive. Invasive BCIs entail surgical implantation of electrodes directly on or in the brain, as depicted in Figure 02.4. Invasive BCIs' primary advantage lies in their ability to detect brain signals in high resolution with significantly improved signal-to-noise ratios compared with non-invasive methods (Drew, 2023). However, this approach carries substantial risks due to the associated surgical procedures (Kawala-Sterniuk et al., 2021). Adoption of these BCIs remains limited due to these challenges, as

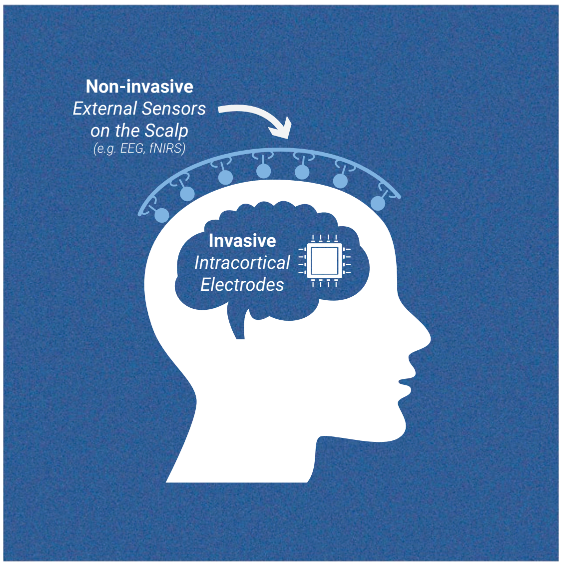

Figure 02.4: Modality of Signal Acquisition. Source: The figure was created by the author.

non-invasive options can perform similar tasks without invasive procedures (Saha et al., 2021). The most common applications are in the medical field, in which companies such as Neuropace use these BCIs to detect epileptic seizures accurately and allow individuals to prepare for their onset (Sheng-Fu et al., 2010). Therefore, invasive BCIs' adoption potential remains minimal for the scope of this dissertation.

Quadrant 3 represents non-invasive, active BCIs that capture and interpret the user's intentional mental activity (Saha et al., 2021). By imagining hand movements or preprogramming mental commands to execute specified actions, algorithms identify these patterns in neural data. Active BCIs enable users to translate thoughts directly into actions, allowing for direct control over external devices (Kawala-Sterniuk et al., 2021). BCIs in this quadrant allow users to interact seamlessly with technology using only their thoughts, thereby enhancing seamlessness and potentially fostering closer social connections with customers when worn by FLEs (Hilken et al., 2022). The Galea BCI headset is one example, allowing for control of (service) robots in collaborative environments through mental commands (Bernal et al., 2021). Furthermore, Emotiv headsets are used to navigate software (e.g., query databases, games) by thinking about actions or as communication devices that translate imagined speech to device commands (Lee et al., 2022; Vasiljevic and de Miranda, 2020). *Devices from this quadrant*, which are the most promising for widespread adoption after non-invasive passive BCIs due to their ability to enable direct control over technology *are in focus of Essay 1, 2, 3 and 4*.

Quadrant 4 encompasses active and invasive BCIs. Utilizing technology similar to that of Quadrant 2, these devices capture high-precision signals to detect intentional mental activity reliably (Aricò et al., 2018). Prominent companies working on these BCIs include Blackrock Neurotech and Neuralink, co-founded by Elon Musk (Drew, 2023). Neuralink's short-term goal is to restore function for individuals with motor disabilities, while its ultimate ambition is to integrate this technology for able-bodied individuals, merging human and artificial intelligence to create superintelligence (Reed and McFadden, 2024). Notably, Neuralink implants have demonstrated that monkeys can play the video game Pong wirelessly, and human trials in 2024 demonstrated BCI-enhanced individuals' ability to control a mouse or play first-person shooter video games with the implant (Drew, 2024). However, challenges remain, as many electrodes have disconnected from brain tissue after several weeks, rendering most of the implant unusable (Robins-Early, 2024). This technology is not covered further in this dissertation as it is not yet market-ready, and widespread adoption by consumers or employees is far off due to the requirement of surgical procedures (Drew, 2023).

Table 02.1 presents a selected literature review on BCI applications, categorized into the identified quadrants in Figure 02.3. Given that BCI technologies requiring surgical implantation are not expected to be market-ready in the near future, this article focuses on integration of non-invasive BCIs, as represented in Quadrants 1 and 3. This focus is also indicated by blue shadow in Figure 02.3. To further illustrate recent advancements in the field, Table 07.3 in the appendix of Essay I showcases currently available consumer-grade BCIs.

02.3 BCIs' Extension through Neurostimulation

Thus far in this dissertation, BCIs have been primarily portrayed as neuroimaging devices that measure individuals' brain activity, which is subsequently processed in an active (i.e. mentally controlling technology) or passive (i.e. assessing mental state) manner (Saha et al., 2021). Most prevalent *neuroimaging* technologies, which are depicted on the left side of Figure 02.5, rely on capturing electrical activity (e.g. EEG-based Neurable headphones) or blood oxygen levels (eg. fNIRS-based Kernel Flow headset) (Drew, 2023; Dubois et al., 2024).

However, BCI functionality can be further extended by neurostimulation, which refers to BCIs' modifying or influencing brain activity in response to input from the digital environment, depicted on the right side of Figure 02.5 (Hilken et al., 2022). Such stimulation may be experienced as sensory information on grip strengths of prosthetics (Klaes et al., 2014), modulation of emotional states (Widge et al., 2014) or olfactory feedback from virtual reality environments (Hilken et al., 2022). Applying neurostimulation is possible through non-invasive options using small electrical or magnetic pulses. Two of the most prominent neurostimulation technologies are transcranial direct current stimulation (tDCS) and transcranial magnetic stimulation (TMS) (Dayan, 2012). tDCS delivers a low electrical current to the brain via electrodes placed on the scalp, while TMS stimulates the brain by generating a brief, high-intensity magnetic field that affects the brain tissue beneath the skull (Hallett, 2007; Nitsche et al., 2008). Both technologies, initially explored in medical contexts, are considered generally safe and have become available for consumer purchase (Wexler, 2018). However, compared to neuroimaging BCIs, consumer-grade neurostimulation is still in its relative infancy (Hildt, 2019). Figure 02.6 depicts an overview of consumer-grade neurostimulation devices. Table 02.2 depicts an overview of available consumer-grade neurostimulation technologies.

Table 02.1: Selected literature review. Source: The table was created by the author.

Authors	Quadrants 1	2	3	4	Summary of Findings
Alimardani and Hiraki (2020)	x				Review how tracking of users' cognitive and affective state can adapt robot decision making for optimized human-robot collaboration, thereby increasing interactivity and job performance.
Aricò *et al.* (2016)	x				Demonstrate that adaptation of workplaces for air traffic controllers by reducing alerts or visual load on displays effectively reduces mental workload during high-demand situations without interfering with operational tasks.
Hunkin *et al.* (2021)	x				Demonstrate that when individuals receive auditory feedback through a BCI during mindfulness-focused attention meditation, mind wandering is reduced and mindfulness increases.
Jamil *et al.* (2021)	x				Review how BCIs enhance individuals' learning outcomes by adjusting learning content based on mental workload, measuring interest in topics, or increasing focus during critical learning periods.
Telpaz *et al.* (2015)	x				Predict customers' future choices by analyzing brain activity through a BCI while they view binary product options without external instruction to select a product.
Yaacob *et al.* (2023)	x				Review studies focusing on BCI use for real-time fatigue detection and find it feasible to prevent vehicle accidents, workplace errors, and emotional exhaustion.
Sheng-Fu *et al.* (2010)		x			Determine whether epileptic seizures can be detected through a portable BCI with a high detection rate between 92 and 99 percent.
Angrisani *et al.* (2020)			x		Develop an augmented reality headset with an integrated BCI for an industry inspection task and demonstrate the feasibility of inspection through BCIs with relatively high accuracy.
Chen *et al.* (2020)			x		Develop a robotic arm control system using augmented reality and BCIs that can pick up objects. This device demonstrated that users could utilize the system reliably, with a 93.96 percent accuracy rate in object selection.
Coogan and He (2018)			x		Develop routing of BCIs' control signals to gaming applications, virtual reality control, and control of smart home devices, and demonstrate feasibility while giving users additional autonomy during tasks at hand.
Krauledat *et al.* (2008)			x		Demonstrate the ability to control the classical game Pong with a BCI, allowing for quick and precise mental commands to move the paddle without lengthy subject training.
Lee *et al.* (2022)			x		Test the feasibility of users imagining speech that is translated via BCIs for communication with a smart home virtual assistant performing tasks.
Liu *et al.* (2021)			x		Demonstrate that in situations in which workers need to interact with robots, BCIs allow for hands-free control of robots with 90 percent accuracy, which is particularly beneficial when workers' ability to control robots is limited physically.
Zhang *et al.* (2019)			x		Develop mechanisms to interpret BCI data reliably to control a simulated robot to perform tasks or type by recognizing users' intentions as realized through an Internet of Things network with smart home appliances.
Kennedy *et al.* (2000)				x	Describe an invasive procedure that reliably captures brain signals, allowing patients to control the cursor on a computer screen.
Musk and Neuralink (2019)				x	Provide an overview of an invasive, wireless BCI system with the potential ability to control devices through mental commands and present a surgical robot that limits the procedure's invasiveness.
Rapeaux and Constandidou (2021)				x	Review recent advances in implantable BCIs, emphasizing enhanced performance of current technologies and innovations aimed at enabling scalable implementation among individuals.

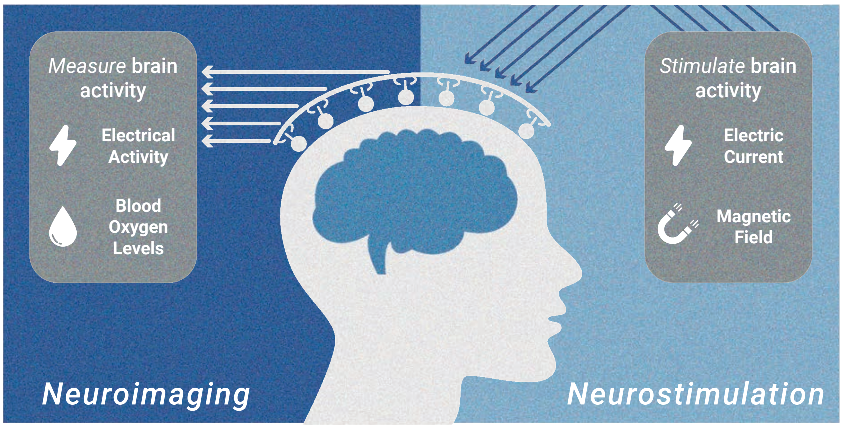

Figure 02.5: Neuroimaging and neurostimulation. Source: The figure was created by the author.

Figure 02.6: Overview of consumer-grade Neurostimulation Devices. Source: The figure was created by the author.

Incorporating neurostimulation into BCIs extends their functionality by enabling bidirectional communication, wherein "digital-to-neural" interactions become feasible (Hilken et al., 2022). Users equipped with such BCIs can not only receive inputs from

Table 02.2: Examples of consumer-grade neurostimulation BCI devices. Source: The table was created by the author.

Device (Company)	Description	Communication Examples	Price (USD)
		Neurostimulation BCIs	
CloudTMS machine	Transcranial Magnetic Stimulation	• Receive communication by magnetically stimulating brain regions	$64,995
LIFTiD	Transcranial direct current stimulation (tDCS)	• Receive communication by electric stimulation • Increase focus and concentration	$159
Xen (Neuvana)	Vagus nerve stimulation through headphones	• Receive communication by electric micropulses • Increased calmness and focus	$449
		Brain-to-Brain BCIs	
PsiNet	Measure neural activity via EEG as input Stimulate neural activity via transcranial electric stimulation (tES)	• Strengthen sense of connection • Distribute mental workload • Control over others state of mind	N/A

digital environments or other individuals but also actively transmit information through their mental commands. This communication affordance can therefore facilitate direct interaction between two or more individuals through brain-to-brain interfaces (Grau et al., 2014). Such interfaces enable the exchange of thoughts, sensory experiences, and motor commands between users, bypassing traditional communication channels (Kerous and Liarokapis, 2017; Nitsche et al., 2008; Wexler, 2020). Moreover, users of neurostimulation BCIs can receive communication from digital (service) environments through tactile feedback, such as that provided by virtual reality settings, thereby enhancing their sense of immersion (Hilken et al., 2022; Racat and Plotkina, 2023). Additionally, these BCIs can facilitate the transfer of emotional states from the environment to the user, enabling them to experience emotional responses directly through neural stimulation (Maksimenko et al., 2018; Valle, 2022; Widge et al., 2014). Table 02.2 presents a research-grade brain-to-brain interface that makes use of bidirectional communication.

02.4
BCIs' Expansion in Service and Communication Research

02.4.1
Frontline Employee Perspective

Fueled by rapid advancements in consumer-grade technology, as evidenced by the typology of BCI devices and various device examples, BCIs are transitioning from (medical) laboratory contexts to the heads of customers and employees (Drew, 2023). Many underlying psychological factors that influence general acceptance, user perception, and how others perceive interactions with BCI-enhanced individuals remain largely unexplored and warrant further research (De Keyser et al., 2021; Hilken et al., 2022; Kögel et al., 2019; Vasiljevic and de Miranda, 2020). Given that BCIs are projected to be first implemented with FLEs, this area will be investigated first for this dissertation (Grewal et al., 2020; UNESCO, 2023). Recent research has begun to conceptually explore BCIs as a type of HET within service settings, focusing on the potential effects on customers when FLE capabilities are enhanced through in service encounters (Garry and Harwood, 2019; Grewal et al., 2020). In this way, BCIs create a new type of interaction between customers and so-called 'frontline cyborgs,' who occupy a unique position between fully autonomous robots and 'pure' humans. These 'frontline cyborgs' can enhance either their cognitive or emotional capabilities to better assist customers during service encounters (Grewal et al., 2020). With a focus on cognitive enhancement, FLEs can achieve superior memory and cognitive abilities, allowing them to interact with systems and devices hands-free. This capability enables FLEs to provide faster and more accurate service, thereby elevating the customer experience (Grewal et al., 2023). Additionally, BCI-enhanced FLEs could benefit from emotional enhancements by reducing distractions and freeing up mental capacity from non-core activities, enabling them to focus more on the emotional aspects of service, such as empathizing with customers (Bandura, 2008; Smith and Collins, 2009). Furthermore, BCIs can adjust the allocation of customers based on neural activity and mental state to ensure the best service is provided at the optimal moment for the customer. Early conceptual work suggests that social cognition theory acts as a mediating mechanism impacting customer evaluations of interactions with BCI-enhanced FLEs (Grewal et al., 2020). Social cognition theory fundamentally posits that effectively discerning and interpreting others' intentions, emotions, personality, and capabilities is essential for individuals to navigate social interactions and calibrate their roles as social agents, assessed by two fundamental dimensions: warmth (moral, helpful, caring, friendly, or trustworthy) and competence (intelligent, skillful, or efficacious) (Cuddy et al., 2008; Fiske et al., 2007; Judd et al., 2005). To form such social cognitions about others, people commonly rely on interpersonal communication cues such as physical appearance, actions, communication style, eye contact, and facial expressions (Frith and Frith, 2012). Established theoretical work in HET and adjacent field of service robots suggests that elevating the emotional or cognitive capabilities of FLEs positively affects the service encounter, mediated by perceptions of warmth and competence (Choi et al., 2021; Grewal et al., 2020).

However, these enhancements not only have the potential to improve the service experience; they are also purported to alter the role of FLEs in service encounters, potentially leading to FLEs being perceived more like robots than humans and raising concerns about dehumanization (Castelo et al., 2019; Garry and Harwood, 2019; Grewal et al., 2020). This body of research indicates that BCI-enhanced FLE may adversely affect customer reactions to 'frontline cyborgs'. Specifically, when customers mechanistically dehumanize, they experience emotional and psychological detachment or indifference towards the dehumanized entity, perceiving it as alien or foreign (Haslam, 2006). As a result, the tendency to dehumanize frontline cyborgs could diminish the anticipated boost in customer-perceived warmth or competence because of BCI-enhancement, making these employees appear more mechanical and less empathetic.

The second project in this dissertation examines BCIs' influence on FLEs using this workplace technology and explores its implications for their well-being. As a key research priority in service (Ostrom et al., 2015), employee well-being is a fundamental consideration for organizations, with a growing body of literature linking it to critical performance metrics, such as enhanced job satisfaction, increased productivity, and reduced stress (Robertson et al., 2023; Ter Hoeven and Van Zoonen, 2015; Tuzovic and Kabadayi, 2021). However, introducing advanced technology such as BCIs alters the organizational frontline's roles and responsibilities (De Keyser et al., 2019). While technology can effectively reduce tedious tasks and make jobs more enjoyable, it can also contribute to increased stress, heightened expectations, and a heavier workload (Day et al., 2010, 2019). Building on this, several extant studies have explored how the job demands-resources model can be integrated with the transactional theory of stress to better understand new workplace technologies' impact on FLEs (Day et al., 2010, 2019). The transactional theory of stress posits that stress emerges from the dynamic interaction between the individual and demands imposed by the environment (Lazarus and Folkman, 1984). When new technologies such as BCIs are integrated into the workplace, stress is likely to arise when BCIs are perceived as taxing or exceeding FLEs' available resources (Barling et al., 1988). Therefore, BCIs can act as "tech-stressors". Drawn from both literature streams this refers to situations in which BCIs are perceived as increasing job demands, thereby heightening the physical or psychological effort required from FLEs and contributing to their stress (Abilleira et al., 2021; Tarafdar et al., 2014). Consequently, BCIs can be perceived as a threat in the workplace, leading to a decline in employee well-being (Fuglseth and Sørebø, 2014; Sonnentag, 2015). For example, continuous monitoring of cognitive load can function as a form of technological invasion (i.e., "BCI is always watching me'), pressuring FLEs to maintain constant high concentration levels, which can lead to increased stress and reduced well-being (Ball, 2010; Drew, 2023). Conversely, BCI technology also can serve as a "tech-resource" that aids task completion, enhances FLEs' motivation, and reduces stress by being perceived as beneficial tools. For example, BCIs can function as cognitive load balancers, redistributing tasks based on FLEs' real-time mental capacity, thereby preventing overload while optimizing performance (Aricò et al., 2016). The transactional model of stress highlights that the perception of technologies, such as BCIs, as tech-stressors or tech-resources varies between individuals and contexts (Huang and Gursoy, 2024). The same BCI integration might be evaluated differently depending on individual and contextual factors (Truța et al., 2023).

02.4.2
Customer Perspective

Expanding the use of BCIs from FLEs to customers, the third dissertation project investigates customers wearing the technology. As both passive and active BCIs become more prevalent for consumer use, understanding the adoption intentions of this technology becomes crucial. Building on well-established theories such as the technology acceptance model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), factors like ease-of-use and perceived usefulness play a major role in consumer adoption intentions (Marangunić and Granić, 2015; Venkatesh et al., 2012). BCI worn by users have multiple implications for improved usefulness in technological interactions (Aricò et al., 2018; Kübler, 2020). For instance, in the gaming context, where early integration of BCI technology is expected (Van Erp et al., 2012), BCIs can enhance levels of immersion and engagement by offering more intuitive ways to interact with the game (Vasiljevic and de Miranda, 2020). Additionally, passive BCIs can provide valuable insights and enable neuroergonomic applications, such as adjusting gameplay to match the user's capabilities and preferences, thus allowing for more seamless and immediate control compared to other technologies (Dehais et al., 2020; Lotte and Roy, 2019). Beyond pure control of technology, BCIs hold the promise of integrating human and artificial intelligence, leading to an augmentation of human cognitive functions by providing access to computational power and knowledge artificial intelligence provides. By allowing individuals to process information more efficiently, this could "superhumanize" individuals and allow them to achieve a state of super well-being (Lima and Belk, 2022). However, current technology faces challenges in ease-of-use, as many devices require extensive training or a complicated setup with wet electrodes that need frequent rehydration (Saha et al., 2021). Newer devices, such as those from NextMind and OpenBCI, utilize dry electrode technology and require minimal training time (Drew, 2023). Despite these advancements, individuals using BCIs may face prejudice when their enhanced abilities differ from those not using BCIs. Research by Castelo et al. (2019) shows that the enhancement of personal abilities is often perceived negatively by peers, potentially impacting individual adoption decisions. Another focus for consumers using BCI technology is the potential difference in interactions for personal use, such as controlling smart home devices, versus interactions with service firms for purchasing products or services. Research suggests that users might feel differently about BCI interactions on an individual level compared to interactions with service firms (Smith, 2020). Despite the potential positive impacts BCIs have on technology interactions, there are also significant privacy and data safety concerns. As BCI handle sensitive neural data and enable insight into real-time emotional and cognitive data, malicious actors could misuse this information (Yuste et al., 2017). For example, users' choices can be detected before they are consciously made which could pose risk of manipulation of this decision (Hibbeln et al., 2017; Xing et al., 2019). Unlike other technologies, where users typically have more control over their data, neural data flows uninterruptable and transmission can be stopped through removing the device only (Vasiljevic and de Miranda, 2020). Furthermore, besides potential manipulation of decisions or collection of data, neural data gives deep insights into individuals health as well, that users may not be aware about. For instance, brain-wave data can accurately identify users and detect potential health issues (Bonaci et al., 2014; Jackson and Snyder, 2008). However, existing research showcases how privacy considerations can be integrated into BCI development, ensuring that users' data is encrypted by default. Integrating encrypted data processing directly on the device, rather than transmitting raw brain signals, mitigates privacy and data safety risks to some extent (Agarwal et al., 2019; Xia et al., 2022). Thus, responsible data management is paramount as the technology evolves (Bonaci et al., 2014; Dignum, 2019).

02.4.3
Communication Perspective

Communication theories serve as essential frameworks for understanding human interaction and the exchange of information (Stacks et al., 2019). With the advent of BCI and brain-to-brain communication (B2B) technologies, these devices extend the communication affordances of users by providing insights into mental states, enabling communication with technology through thoughts, and facilitating the reception of messages from others (Drew, 2024; Hilken et al., 2022). This novel medium for communication can enhance well-being by allowing individuals to share emotional experiences and enabling effortless and rapid exchange of communications, thereby deepening connections and mutual understanding (Lee et al., 2022; Nijholt et al., 2018; Zander et al., 2010). This is particularly relevant in the metaverse - a digital environment facilitating virtual interactions - where the blending of physical and virtual worlds demands greater technological embodiment (Flavián et al., 2021; Rubo et al., 2021). In this digital realm, individuals employ augmented reality (AR), virtual reality (VR), and haptic feedback technologies to participate in immersive and interactive communication experiences (Hilken et al., 2022; Racat and Plotkina, 2023). Established research sees communication through BCIs and B2Bs as most promising in conjunction with metaverse technologies. These technologies serve as a medium for adapting environments based on neural data, sending communications with active BCIs, and receiving communication through neurostimulation. This convergence provides a fertile ground for investigation and context (Hilken et al., 2022; Rehm et al., 2015).

Applying neuroimaging and neurostimulation technologies in metaverse contexts offers multiple avenues to increase immersion and enhance communication by bypassing traditional muscle or speech-based methods (Kerous and Liarokapis, 2017; Maksimenko et al., 2018). For example, neurostimulation can relay sensory information to the user, such as grip strength of a prosthetic hand holding a glass of water, thus enriching communication by enabling reception of additional depth (Klaes et al., 2014). As a result, tactile feedback in metaverse environments can enhance the realism of virtual interactions, deepening the sense of immersion within the experience (Hilken et al., 2022; Racat et al., 2021). Additionally, neurostimulation can transfer or modulate emotional states like happiness or sadness, offering a unique way for emotions to be shared and experienced directly between individuals when metaverse environments adjust to these states (Maksimenko et al., 2018; Valle, 2022; Widge et al., 2014). Thus, neurostimulation technology presents opportunities for enriched communication, enabling the transmission of somatosensory, auditory, and olfactory information to users (Petit et al., 2019). Additional applications include artistic creation within the metaverse, where users can transform their brainwaves and intentions into visual art, expanding the realm of creative expression (Nijholt et al., 2018). Conversely, neuro-enhanced communication also poses potential risks to well-being. Issues such as digital overload and addiction become critical, as users might engage excessively with virtual interfaces, disrupting their cognitive and emotional balance (Rehm et al., 2015; Rubo et al., 2021). The appeal of digital experiences could foster compulsive behaviors, leading to the neglect of real-life responsibilities and social connections (Bojic, 2022).

03

Research Gap and Questions

Better comprehension of BCIs' impact from the perspectives of employees, customers, and organizations is crucial for identifying both potential benefits and challenges, thereby providing valuable insights for optimizing their implementation in service and communication settings. Given that employees are likely to be the initial adopters of BCI technology (Grewal et al., 2020; UNESCO, 2023), the first two essays focus on examining its impact when integrated into FLE roles. Furthermore, it is valuable to empirically investigate consumer adoption and individual decision-making processes related to BCI technology - a focus addressed in the third project. The fourth project details the impact on communication when multiple BCI users communicate and collaborate through the technology.

03.1
Research Gap and Research Questions Essay I

With the next wave of technological service innovation targeting enhancements to FLEs' cognitive and emotional capabilities, BCI technology holds the potential to deliver dual benefits: improved employee performance and heightened customer focus (Lima and Belk, 2022; Marinova et al., 2017). As BCIs translate employees' thoughts into technology commands at the speed of thought, interactions with technology can be performed with unprecedented efficiency and precision. By preventing the typical diversion of attention caused by traditional technology use, BCIs ensure that FLEs can respond more quickly and accurately to customer needs, ultimately improving service quality and customer satisfaction. However, despite the rapid advancement in consumer-grade BCI technology in recent years, the consequences for customers' perceptions of interactions with BCI-enhanced FLEs remains underexplored (Drew, 2023; Garry and Harwood, 2019; Grewal et al., 2020).

While the benefits of FLEs' BCI enhancements are apparent, there is a looming threat evident in other emerging service technologies (e.g., AR/VR headsets, service robots) that BCIs may not gain widespread acceptance, face resistance from customers, and fail to achieve substantial market penetration (Mani and Chouk, 2018). Individuals who function differently from the norm frequently face prejudice (Parens, 2015), and research indicates that enhanced individuals are perceived as having fewer human traits, leading to their potential negative perception as 'cyborgs' (Castelo et al., 2019). It is, therefore, crucial to gain an in-depth understanding of how customers perceive BCI-enhanced FLEs as 'frontline cyborgs' and how these perceptions impact service evaluations. Insights can be drawn from early conceptual works on 'frontline cyborgs' (Garry and Harwood, 2019; Grewal et al., 2020) and the adjacent field of service robots, which emphasizes the challenge of achieving a social connection between non-humans and humans in terms of warmth and competence (Belanche et al., 2021). Despite the extensive body of literature covering the technical aspects of BCIs (Kawala-Sterniuk et al., 2021; Nicolas-Alonso and Gomez-Gil, 2012; Zander and Kothe, 2011), there remains a lack of research on customer perceptions of interactions with BCI-enhanced employees - an essential research gap that requires attention.

In the first essay, we address this gap in the service literature. We employ a mixed-methods approach as it combines qualitative insights to explore complex perceptions of BCI use with quantitative analysis to validate findings and establish generalizable patterns (Creswell et al., 2003). The first objective of this dissertation project is to shed light on how customers and FLEs perceive the integration of BCI technology in frontline service roles. To achieve this, we conducted two exploratory qualitative studies with both customers and FLEs to gain an initial understanding of BCI-enhanced FLEs and to reveal both the bright and dark sides of BCI adoption at the frontline. These qualitative insights were then followed up by three confirmatory experimental studies, allowing us to quantitatively verify the findings from our interviews. Through this mixed-methods approach, we aim to identify the mechanisms that drive customer perceptions of BCI-enhanced FLEs in frontline service interactions. This research project is guided by the following research questions, whereas RQ1 refers to the research question for the qualitative inquiry and RQ2 refers to the research question for the quantitative follow-up studies:

RQ1: *How do customers perceive their interactions with BCI-enhanced frontline employees, and what factors influence these perceptions in service encounters?*

RQ2: *Does the psychological construct of social cognition mediate the impact of customer evaluations in interactions with BCI-enhanced FLEs?*

03.2 Research Gap and Research Questions Essay II

As the primary point of contact between firms and customers, FLEs perform essential boundary-spanning functions (Lages and Piercy, 2012). However, their roles are undergoing significant transformation. Today's increasing labor shortages, continuous adaptation to emerging technologies, and heightened customer expectations have intensified the risk of cognitive overload and emotional exhaustion (Chen et al., 2019; Day et al., 2019).

For example, a recent American Psychological Association report about psychological safety in the workplace revealed that 30 percent of FLEs report fair or poor mental health (APA, 2024). This growing pressure poses adverse consequences for FLEs' well-being, which is defined as the comprehensive evaluation of one's life satisfaction and the extent to which FLEs experience "optimal psychological functioning" (Ryan and Deci, 2001, p. 142). Left unchecked, these strains can culminate and lead to burnout, diminished job performance, and increased turnover, all of which threaten not only FLEs' well-being, but also the firm's long-term success and profitability (Chen et al., 2019).

BCIs are being put forth as one promising solution to help FLEs function better in today's rapidly changing and highly taxing workplace environments (Grewal et al., 2020). Unlike traditional mouse, keyboard, or touchscreen-based interfaces, BCIs allow FLEs to interact with devices solely through their brain activity, eliminating the need for muscular movement (Nicolas-Alonso and Gomez-Gil, 2012). This marks a significant shift toward more seamless and natural engagement with digital environments (Hilken et al., 2022, Vasiljevic and de Miranda, 2020), enabling, among other things, more efficient work processes and a greater emphasis on customers. Workplace BCIs can analyze FLEs' cognitive and affective states, including emotion, relaxation, fatigue, and cognitive workload levels (Saha et al., 2021). By tracking brain activity, BCIs provide users with feedback on their mental states, allowing for real-time analysis and long-term logging to gain detailed insights over time (Zander and Kothe, 2011). For example, air traffic controllers' workplaces can be adjusted based on their current stress levels, such as reduction of visual load by displaying fewer aircraft on the screen or minimizing auditory alerts to prevent distractions from noncritical notifications. This adaptation has been demonstrated to reduce employees' stress levels while increasing operational safety and efficiency (Aricò et al., 2016).

Despite the importance of BCI adoption's implications for FLEs and its expected massive impact on many service providers' work environments, scant extant research on this topic exists in the service marketing and service management field. Therefore this second dissertation project is guided by the following research questions:

RQ1: *How can BCIs be conceptualized as workplace technology?*

RQ2: *What is BCIs' impact on FLEs' well-being?*

By pursuing this goal, this study addresses calls from marketing and service scholars to explore BCIs' potential and applications, as well as from well-being researchers seeking to understand emerging technologies' impact on FLEs (Grewal et al., 2020; Subramony et al., 2021).

03.3
Research Gap and Research Questions Essay III

The third dissertation project shifts the user of BCI technology from FLEs to customers. While BCIs hold significant potential to enhance user interactions with devices for more intuitive and seamless control, little research has examined customer perceptions towards adopting BCI technology in consumer settings (Drew, 2023; Lima and Belk, 2022). This technology has primarily been investigated 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 information systems 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 and de Miranda, 2020). However, few other technologies process sensitive data such as neural information, providing companies with insights into users' health, focus, or anticipated decisions (Bonaci et al., 2014; Hibbeln et al., 2017; Jackson and Snyder, 2008; Xing et al., 2019). Literature in service marketing suggests that when users feel that their interaction data is at risk of being shared with companies, they would fear being controlled as a result (Ackermann et al., 2022; Chandra et al., 2022). These considerations highlight interaction modality as a potential aspect of investigation in consumers' perception about BCI adoption. Users might have different perceptions of interacting with BCIs on an individual level, such as controlling their smart home devices, compared to interactions with organizations where BCIs are used to purchase products or services (Smith, 2020). Furthermore, BCIs offer new forms of enhancement that could significantly alter how consumers perceive themselves (Castelo et al., 2019). This essay incorporates well-established constructs, such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT), which posit that ease of use and perceived usefulness significantly impact users' intention and subsequent adoption behavior (Marangunić and Granić, 2015; Venkatesh et al., 2012). However, there may be additional factors beyond traditional technology acceptance that are unique to BCI use by customers.

It is evident that user perceptions of BCIs in both personal and organizational contexts play a significant role in shaping their future intentions to adopt such technologies. However, despite the extensive literature on the technical aspects of BCIs, research on the perceptions and outcomes for regular users remains limited but critically needed (De Keyser et al., 2021). Recognizing this research gap, our study aims to address an overarching research question, supported by several sub-research questions:

RQ1: *How do users perceive interactions with consumer-grade BCI technology?*

RQ1.1: *What are the key drivers and barriers that influence users' interactions with BCI?*

RQ1.2: *How does the interaction setting impact user-evaluations of BCI technology?*

RQ1.3: *To what extent does the level of BCI functionality shape user perceptions?*

RQ1.4: *How does the BCI context influence the self-perception as cyborgs?*

03.4 Research Gap and Research Questions Essay IV

The fourth dissertation project examines how multiple BCI users communicate and collaborate in metaverse settings, offering insights into technology-mediated social dynamics and human-technology interaction. Established research streams have extensively demonstrated that communication through BCIs enables the typing of words, and that brain-to-brain communication is feasible for sharing cognitive and emotional states (Semertzidis et al., 2023, 2024), thereby fostering closer social connections (Keyes, 1998). Despite the potential for enriching communication by adding an additional channel to convey information within the metaverse context, significant research gaps remain. There is a paucity of studies examining how BCIs can transform communication affordances and the subsequent impact on individual well-being. Traditional communication methods rely heavily on verbal and nonverbal cues, which are fundamentally altered when users communicate directly through neural signals (Hilken et al., 2022; Tomasello, 2010; Widge et al., 2014). This transformation presents both opportunities and challenges that are yet to be comprehensively studied. While the metaverse promises enhanced immersion and interaction, the psychological and social implications of BCI-mediated communication are under-researched (Krepki et al., 2007; Van Erp et al., 2012). Understanding how these new forms of interaction affect users' mental health, social relationships, and overall well-being is crucial. For instance, the potential for digital overload and addiction in immersive environments could impact users' cognitive and emotional balance, warranting further investigation (Rehm et al., 2015; Rubo et al., 2021). Additionally, ethical considerations such as privacy, consent, and the potential misuse of neural data are critical areas that require attention to ensure the responsible deployment of BCIs in the metaverse (Burwell et al., 2017; Kreitmair, 2019; Steinert and Friedrich, 2020; Wexler and Thibault, 2018; Yuste et al., 2017).

To address this gap, this project integrates literature from communication theories, information systems, and BCI research to conceptualize new pathways for human-technology interaction and their effects on individual well-being. This model, based on actor-network theory (Latour, 2007), aims to demonstrate how BCIs integrated with neurostimulation technologies can transform communication, offering avenues for enriching communication while also delineating the potential negative impacts for users. Through this conceptual investigation, the research seeks to provide a robust foundation for future empirical studies, informing how the implementation of such technology can enhance well-being through communication in the metaverse. This research project is guided by the following research questions:

RQ1: *How do BCIs and neurostimulation alter the communication affordances for users in the metaverse?*

RQ2: *What impact do these changes in communication affordances, facilitated by BCIs, have on the well-being of individuals?*

04

Summary of Research Essays

This chapter provides a synopsis of the four research essays included in this dissertation, outlining their overarching motivations, research methodologies, and key findings. Collectively, the essays examine the impact of BCIs and neurostimulation technology within service marketing contexts. Table 04.1 gives an overview over all four essays. They shed light on underinvestigated areas by addressing the research questions derived in the previous chapter. The four essays were written with different co-authors (Essay I with Tim Hilken, Jonas Heller and Stefanie Paluch; Essay II with Arne De Keyser, Susana Jaramillo, Jiarui Li, Yihui (Elina) Tang and Ihtesham Ud Din; Essay III with Stefanie Paluch; Essay IV with Stefanie Paluch).

04.1 Research Essay I

This essay received a major revision decision post first-round reviews. Revision in progress at *Journal of Service Research* (VHB-JOURQUAL3: A). This paper was presented in various forms at *Winter AMA 2023*, *Frontiers in Service 2023*, *SERVSIG 2024* and *Frontiers in Service 2024*.

The next wave of technological service innovation is aimed at human enhancement, leveraging cutting-edge technologies to augment a person's physical, cognitive and emotional capabilities beyond their usual limits (Lima and Belk, 2022; Marinova et al., 2017). While fitness and health trackers and other smart devices are already commonplace, so-called Brain-Computer Interfaces (BCIs) are heralded as the next key technology in these developments (Garry and Harwood, 2019). While consumer adoption of BCIs is still nascent, service providers are beginning to explore their use for enhancing the capabilities of frontline-employees (FLEs) in effort to improve the quality of service interaction (Grewal et al., 2020). This research paper empirically investigates the impact of BCI-enhanced FLE on service encounters in a mixed-methods approach, building on previous work that has only conceptually established this connection.

In the first step, we conducted 29 exploratory qualitative interviews with customers and FLEs, which, together with a literature review, were used to establish our research hypothesis. The results from the qual-

Table 04.1: Overview of the four essays of this dissertation. Source: The table was created by the author.

	Essay I	Essay II:	Essay III:	Essay IV:
Title	Reversing the Cyborg Effect: Enhancing the Service Quality of Frontline Employees with Brain-Computer Interfaces	Wired for Work: Brain-Computer Interfaces' Impact on Frontline Employees' Well-Being	Examining User Perceptions of Brain-Computer Interfaces for Practical Applications: An Exploratory Study	Beyond Words: The Future of Metaverse Communication Through Brain-Computer Interfaces
Topic	Examine the impact of BCI-enhanced FLE on customers' perception of the service encounter	Investigate BCIs' impact on FLEs' well-being, when BCIs are introduced as workplace technology	Users' perception to interact with technology through BCIs and its impact on attitudinal and behavioral outcomes	BCIs' impact on communication affordances of regular users in metaverse settings
Theory	Social cognition theory	Job demands-resources theory Transactional Theory of Stress	Technology acceptance model (TAM) Unified Theory of Acceptance and Use of Technology (UTAUT)	Actor-network theory
Method	Mixed Methods: Qualitative interviews, behavioral experiments with real BCI use	Conceptual Paper	Qualitative interviews, behavioral experiments	Conceptual Paper
Data Collected	29 qualitative interviews 3 experimental studies (n_{total}=636)	-	26 qualitative interviews 1 experimental study (n=189)	-
Unit of Analysis	Customer, Frontline employee	Frontline employee	Individual customer / user	Individual customer / user

itative studies indicated mixed views on BCI-enhanced FLEs in service encounters. While some customers embraced the increased efficiency, others feared the loss of the human touch. Integrating findings from these studies and the literature, we hypothesize that customers will evaluate the quality of a service encounter with a BCI-enhanced FLE lower compared to one in which the FLE uses a conventional device (e.g., laptop or tablet).

This phenomenon is referred to as the 'cyborg effect.' Furthermore, based on findings from our qualitative research and literature, we hypothesize that the social cognition theory factors of warmth and competence mediate this relationship.

In three experimental studies (Study 2: online study, n=125; Study 3: field-in-a-lab with real BCI-enhanced FLE interaction, n=142; Study 4: online study with Prolific, n=369), we firmly establish the 'cyborg effect' as a baseline negative effect of deploying BCI-enhanced FLEs in the frontline. Moreover, we find strong support for warmth as a mediator and mixed support for competence as a mediator in this effect. As this finding threatens to counteract the positive effects BCI-enhancement may bring to service encounters, as mentioned by respondents in qualitative interviews, we hypothesized two ways the 'cyborg effect' can be counteracted. First, the type of FLE enhancement may impact the 'cyborg effect.' Prior research suggests that framing the purpose of BCIs might be an effective strategy (Castelo et al., 2019; Grewal et al., 2020). In contrast to a cognitive enhancement framing, which emphasizes the augmentation of FLEs' cognitive abilities through technology (Cinel et al., 2019; Jamil et al., 2021; Van Erp et al., 2012), framing for emotional enhancement highlights how BCIs can free up mental resources, enabling FLEs to engage more deeply and personally with customers (Cascio and Montealegre, 2016; Grewal et al., 2023). Our findings from Study 3 and 4 reveal that framing BCIs for emotional rather than cognitive enhancement of FLEs' capabilities can mitigate the 'cyborg effect,' where interactions with BCI-enhanced FLEs do not lead to baseline negative effects on service evaluations. Second, research suggests that, like other technologies, the benefits of BCIs will likely differ across service contexts due to variations in customer demands, technology fit, and specific emotional and cognitive requirements for each setting (Huang and Rust, 2017; Larivière et al., 2017). We show that for service contexts characterized by the occupational stereotype of low warmth and high competence, framing for emotional enhancement mitigates the 'cyborg effect.' Interestingly, in contexts with a directional flip for warmth and competence, customers perceived BCI-enhanced FLEs as warmer and more competent than employees using a tablet.

In sum, this research establishes the 'cyborg effect' where BCI-enhanced FLEs can negatively impact service evaluations of customers due to diminished human connection. In our findings we show that framing FLEs' use of a BCI for service personalization (vs. efficiency) and using BCIs in more (vs. less) complex service encounters can mitigate this effect.

04.2

Research Essay II

This essay is accepted for publication at the *Journal of Service Management* (VHB-JOURQUAL3: B). This paper was presented at *Frontiers in Service 2024*.

Neurotechnologies such as BCIs are rapidly moving out of laboratories and onto FLEs' heads. These devices can enable thought control of software and robots or monitor employees' cognitive load to recommend breaks for employees experiencing mental fatigue (Liu et al., 2021; Yaacob et al., 2023). Thus, BCIs promise the dual advantage of enhancing human capabilities by increasing employee efficiency and reducing the cognitive and emotional strain associated with work tasks (Garry and Harwood, 2019). However, BCIs also carry a potential dark side, with the risk of exploitative employee treatment raising concerns about increased surveillance, privacy and reduced autonomy (Yuste et al., 2017). Firms face a clear risk of building BCI solutions that employees will not embrace, undermining the potential benefits BCIs could offer. As BCIs' impact as workplace technology on FLE well-being remains uncertain, this research paper aims to conceptualize what BCIs entail and introduce a framework to understand BCIs' impact on FLEs' well-being.

Our first step involved to conceptualize what BCIs entail for frontline roles by providing a comprehensive overview of four distinct types of BCIs. Differentiated by BCI category (passive vs. active) and modality of signal acquisition (non-invasive vs. invasive), these types are illustrated with existing and nascent usage examples of BCIs on the service frontline. Due to this conceptualization, we find that non-invasive passive BCIs are poised for immediate integration into frontline roles, as service firms can already access these devices at a reasonable cost (Drew, 2023; Grewal et al., 2020). Active BCIs, though currently limited in detecting complex mental commands, are anticipated to improve significantly within the next decade (Maiseli et al., 2023). Building on this overview of BCIs, we develop a conceptual framework that examines the impact of BCI integration on FLEs' well-being, influenced by two mediating and three moderating factors.

We posit that BCI implementation's impact on FLEs' well-being is mediated by whether FLEs perceive the technology as a tech-resource (i.e., primarily positive impact) or a tech-stressor (i.e., primarily negative impact), based on job demands-resources theory (Demerouti et al., 2001) and the transactional theory of stress (Lazarus and Folkman, 1984). We argue that FLEs' perception of BCIs' purpose in the workplace significantly shapes their evaluation of the technology's effect on their well-being. Our findings suggest that BCIs are more likely to be accepted when integrated to support or augment job performance (e.g., increased efficiency) rather than as tools of excessive oversight and monitoring (e.g., increased performance tracking). First, we identify FLE resources—personal and social factors—as key moderators that shape whether BCIs are seen as tech-resources or tech-stressors (Bakker and Demerouti, 2017). We propose that BCIs can influence perceptions of self and others, which affects their evaluation. Second, we find that BCI usability and device design also serve as crucial moderators, with passive BCIs likely to be viewed more favorably due to their ease of use and non-intrusive form factors (Ayyagari et al., 2011; Dehghani and Kim, 2019; Drew, 2023). Third, we identify managerial interventions as a moderating force influencing how BCIs are implemented in the workplace. Neuroergonomic approaches offer a valuable opportunity to optimize workplace environments, enhancing FLE efficiency while preserving cognitive and emotional resources.

To summarize, this research conceptualizes BCIs for frontline roles and introduces a framework to assess BCIs' impact on FLEs' well-being. Depending on the integration characteristics of BCI as workplace technology, FLEs perceive the technology as a tech-resource (i.e. predominant positive impact) or tech-stressor (i.e. predominant negative impact). When FLEs see BCI as tech-resources, they perceive the technology as aiding in task completion, enhancing their motivation, and reducing stress. Conversely, when BCIs are perceived as tech-stressors, FLEs' perceive to be surveilled by technology, overwhelmed by its complexity that lead to the view of BCIs as taxing or exceeding FLEs' available resources.

04.3
Research Essay III

This essay is published in the 2023 *Proceedings of the International Conference on Information Systems (ICIS)* (VHB-JOURQUAL3: A).

Beyond the enhancement of FLE capabilities, the next frontier is customer adoption of BCIs, enabling interaction with devices and firms through their neural data. 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 (Hilken et al., 2022; Vasiljevic and de Miranda, 2020). Against this backdrop, Essay III examines how regular users perceive the adoption of consumer-grade BCIs for individual use. In doing so, it sheds light on the facilitators and inhibitors of adoption and explores the differences between using BCI technology for individual purposes (e.g. controlling smart home) and interactions with service organizations (e.g. purchasing products or services). Despite the improving capabilities and smaller form factor of BCI, its potential usage by non-medical users remains largely unexplored (Drew, 2023; Van Erp et al., 2012).

To address this research gap, the authors employed a mixed-methods approach, beginning with 26 exploratory qualitative interviews to gain insights into users' perceptions of the technology and identify the attitudinal and behavioral impacts of BCIs. A thorough analysis of the interview results, combined with well-established frameworks such as TAM and UTAUT, resulted in the development of a comprehensive research model (Marangunić and Granić, 2015; Venkatesh et al., 2012). The main findings from this model indicate that users are more willing to engage with BCIs for individual use rather than for interactions with organizations. Additionally, the self-view of enhancement through BCIs plays a significant role. Users who felt superhumanized by the extended abilities offered by the technology were more inclined to use it. However, some individuals expressed concerns about losing the human touch and becoming dehumanized, leading to a negative self-perception as cyborgs. To triangulate these findings, the research model was partially validated with a pre-study involving 189 participants. The pre-study revealed that participants could accurately distinguish between individual and organizational BCI interactions. Ease of use control measures indicated that manipulated BCI functionality in organizational contexts was perceived as easier to use. Further studies aim to validate additional aspects of the model to provide a more comprehensive understanding of BCI adoption and its impacts.

In sum, this research explores how regular users perceive consumer-grade BCI adoption, highlighting facilitators and inhibitors of its use for personal applications (e.g., smart home control) versus organizational interactions (e.g., service purchases). Findings suggest users are more willing to adopt BCIs for individual use, with perceptions influenced by the balance between feeling ”superhumanized” through technology-enhancement and concerns of ”dehumanization” or loss of personal agency.

04.4
Research Essay IV

This essay is currently being prepared for submission to a special issue in *Internet Research* (7.9 5-year Impact Factor).

Expanding the use of BCIs beyond their sole application as passive and active interfaces to interact with technology, BCIs and neurostimulation technologies offer enhanced communication affordances that lead to profound transformations in how individuals communicate in the metaverse. This essay discusses the changing nature of communication and develops a conceptual framework for BCI-infused communication based on actor-network theory (Latour, 2007). Central to this transition are BCIs, which are defined as communication and control technologies that enable users to send and receive messages and commands to and from external devices by detecting and interpreting their brain activity, without requiring muscular stimulation or speech (Lotte and Roy, 2019; Nicolas-Alonso and Gomez-Gil, 2012). These BCIs extend the communication affordances of users by providing insights into mental states, enabling communication with technology through thoughts, and facilitating the receipt of communication from others (Drew, 2024; Hilken et al., 2022). This novel medium for communication enhances well-being by allowing individuals to share emotional experiences and enabling effortless and rapid exchanges of communication, thereby deepening connections and mutual understanding (Zander et al., 2010). This is particularly relevant in the metaverse, where the blending of physical and virtual worlds demands greater technological embodiment (Rubo et al., 2021).

To this end, we adopted a multidisciplinary approach, integrating literature streams from communication, neurotechnology, and reality-enhancing technologies, to define and conceptualize communication affordances BCI technology offers in the metaverse, as well as its significant effects on individual well-being. Augmenting the communication capabilities of individuals through the addition of a channel for sending and/or receiving messages, leads to enriched interactions with others and a greater satisfaction with their unique identities. Among these innovative interaction methods that facilitate communication between BCI users and virtually enhanced environments, certain forms stand out for their potential to enhance well-being: (a) the impact when both parties in an interaction employ BCIs, (b) interactions to or from the metaverse, (c) the effect of BCI on self-communication, and (d) interactions in one-sided BCI interactions for communication. Given the significance of ethical considerations arising from this communication model, aspects of privacy, agency, safety, responsibility and justice are thoroughly discussed.

In sum, we conclude that the potential role of BCI in enhancing interpersonal interactions and relationships is profound, illustrating how BCIs serve as innovative mediums for communication and empathy. By challenging the notion of computers and humans as distinct entities, the advent of BCI suggests a more intimate integration with technology, fostering a shared experience among users, enriched by the context and feedback within the metaverse.

05

Overall Contributions

The four essays in this dissertation aim to deepen our understanding of BCIs as a novel form of technology interaction mediated through neural activity. These essays provide insights into the conceptual and perceptual nuances relevant to the fields of service marketing, well-being, and human-technology interaction. To make a significant contribution to the field, this dissertation offers three overarching contributions, which are discussed before delving into the specific contributions of each essay.

First, this work is among the first to introduce BCI technology in service settings, extending its application beyond medical contexts. Most existing BCI research has centered on extracting features from brain waves or developing medical applications to assist users with brain injuries or locked-in states in communicating or controlling robotic devices (Kawala-Sterniuk et al., 2021; Nicolas-Alonso and Gomez-Gil, 2012). In response to calls for research that examines the broader implications of BCIs for service and communication (Garry and Harwood, 2019; Grewal et al., 2020; Hilken et al., 2022), this dissertation investigates BCIs from multiple perspectives to understand their impact in these new contexts. This includes examining customers' perceptions of interactions with BCI-enhanced frontline employees, conceptualizing the well-being impact of BCIs as workplace technology, understanding customers' attitudes toward using BCIs, and exploring the enhanced communication affordances enabled by BCI-mediated interactions. Second, employing a variety of methods, including qualitative interviews, experimental studies, and conceptual analyses, enables this dissertation to provide a comprehensive understanding of BCI technology from multiple perspectives, enriching both theoretical insights and practical implications (Creswell et al., 2003; Jaakkola, 2020; Morales et al., 2017). Third, drawing on multiple theoretical perspectives such as social cognition theory, well-being, job demands-resources theory, transactional theory of stress, technology acceptance models, and actor-network theory enriches this dissertation by providing a multifaceted view of BCI technology's impact on service and communication settings.

The following subchapters discuss the theo-

Table 05.1: Overview of the key research and managerial contributions of the four essays. Source: The table was created by the author.

	Essay I	Essay II:	Essay III:	Essay IV:
Key Contributions for Research	• Provide empirical evidence on customer and FLE perceptions of BCI-enhanced service interactions, revealing both the potential bright and dark sides of BCI adoption. • Establish the "cyborg effect," a baseline negative impact of deploying BCI technology for cognitive enhancement of FLEs in service encounters, which can be explained by mediators' warmth and competence. • Identify critical interventions to mitigate the negative impacts of the cyborg effect: Framing FLEs' use of BCIs for improved service personalization rather than efficiency, and increased service context complexity, can mitigate or even reverse the cyborg effect.	• Conceptualizes what BCIs entail for frontline roles by providing an overview of four distinct types of BCIs—differentiated by category and signal acquisition modality—and illustrates these with existing and emerging usage examples • Conceptualizes BCIs' impact on FLEs' well-being, positing that this impact is mediated by FLEs' perception of the technology as either a tech-resource (dominantly positive impact) or a tech-stressor (dominantly negative impact), and delineates three categories of moderators influencing this relationship • Proposes avenues for future research, along with propositions and research directions	• Advances the limited research on regular user interactions with technology through BCIs and takes a pioneering step toward understanding how individuals perceive interacting with technology through BCIs, offering an additional perspective on BCI utilization in both individual and organizational interactions. • Investigates the determinants and underlying psychological processes driving users' perceptions and attitudes toward BCI applications. • Proposes a research model identifying distinctive factors that drive or hinder BCI adoption, thus shaping users' intentions to embrace or reject its application.	• Synthesizes existing BCI literature to provide an overview of BCIs as a communication technology, exploring neuroimaging (using BCIs to control technology) and neurostimulation (receiving external stimulation as an additional communication channel). • Conceptualizes BCI-enhanced communication affordances based on actor-network theory, discussing the impact of BCI-to-BCI communication, BCI interaction with the metaverse, BCI-enhanced self-communication, and one-sided BCI communication. • Reviews ethical concerns associated with direct-to-consumer BCIs and proposes a research agenda.
Key Contributions for Practice	• Highlight the compelling business case for integrating BCIs in service operations, where BCI-enhanced FLEs seamlessly link human intuition and empathy with artificial intelligence to enhance employee efficiency and improve customer outcomes through superior service. • Recommend that service managers present a brief service script to customers, clearly communicating the benefits of BCI use as customers explicitly want to be educated on how the device enhances their service experience. • In high-complexity industries (e.g., financial advisory, accounting), emotional enhancements via BCIs can counteract perceived lack of warmth and provide a competitive advantage by building closer rapport between customers and FLEs.	• Advise service organizations on leveraging current BCI technology—particularly passive BCIs—to optimize FLEs' resource utilization while serving customers more efficiently. • Recommend that managers optimize workplace design by utilizing BCIs to dynamically distribute tasks, tailor feedback, and monitor FLEs' cognitive and emotional states, while ensuring FLEs are involved in decision-making about these adaptations to promote acceptance and effectiveness. • Ensure proper management of sensitive neural data to prevent BCIs from being perceived as tech-stressors through transparency and opt-out possibilities.	• Reveals that customers are generally receptive to engaging with their technological environments using BCIs, presenting opportunities for firms to develop offerings (e.g., smart home control, neuro-adaptive gaming mechanics) that enhance user experience and create competitive advantages. • Highlights that customers express greater hesitation when it comes to interacting with firms using BCIs, indicating the need for firms to implement clear measures and transparent communication regarding data usage to build trust and mitigate apprehension. • Offers critical guidance for managers on designing and enhancing the usability of BCIs, emphasizing that the form factor should be integrated into everyday technology.	• Encourages managers to integrate BCIs into virtual and augmented environments to enhance user well-being through personalized interactions, leveraging bidirectional communication and real-time adaptation for richer and more intuitive experiences. • Highlights significant implications for service research and marketing, as BCIs enable companies to create highly tailored and immersive experiences that align with customers' cognitive and emotional states, potentially improving satisfaction, loyalty, and brand perception in the metaverse.

retical and managerial contributions of each paper individually, and Table 05.1 provides an overview comparing these key contributions.

05.1 Academic and Managerial Contributions of Essay I

The first essay investigates how BCIs can enhance the cognitive and emotional performance of FLEs and examines its impact on customers' perceived service quality. This research makes several key contributions to the existing academic literature. First, while there is important conceptual research on customer interactions with BCI-enhanced frontline employees (Garry and Harwood 2019; Grewal et al. 2020), there is a notable lack of empirical evidence into these service encounters. We provide insights from two exploratory qualitative inquiries into how BCIs are perceived by customers and FLEs in service interactions. Our findings reveal both the potential bright and dark sides of BCI adoption. Catalysts for positive experiences include increased service convenience and enhanced frontline employee proficiency. Conversely, inhibitors such as the diminished human connection led to negative outcomes. We further empirically investigate these findings in three experimental studies. Second, we firmly establish the cyborg effect, which denotes a baseline negative effect of deploying BCI technology for cognitive enhancement of FLEs in service encounters. Our findings demonstrate that the cyborg effect is consistent across various service contexts and diverse samples. This finding is crucial as it highlights and empirically validates the inherent challenges in enhancing the cognitive capabilities of FLEs in service settings, indicating that without addressing customer apprehensions, the significant potential of BCI-enhanced FLEs may be overshadowed by negative perceptions. Moreover, we identify mediators explaining the cyborg effect through the lens of social cognition theory. This theory has been widely utilized to assess customer reactions to human employees (e.g. Wang et al., (2016) and, more recently, robots in frontline roles (e.g. Choi et al., (2021). We contribute to this body of research by examining the roles of warmth and competence in interactions with BCI-enhanced FLEs, who occupy a position between the extremes of human and robotic entities (Grewal et al. 2020). Third, we enrich existing literature by identifying critical interventions that can mitigate the negative impacts of the cyborg effect on service evaluations. Our findings reveal that framing the FLE's use of a BCIs for improved service personalization rather than service efficiency can mitigate the cyborg effect. In addition, our results underscore the role of service context in mitigating the negative effects of the cyborg effect. We show that for service contexts characterized by higher levels of complexity, framing for service personalization not only mitigates the cyborg effect at moderate levels of complexity, but even reverses it at high levels of complexity.

Integrating BCIs in service operations makes a compelling business case. BCI-enhanced FLEs link intuitive and empathetic abilities of human brains directly with computers, enabling a seamless integration of human and artificial intelligence (Drew, 2023). This holds the potential to enhance the efficiency of employees, while also improving customer outcomes through superior service (Grewal et al., 2023). This research offers key insights for firms considering adopting BCIs in their service operations. We recommend that service managers present a brief service script to customers, clearly communicating the benefits of BCI use for service personalization. Our findings indicate that customers explicitly want to be educated on how the device contributes to their service experience. As managers strive to establish an emotional connection with their customers (Kumar and Pansari, 2016), BCIs offer a valuable opportunity to achieve this objective. Our work also reveals that the service context is crucial when implementing BCI technology in the frontline. In service industries characterized by higher complexity, such as financial advisory, legal or accounting services, emotional enhancements possible through BCIs offer high potential. By counteracting the perceived lack of warmth, BCIs can provide a significant competitive advantage for service managers in these industries by building closer rapport between customers and FLEs. When enhanced FLEs are perceived as warmer and more competent, this dual enhancement can lead to improved service evaluations. Another important factor for managers to consider is the privacy and ethical implications of using BCI technology in service encounters. Our results indicate that both FLEs and customers have raised concerns about privacy, particularly regarding the sensitive neural data of employees being processed.

05.2 Academic and Managerial Contributions of Essay II

The second essay conceptualizes BCIs' impact as workplace technology of FLEs' well-being. The article makes three academic contributions to service and well-being research. First, this article conceptualized what BCIs entail for frontline roles, providing a comprehensive overview of four distinct types of BCIs. Differentiated by BCI category (passive vs. active) and modality of signal acquisition (non-invasive vs. invasive), these types are illustrated with existing and nascent usage examples of BCIs on the service frontline. Due to this conceptualization, the authors predict that non-invasive passive BCIs are primed for immediate integration into frontline roles. Service firms can acquire commercially available devices at a reasonable cost, presenting a significant opportunity to serve customers more efficiently (Drew, 2023; Grewal et al., 2020). Active BCIs, currently limited in their ability to detect complex mental commands reliably, are expected to undergo substantial improvements in the next decade (Maiseli et al., 2023). Second, this research conceptualizes BCIs' impact on FLEs' well-being drawing on the transactional theory of stress and the job demands-resources theory (Demerouti et al., 2001; Lazarus and Folkman, 1984). The authors posit that BCI implementation's impact on FLEs' well-being is mediated by FLEs' perception of the technology as either a tech-resource (i.e., dominantly positive impact) or tech-stressor (i.e., dominantly negative impact). This study's findings suggest that BCIs are more likely to be accepted when integrated to augment or support FLEs in performing their job duties (i.e., increase efficiency), compared with when they are perceived as tools of excessive oversight and monitoring (i.e., increased performance monitoring). Additionally, this paper delineates three categories of moderators, that influence the relationship of BCI implementation on FLEs' perception of BCIs as tech-stressors or tech-resources: FLEs' resources describing personal and social factors that affect the perception of BCIs, BCI usability and device design and managerial interventions, explaining how implementation decisions of organizations shape FLEs' perceptions. Third, avenues for future research are proposed, based on the identified variables in the conceptual framework, along with propositions and research directions.

Besides contributions to academic research, this work presents valuable managerial contributions for service organizations intending to implement current and emerging BCIs at the organizational frontline to enhance FLE performance. Service managers implementing BCI technology can optimize the utilization of FLEs' resources, while serving customers more efficiently (Grewal et al., 2020; Marinova et al., 2017). Current BCI technology is advancing rapidly, particularly with passive BCIs, which are now primed for immediate integration into frontline roles (Drew, 2023). Managers can optimize workplace design by leveraging BCIs to dynamically distribute tasks, tailor feedback, and monitor FLEs' cognitive and emotional states (Drew, 2023; Mehta and Parasuraman, 2013). However, managers should ensure to involve FLEs in decision-making about these adaptations. Managers can use BCI feedback to support employee well-being by providing insights into cognitive and emotional states, offering recommendations to prevent burnout, or encouraging breaks based on mental fatigue (Hunkin et al., 2021; Tement et al., 2016; Wascher et al., 2023). However, this feedback should be presented transparently and with the option to opt-out to avoid perceptions of surveillance or overreach. Furthermore, managers should ensure proper management of sensitive neural data to prevent perceptions of BCIs as tech-stressors (Ayyagari et al., 2011; Day et al., 2010; Nicolas-Alonso and Gomez-Gil, 2012).

05.3
Academic and Managerial Contributions of Essay III

The third project examines customers' perceptions of using BCIs to interact with technology or engage with service firms. This article makes two contributions to academic literature. 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, 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 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 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. Furthermore, we provide four propositions which offer fruitful avenues for additional research.

This research offers valuable managerial insights, as the findings indicate that customers are generally receptive to engaging with their technological environments using BCIs, presenting a promising opportunity for firms to develop offerings (e.g. smart home control or neuro-adaptive gaming mechanics) that enhance user experience and can create competitive advantages (Lee et al., 2022; Vasiljevic and de Miranda, 2020). However, when asked about interactions with firms using BCIs, customers expressed greater hesitation: "Actually, I don't want that at all, I don't want them to have all my thoughts somewhere" (I.12). To address these concerns, our results indicate that firms should implement clear measures and transparent communication regarding data usage to build trust and mitigate apprehension (Yuste et al., 2017). Furthermore, we offer critical guidance for managers on designing and enhancing the usability of BCIs. One important consideration is the form factor of the device, which should be integrated into everyday items like headphones and glasses, preferably with comfortable-to-use dry electrodes. Manufacturers should investigate ways to integrate technology with high temporal resolution to improve customers' willingness to adopt the technology.

05.4
Academic and Managerial Contributions of Essay IV

The fourth essay conceptualizes the impact of BCI-enhanced communication pathways within reality-augmented contexts on users' well-being. This research makes several key contributions to the existing academic literature. First, the essay synthesizes BCI literature and provides an overview of BCIs as a communication technology (Kawala-Sterniuk et al., 2021). It further explores the constructs of neuroimaging, which involves using BCIs to control technology, and neurostimulation, where external stimulation is received as an additional communication channel (Hilken et al., 2022). By delineating the impact of integrating neuroimaging and neurostimulation technologies, this essay advances literature by examining the communication impact of brain-to-brain interfaces and technology-to-brain interactions. Second, this research conceptualizes BCI-enhanced communication affordances based on actor-network theory discussing the impact of BCI-to-BCI, BCI to the metaverse, BCI-enhanced interaction for self-communication, and one-sided BCI communication. Third, we draw upon established literature to review the ethical concerns associated with direct-to-consumer BCIs across dimensions of privacy & consent, agency & identity, safety, responsibility, and justice (Burwell et al., 2017; Kreitmair, 2019; Lima and Belk, 2022; Steinert and Friedrich, 2020; Vlek et al., 2012; Wexler and Thibault, 2018; Yuste et al., 2017). Lastly, we propose a research agenda that aligns with the dimensions outlined in our conceptual framework, aiming to investigate these critical issues further.

Besides contributions to academic research, this work presents valuable managerial contributions. Managers should consider integrating BCIs in virtual and augmented environments to enhance user well-being through personalized interactions. The ability of BCIs to support bidirectional communication and real-time adaptation of digital environments enables richer and more intuitive interactions, potentially enhancing well-being (Jiang et al., 2019; Semertzidis et al., 2023). This has significant implications for service research and marketing, as it allows companies to create highly tailored and immersive experiences that align with customers' cognitive and emotional states, potentially improving satisfaction, loyalty, and brand perception in the metaverse and other digitally enhanced contexts (Drew, 2023; Grewal et al., 2023; Mehta and Parasuraman, 2013).

06

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07

Appendix: Essay I

Reversing the Cyborg Effect: Enhancing the Service Quality of Frontline Employees with Brain-Computer Interfaces

by Alexander Kies, Tim Hilken, Jonas Heller and Stefanie Paluch

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07.1 Abstract

In the rapidly evolving service economy, frontline employees (FLEs) are pivotal in delivering exceptional customer experiences. Traditional methods to enhance FLE performance often focus on training, motivation, and environmental adjustments. However, recent advancements in technology present new opportunities for performance enhancement through Brain-Computer Interfaces (BCIs). This study explores the potential of BCIs to enhance the cognitive and emotional performance of FLEs and its effect on perceived service quality in various service contexts. By leveraging BCIs, organizations can potentially improve service quality and customer satisfaction. Through qualitative and experimental study, this paper assesses the impact of BCI enhanced FLE's on service quality. Our findings establish the 'cyborg effect' where BCIs can negatively impact service evaluations due to diminished human connection, but framing BCIs for emotional enhancement mitigates this effect. Managers should frame BCI enhancements as emotional to improve service interactions and address privacy concerns with clear guidelines and transparency about neural data usage.

Keywords: Brain-Computer Interfaces, Frontline Employees, Service Quality, Warmth, Competence

07.2 Introduction

The next wave of technological service innovation is aimed at human enhancement, leveraging cutting-edge technologies to augment a person's physical, cognitive and emotional capabilities beyond their usual limits (Lima and Belk 2022; Marinova et al. 2017). While fitness and health trackers and other smart devices are already commonplace, so-called Brain-Computer Interfaces (BCIs) are heralded as the next key technology in these developments (Garry and Harwood 2019). BCIs are defined as a wearable technology that establishes a direct communication link between a person's brain and external devices by recording and decoding neural activity (Nicolas-Alonso and Gomez-Gil 2012). BCIs thus have the capability to translate thoughts into mental commands, to control and manage technology with unprecedented efficiency and precision (Hilken et al. 2022). While customer adoption of BCIs is still nascent, service providers are beginning to explore their use for enhancing the capabilities of frontline employees (FLEs) in effort to improve the quality of service interaction (Grewal et al. 2020). For example, BCIs could allow FLEs to deliver high-quality service at the speed of thought, while staying focused on building personal rapport. As a result, FLEs could interact more seamlessly with customers by minimizing distractions that divert attention from the customer (e.g., looking up product information on a laptop or tablet).

This is not a distant vision for the future, as hardware and applications for everyday service settings are rapidly emerging (Drew 2023). For example, the NextMind BCI headset allows users to interact with smart objects in the servicescape, for example changing the music, lights, and TV volume, or activating a laptop or tablet (Heater 2022). Similarly, the Emotiv BCI headset enables users to stably and reliably control (service) robots hands-free, enhancing collaboration and usability (Cinel, Valeriani and Poli 2019). A notable indicator of their potential for mainstream rollout is Apple's patent application, proposing the integration of BCI sensors into their popular AirPods headphones (Purcher 2023). With a market size of $1.74 billion in the year 2022, projections suggest that this figure will reach $6.18 billion by the year 2030 (GrandViewResearch 2022), indicating the wider adoption of BCIs in different service settings.

Despite the promise of BCIs, there is a looming threat from other emerging service technologies, which have faced intense user resistance (Keeling et al. 2019; Mani and Chouk 2018). This resistance is particularly pronounced for technologies that blur the boundaries between humans and machines, such as chatbots and service robots (Uysal, Alavi and Bezençon 2022). BCIs pose the distinct challenge that they might make their user appear less human and more robotlike, essentially turning them into 'cyborgs' (Grewal et al. 2020). Indeed, prior research indicates that people who use enhancement technologies like an augmented reality device are negatively perceived as less human (Castelo, Schmitt and Sarvary 2019).

Thus, it is important to gain an in-depth understanding of how customers perceive BCI-enhanced FLEs and how these perceptions might impact the evaluation of service interactions. Despite the extensive body of literature covering the technical aspects of BCIs (Kawala-Sterniuk et al. 2021), there is a lack of research into how customers perceive interactions with BCI-enhanced employees. However, we can learn from early conceptual works about 'frontline cyborgs' (Garry and Harwood 2019; Grewal et al. 2020) and the adjacent field of service robots, which emphasizes the challenge of achieving a social connection between humans and machines in terms of warmth and competence (Belanche et al. 2021). On this basis, we investigate customers' perceptions of interactions with an FLE using a BCI and seek to make three contributions with our research.

First, we address the lack of empirical insights into the nature and dynamics of service encounters between customers and BCI-enhanced FLEs by presenting findings from two qualitative studies. By interviewing both FLEs and customers, we elucidate key themes that highlight both opportunities and challenges, such as enhanced service convenience, loss of human touch, framing of BCI use, and varying service context fit. These themes complement earlier conceptual works (Garry and Harwood 2019; Grewal et al. 2020) and enable us to develop hypotheses for BCI-enhanced service encounters. Second, building on these qualitative insights, we conceptualize and empirically demonstrate the 'cyborg effect' using actual BCI technology and real-life service interactions. We find that when customers interact with a FLE who uses a BCI, it negatively impacts their perceived service quality. In doing so, we extend the application of social cognition theory (Fiske, Cuddy and Glick 2007) from robotics (van Doorn et al. 2017) to BCI-enhanced FLEs, demonstrating that the cyborg effect is explained by reduced perceptions of warmth and competence. Third, we identify two remedies to counteract the cyborg effect and mitigate negative customer perceptions of warmth, competence, and service quality: (1) framing the FLEs use of a BCI for service personalization (vs. efficiency); and (2) using BCIs in more (vs. less) complex service encounters. In sum, our study represents one of the first empirical investigations into the consequences associated with the use of BCIs by FLEs and the impact on service encounters.

07.3
Literature Review

Brain-Computer Interfaces

Unlike traditional desktop- or touchscreen-based interfaces, BCIs allow users to control devices purely through intentional mental commands (Wu, Xu and Lu 2022). This marks a significant shift towards a more seamless way of engaging with digital environments (Hilken et al. 2022; Vasiljevic and de Miranda 2020). Synthesizing established definitions from prior research (Kawala-Sterniuk et al. 2021; Nicolas-Alonso and Gomez-Gil 2012), we define BCIs as *wearable devices that identify and interpret intentional brain activity of the user into digital commands in real-time, enabling direct communication between the users' brain and external devices*. This definition emphasizes our focus on non-invasive technology, which does not require any surgical intervention or penetration of the skull to interact with the brain (Kawala-Sterniuk et al. 2021). Non-invasive BCIs use external sensors, most commonly electroencephalography (EEG) (Nicolas-Alonso and Gomez-Gil

2012), to detect brain activity and thus stand out for their safety, ease of use, and acceptable capabilities for detecting and translating brain signals into actionable commands (Houssein, Hammad and Ali 2022). Furthermore, advancements in machine learning and quantum computing suggest significant reduction in training times to accurately recognize mental commands in the near future (Huang et al. 2022).

Furthermore, the practicability for potential everyday has significantly improved in recent times, as BCIs have transitioned from laboratory-grade wired brain-caps with wet EEG electrodes to more user-friendly versions (Vasiljevic and de Miranda 2020). Several service providers now integrate BCIs into accessible devices such as headbands, headphones, or headset-like devices that transmit signals wirelessly to a connected computer or mobile device (Kawala-Sterniuk et al. 2021). These consumer-grade BCIs not only allow users to gain insight into their mental states (e.g., concentration, focus or meditation), but also increasingly enable control of devices such as smartphones or in-game controls (Houssein, Hammad and Ali 2022; Nicolas-Alonso and Gomez-Gil 2012). Reflecting recent progress in the field, Table 07.3 in the appendix shows BCI devices currently on the market, complete with details on pricing, detection technologies, and their respective functionalities.

Thus far, BCIs have mainly been researched for restoring, replacing, or enhancing the capabilities of individuals with brain injuries or in “locked-in” states, where patients are mentally alert yet physically immobilized (Nicolas-Alonso and Gomez-Gil 2012). For example, BCIs enable individuals to operate electronic wheelchairs and robotic limbs, as well as facilitate communication by enabling the selection of letters or words on computer screens (Kawala-Sterniuk et al. 2021). More recently, the application of BCIs has expanded towards the wider customer market, offering improvements in attentional focus, decision making, working memory, and learning (Cinel, Valeriani and Poli 2019; Jamil et al. 2021; van Erp, Lotte and Tangermann 2012). In the gaming context, studies have demonstrated the feasibility of using BCIs as controllers , thus enhancing immersion and providing a more intuitive form of interaction (Vasiljevic and de Miranda 2020). Another application is the use of BCIs to control smart home devices (Zhang et al. 2019), enabling users to effortlessly adjust lights, thermostats, and speakers, through thought alone. This thought-based control surpasses established touch or voice-based interactions, offering greater flexibility and faster response times. It provides users with an interaction that aligns more closely with their natural thought processes (Zander et al. 2010).

Research on BCIs in Service Encounters

Research has begun to explore BCIs within everyday service settings, focusing on their potential effects on interactions between customers and FLEs (Garry and Harwood 2019; Grewal et al. 2020; Hilken et al. 2022; Lima and Belk 2022). This stream of research suggests that enhancing FLEs, rather than customers, is a likely first step in the market trajectory of BCIs (Grewal et al. 2020). The creates a new type of service encounter between customers and so-called frontline 'cyborgs', positioned between fully autonomous robots and 'pure' humans (Grewal et al. 2020). Specifically, BCIs such as the Emotiv Epoc X promise to increase service efficiency by enabling FLEs to multi-task. They can operate devices such as laptops or tablets through mental commands to search for product information, fill out a checklist, or take notes. By the same virtue, BCIs help reduce distractions and free up FLEs' mental capacity from non-core activities to instead focus on 'emotional labor' and personalizing the service encounter, for example through emphasizing with customers (Garry and Harwood 2019; Grewal et al. 2020).

However, the use of BCIs by FLEs not only has the potential to improve service quality, but also poses potential adverse consequences. Most notably, FLEs using BCIs might be perceived more like robots than humans (i.e., "cyborgs"), raising concerns about dehumanization (Castelo, Schmitt and Sarvary 2019; Garry and Harwood 2019). Indeed, research shows that when individuals use technology for personal enhancement, they tend to be viewed as less human compared to those employing technology for restorative purposes (Castelo, Schmitt and Sarvary 2019). Prior conceptual work thus suggests that a FLE's use of a BCI needs to be clearly communicated and appropriately framed towards customers, including relevant reasons for and benefits of the enhancement (Grewal et al. 2020), such as whether it is used for greater service efficiency or improved personalization. However, while these conceptual insights lay the groundwork for understanding BCI-enhanced service encounters, an empirical examination of the implied dynamics is currently missing in the literature.

07.4

Study 1A and 1B: Exploring BCIs in Service Encounters

To generate initial insights and guide our conceptual development regarding the potential impact of an FLE using a BCI on service interactions with customers, we carried out two exploratory qualitative studies. In Study 1a, we conducted exploratory semi-structured interviews with 15 customers (Mays and Pope 1995). Data was gathered using a semi-structured interview guide, which underwent periodic refinement following an iterative transcript review process (Patton 2015). The guide consisted of four sections. (1) Personal technology use and introduction to BCIs in service encounters. Given the novelty of BCIs in service interactions, we provided participants with an easy-to-understand definition, along with images of a FLE wearing a BCI, operational videos of consumer-grade BCI devices and diverse scenarios showcasing its use in inquiry response, sales or support tasks in service contexts. We prompted interviewees to express their thoughts and emotions verbally as they engaged with the images and videos. We opted for this design to facilitate a direct observation of customers' individual reactions as they envision interacting with a FLE using a BCI (Comi, Bischof and Eppler 2014). Participants were asked: "What are your first impressions of BCI-enhanced

Employee in the service interactions just described to you?” and “What thoughts and feelings do you experience seeing BCI being used by employees to help you as a customer?”. (2) The perceived impact of BCI-enhanced FLE’s on the quality and dynamics of service encounters, with exemplary questions “How do you think a BCI enhanced employee could change your overall experience in a service encounter?” and “In what ways do you believe BCI-equipped employees might improve or worsen the quality of service you receive?”, (3) changes in perception about FLE, using illustrative questions like: “How would interacting with a BCI-enhanced employee change your perception of the employees skills or capabilities? In what way?” and “ Do you feel that a BCI could impact the human element or personal touch in service interactions?”, (4) privacy and data safety concerns of respondents for which we asked questions like “What do you expect regarding the handling of your personal data by BCI-equipped employees?” and “How important is the transparency of data usage and privacy measures to you when interacting with these technologies?”. We applied a heterogenous sampling strategy (Patton 2015), ensuring diversity among respondents in terms of age (23-60 years, M_{age}=32.2), gender (8 female, 7 male) and self-assessed experience with new technologies. Our final sample varied across professions, educational and social background. The interviews, ranging in duration from 41 to 59 minutes ($M_{duration}$=51), were audio recorded and subsequently transcribed, resulting in 257 pages of single-spaced text.

Study 1b followed a similar approach. We conducted n=14 exploratory semi-structured interviews with FLE as users of BCI technology, aiming to comprehend its potential impact on customers in service settings (Mays and Pope 1995). The semi-structured interview guide was divided in 4 sections. (1) Current use of technology in FLEs jobs, followed by an introduction to BCIs, complete with definitions, photos and videos demonstrating its functionality. Respondents were prompted to share their immediate thoughts and reactions aloud while seeing the provided media. This included questions like: “Can you envision any specific ways in which BCI technology could be integrated into your current job role?”, (2) Scenarios specifically designed for each interviewee’s role as an FLE, focusing on the expected influence of BCI on interactions with customers in service settings, with queries like “Do you see unique advantages BCI technology would offer you in your specific service role compared to other technologies?”, (3) anticipated customer perception about self as a BCI-enhanced FLE, where individuals were asked “How do you think customers would react to knowing you are using BCI technology while serving them?”, and (4) expected challenges in customer acceptance related to FLE job functions, which included questions like: “How might you address customer concerns or skepticism about BCI technology if they arise during your interactions?”. Our sampling included a variety of service contexts including retail and service sectors, along with diversity in age (23-50 years, M_{Age}=31.7) and gender (7 female, 7 male). Each interview, spanning between 23 and 67 minutes ($M_{Duration}$=37), was audio recorded and transcribed, producing 213 pages of single-spaced text.

Qualitative Coding Process

We performed a thematic content analysis of both transcripts in MaxQDA24 (Boyatzis 1998; Braun and Clarke 2006). Two researchers who were trained in the method read the transcripts sentence by sentence and carried out an initial coding, pinpointing recurring and notable aspects within the data. The full coding system was then developed inductively through in-depth textual analysis in three steps (Braun and Clarke 2006; Thomas and Harden 2008). First, each researcher independently created separate coding trees for each dataset. This involved generating new codes through iterative review, aimed at refining the meaning of the initial code groups and arranging them hierarchically in the coding trees. Second, the two researchers labeled, discussed, and reviewed the identified themes within each dataset's coding tree. This collaborative process led to immediate agreement on certain themes and the rejection of others. Third, the two researchers combined the previously agreed-upon coding trees for each dataset into a unified set of themes. These themes, highlighting the salient features of the dataset, were centered around the impact of BCI-enhanced FLE in service encounters on customers. One of the researchers then conducted a final coding process, focusing on refining the themes for clarity and consistency (Patton 2015).

Results

Nine themes emerged from the analysis, addressing how customers perceive service encounters with BCI-enhanced FLEs. Table 07.1 summarizes these themes, along with selected quotes from both customer and FLE viewpoints.

Service convenience: Both customers and FLEs highlighted a potential favorable impact on interaction speed and quality, with customers benefiting from the swift thought-based interaction style. For example: "He can stay by my side the entire time [...] and talk to me and give me advice. He needs less time not talking to me as the customer." (C12, l. 522) or: "You're saving time, you don't have to click around constantly, what customers can hear, and its faster for them." (F9, l. 81). However, both parties also pointed out potential negative aspects of such enhanced convenience, as stated by one customer: "Also a kind of disinterest, where someone makes it clear to you: Okay, I'm not really interested in you. My world is inside here. And if you want to talk to me, then you have to knock first." (C15, l. 257), or a FLE questioning the added value of BCI in service encounters: "Well if I change [data] by hand or by thoughts, I have to change it anyway and it's not really more helpful for the customer." (F3, l. 240)

Uncanniness: The novelty of the interaction style, however, also left many customers feeling uneasy: "I would probably be really skeptical about it. I mean, my first gut reaction would be: Oh, it's kind of strange that he controls that with his thoughts. I wouldn't

Table 07.1: Themes Identified in Study 1 a and b with Representative Quotes

	Sample Quotes		Definition of Construct
	Customer Perspective (1a)	**FLE Perspective** (1b)	
Service Convenience	"It's **way faster** for me than looking it up manually. They **just think about it.**" (7 296) "I don't know that they are 100% with me, or if they are listening to me in this moment. More like **communication is disrupted.**" (C4, l. 204)	"While talking to clients I could **advise my client faster** because of the thoughts in my head." (F7, l. 281) "I think customers **won't believe** in **the benefit** of it. They will be annoyed with BCI." (F5, l. 120)	Dual impact of BCIs: increasing efficiency and saving time, enhancing customer interactions; but they may lead to diminished experiences due to limitations in BCI functionality and employee attention.
Uncanniness	"Reading thoughts and processing them, I think it's cool but also **a bit spooky**." (C9, l. 44) "It's not an improvement, **it's strange**. I would avoid this company." (C15, l. 500)	"It will be **perceived as strange** in customer interactions, especially in the beginning." (F1, l. 57) "Simply that a device reads you thoughts is **frightening** for some." (F9, l. 253)	This category reflects individuals' discomfort and apprehension about BCIs worn by FLEs in service interactions.
Human Touch	"**You still are talking to a human**, you just get more information thanks to BCI" (C5, l. 606) "When he's wearing a BCI he would perhaps be **less lively and less empathetic**." (C1, l. 543)	"Maybe you **lose some of the human touch**, while looking for their products, you do small talk and witch the device you wouldn't have the freedom for **small talk** with customers, the human aspect comes too short." (F2, l. 244)	Human Touch focuses on empathetic, personal interactions in service, with individuals reporting that BCI has a minimal or even detrimental effect on these warm, genuine connections.
FLE Proficiency	"He seems **more competent** than someone without a BCI Headset." (C3, l. 463) "Why does he need this thing? Maybe he's **too dumb** to manage this himself?" (C8 l. 176)	"I would feel **more professional**, because I can open this via thought transmission and can **answer** a customer's question **right away**." (F7, l. 201)	Perceived enhancement of employee competence through advanced technology, specifically highlighting improved skills and efficiency via interactive, thought-driven interfaces
Dehumanization of FLE	"Even if I didn't know what the BCI can do the **employee looks remote controlled** and **robot-like.**" (C1, l. 812) "I would feel like talking to a **computer and not a human**." (C12, l. 236)	"It's cool and all buy you would **lose humanness** a bit if you became somewhat of a **robot**." (F2, l. 214) "I would feel like a **cyborg**, it would somewhat **dehumanize** me." (F5, l. 222)	Dehumanization of FLE involves the perception of employees as 'cyborg-like', diminishing their human essence in customer interactions.
Information about BCIs in encounter	"**I want to know as a customer**, can he make better recommendations by using BCI? Is he more focused on me?" (C14, l. 342) "He has to **explain it** in the beginning what the BCI does. Then he can show me that he finds the best products for me personally." (C8, l. 368)	"Maybe the first impression of people would be that I'm in a call. I would have to **explain this to people** that my focus is on them." (F8, l. 178) "I think it looks very futuristic and I would have to give a **few explanations** as to why I have on exactly, what it's for and so on." (F4, l. 141)	This category captures customers' preferences on how they wish to be informed about the capabilities and benefits during interactions with FLE wearing BCIs.
Context fit	"If there was a benefit, it **wouldn't matter** for me in **what contexts** BCI are used." (C2, l. 303) "In areas where people work with a **lot of technology**, this would be **great**. In kindergartens not so much." (C4, l. 466)	"If I'm in **sales for a tech company** it would be positively accepted [by customers]." (F1, l. 185) "It's better suited for sectors with **less customer contact**, like **offices**, and can be introduced to **retail** once BCI becomes more well-known." (F2, l. 265)	This category suggests that BCI in FLE roles is more aptly suited to innovative and technical contexts, aligning with environments that embrace technological advancements
Data & Privacy Concerns	"They can **access my data with their thoughts** and immediately know where I live. I don't like that." (C11, l. 523) "The firm has access to my data anyways. The **BCI** does **not** make it **different** for me." (C6, l. 501)	"That my **thoughts stay private** and that not everyone can see what I think." (F13, l. 328) "If I do it via the PC or per thoughts, I **still keep the data safe** from third parties." (F3, l. 312)	This category addresses concerns regarding data safety and privacy, highlighting apprehensions about the secure handling of personal information in BCI-enabled services.
BCI Reliability & Accuracy	"The Pilot thinks of Hawaii and how warm it was and **instead flies us there**." (C13, l. 431) "If it works smoothly and they have the **answer within seconds.**" (C6, l. 154)	"The BCI could pick up something **I didn't want** to do, it's a **reflex** and then it changes all prices" (F6, l. 350)	Emphasizing the necessity for precise and consistent technology interpretation of intentions, this category highlights the importance of reliability and accuracy in BCI applications.

like that." (C1, l. 138). A sentiment which is shared by FLEs concerning their customers: "If you would introduce it right now, then of course they would be quite shocked or irritated by [BCI]." (F4, l. 140). Consequently, some individuals mentioned avoiding future interactions with BCI-enhanced staff.

Human Touch: Customers noted that BCIs could support a more personalized service encounter: "When he uses this BCI, then he does [the interaction] in his thoughts and can still hold eye contact" (C13, l. 622), and allowing FLEs more time for interpersonal engagement: "I know my customers well. [...] And if I could do my tasks faster [with BCI], I could take this time I gained to spend more quality time with the customer." (F6, l. 163). However, some customers expressed criticism, viewing the FLE as less empathetic and harder to relate to: "If he can tell me everything right away, I would think: What kind of pissed-off genius is this? Does he have [...] all this memorized? [...] He wouldn't be very likable to me. Like an arrogant smartass." (C13, l. 243). FLEs noted that managing BCI technology could be distracting, potentially harming their interpersonal relationships: "We're always distracted by technology. [...] And with a [BCI] this could interfere with our interpersonal relationships [with customers]." (F1, l. 289).

FLE Proficiency: Both customers and FLEs indicated that BCIs might make an FLE (appear) more capable in responding to requests: "If he is able to access specific information and data, I'd view him as much more capable, as he can access a lot of information beyond the reach of ordinary humans with this [BCI]." (C11, l. 232); "[Customers] would think I have magic powers, when I explain that I'm using this BCI" (F13, l. 275). However, customers also raised concerns that BCI might be used to artificially elevate lower-skilled employees to the level of well-trained FLEs, as a cost-saving measure by firms: "They will hire any numbnut to digitally enhance them to be a somewhat okayish customer service employee." (C15, l. 492). Some FLEs acknowledged that while BCI do not necessarily increase their proficiency, it does change the way they provide help: "Not necessarily more capable, because [the BCI] doesn't do things that others couldn't, it might just do them a bit faster." (F6, l. 313).

Dehumanization of FLE: Customers and FLEs perceived BCI-enhanced FLEs as more robotic or machine-like, resulting in dehumanization. One customer mentioned: "If [the FLE] wears a [BCI], he would appear robotic to me. [...] It blurs the boundaries between human and machine." (C1, l. 555) and one FLE commented: "I hope I don't become too electronic or robotic towards my clients. I prefer engaging with them, sharing jokes, and maintaining an easy-going interaction, rather than appearing robotic." (F12, l. 306).

Information about BCI Technology: Customers desire clear communication about how the BCI enhances their service experience: "It's a new situation. And I wouldn't know how to handle it. There has to be a lot of explanations up front that I can feel safer." (C8, l. 359); "It would be enough if [an employee] with a [BCI] explains what it is and what it's used for, that would be great. That would be my expectation of such companies [that use BCI]." (C12, l. 429). FLEs similarly noted that customers will likely demand such information: "And until I have explained to each person what [BCI] is, what I am wearing, [...] it's not for me." (F8, l. 424).

Context Fit: There were varying views on the usefulness of BCIs in different service contexts. While some customers are receptive to widespread BCI use: "I would say, I can't think of any specific situations where [BCI] use would be less appropriate. [...] Any kind of service, whether it's the financial advisor, someone at a government office or someone in a workshop. It's all the same to me." (C10, l. 280), others noted different levels of suitability across service contexts: "There will be areas where it can be beneficially applied, whether in medical applications or industry. For activities connected with emotions and humanness, I imagine it to be more difficult, because gestures, facial expressions, and all sorts of things come into play" (C13, l. 863). FLE also commented on the technology's suitability, viewing BCI as a good fit particularly in high-technology customer interactions: "Maybe businessmen at Wall Street, they could see everything with [BCI] paired with a computer. That would be a great fit." (F6, l. 106).

07.5
Conceptual Framework and Hypothesis

A Social Cognition Perspective on Frontline Cyborgs

The themes identified in our qualitative studies closely align with the principles of social cognition theory, a connection further supported by current literature on frontline cyborgs (e.g., Grewal et al. (2020)) and service robots (e.g., van Doorn et al. (2017)). Fundamentally, social cognition theory posits that discerning and interpreting others' intentions, emotions, personality, and capabilities is essential for individuals to calibrate their roles as social agents and navigate interactions with others (Bandura 2008; Smith and Collins 2009). To form such social cognitions, people rely on interpersonal communication cues such as physical appearance and actions, communication style, eye-contact, or facial expressions (Frith and Frith 2012). Social cognition theory thus provides a relevant lens to study how customers interpret and react to FLEs equipped with BCIs that alter their physical appearance (e.g., wearing a headset), way of performing work (e.g., 'thought-controlling' devices), and communication style (e.g., maintaining eye-contact while operating a device) (Grewal et al. 2020). This relevance is reflected in our qualitative studies, where customers were conflicted about their ability to ascribe a social role to the BCI-enhanced FLE, seen as "blurring the lines between human and robot" (C1, l. 563) or others mentioning "[the BCI] makes no difference. There is still a human in front of me"

(C8, l. 463).

Furthermore, social cognition theory recognizes two key dimensions that underlie the process of assigning social roles to others: perceived warmth and competence (Fiske, Cuddy and Glick 2007). These two attributes shape first impressions, collectively contributing to the majority of how people describe someone upon initial encounter (Cuddy, Glick and Beninger 2011). Perceptions of warmth encapsulate assessments of a person's friendliness, helpfulness, and trustworthiness, reflecting their inferred intentions, which can range from bad (cold) to good (warm) (Cuddy, Fiske and Glick 2008; Judd et al. 2005). For instance, when FLEs are perceived as warm, it enhances service outcomes such as likeability, loyalty, and outcome evaluations, while also positively influencing customer mood (Hennig-Thurau et al. 2006; Lemmink and Mattsson 2002). Competence reflects views about the intelligence, capability, and skillfulness of others (Fiske et al. 2002; Judd et al. 2005), such as whether FLEs is knowledgeable about the service and adept at solving problems. Ultimately, this perception leads to enhanced trust and reliability in the eyes of customers, thereby assuring a positive service experience (Sirdeshmukh, Singh and Sabol 2002; Wu et al. 2015). Social cognition is widely used to explain how people react to FLEs, including both human workers (e.g., Wang et al. (2016) and service robots (e.g., Choi, Mattila and Bolton (2021)). Most recently, its applicability to 'frontline cyborgs' has been conceptually established (Garry and Harwood 2019; Grewal et al. 2020).

Prior research has also established that the dimensions of warmth and competence both have comparable predictive power for subsequent customer judgments (Aaker, Garbinsky and Vohs 2012). In particular, warmth and competence are widely recognized as key drivers of perceived service interaction quality (Belanche et al. 2021; Lemmink and Mattsson 2002) – defined as the customer's overall assessment of the degree of excellence or adequacy of a service (Cronin and Taylor 1992; Parasuraman, Zeithaml and Berry 1985), which is considered an essential KPI of successful service encounters (Lee, Lee and Yoo 2000). Research on service interaction quality continues to be significant in the literature (Cabano and Minton 2023; Noor, Rao Hill and Troshani 2022). Serving as a comprehensive evaluation of service interaction, service quality captures both the distinctive attributes of service agents and the dynamics of service delivery in both human-centric and robot-assisted service encounters (Choi, Mattila and Bolton 2021; Xiao and Kumar 2021). The significance of exploring service interaction quality lies in its role as a pivotal metric for evaluating the effectiveness and success of service encounters across various contexts.

Establishing the Cyborg Effect: Mechanization of FLEs

BCIs promise to enhance a FLE's capabilities to respond to customer needs in an efficient and more personalized manner (Grewal et al. 2020; Hilken et al. 2022). However, social cognition theorizing (Frith and Frith 2012) implies that precisely this potential for FLE enhancement beyond 'normal'

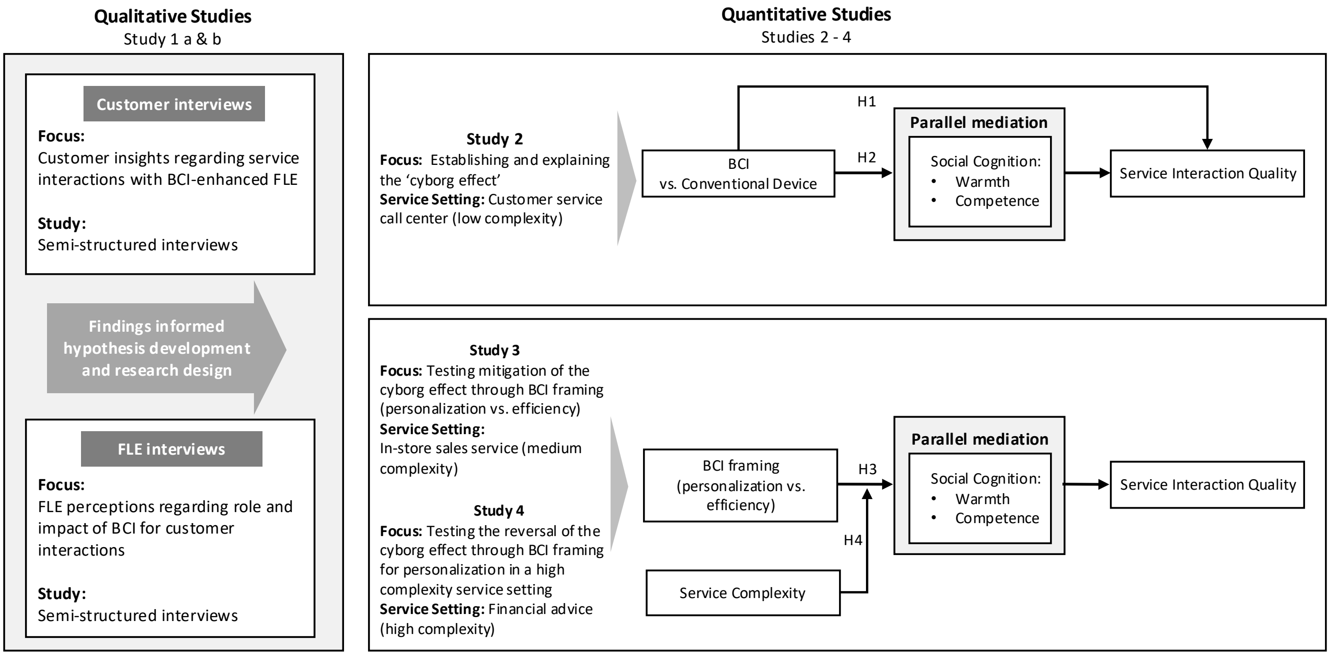

Figure 07.1: Overall Research Framework

human capabilities might have unintended consequences due to conflict with existing social norms about a human FLE's role, appearance, and behavior. (Grewal et al. 2020) describe the potential for dehumanizing or technomorphizing (i.e., assigning machine qualities to humans) FLEs that use technology to enhance their capabilities, based on the 'uncanny valley' effect documented in service robotics research. That is, BCIs are likely to shift social cognitions from human to more robotic, which "might violate norms of human appearance or movement and thereby elicit unintended negative responses, including perceived eeriness [...]" p. 18). We thus expect a negative impact on customers' perceived quality of the service encounter when they interact with a FLE equipped with a BCI device (i.e., a 'cyborg'). We base this conjecturing on recent meta-analytic evidence of such effects when customers interact with less anthropomorphic AI-based FLEs (Blut et al. 2021). Furthermore, Castelo, Schmitt and Sarvary (2019) demonstrate that individuals dehumanize others who augment their cognitive abilities through any type of enhancement technology. In turn, research has shown that dehumanizing employees results in harsher treatment of employees by customers (Henkel et al. 2018), which is indicative of lower perceived quality of the service encounter. Connecting these findings to our qualitative studies, some customers perceive the BCI-enhanced FLE as eerie and diminished in their ability to provide a human touch in the encounter, which may have a detrimental impact on customers' service evaluation: "It's not an improvement, it's strange" (C15, l. 500), while FLEs mentioned that: "It will be hard to sell [BCIs] to customers, they might be angry about it." (F5, l. 123). We therefore posit:

Hypothesis 1: Customers will evaluate the quality of a service encounter with FLE using a BCI lower compared to one in which the FLE uses a conventional device such as a laptop or tablet.

Explaining the Cyborg Effect: Social Cognitions of Cyborgs

Based on social cognition theory (Fiske, Cuddy and Glick 2007; Judd et al. 2005) and consistent with current frameworks of service encounters with robots (van Doorn et al. 2017) and frontline cyborgs (Grewal et al. 2020), we anticipate that the negative cyborg effect is explained by customers' diminished perceptions of FLE warmth and competence. The social robotics literature has long acknowledged that uncanny combinations of human and non-human features in FLEs pose challenges to the forming of positive social cognitions. For example, a less anthropomorphic, more robot-like visual appearance and interactional style are linked with reduced perceptions of both warmth and competence (Blut et al. 2021; Pizzi et al. 2023; Roy and Naidoo 2021). Grewal et al. (2020) extend this logic to the human FLE context, arguing that when customers de-humanize (or technomorphize) FLEs, the perceived cognitive and emotional enhancement might backfire and cause reduced perceptions of competence and warmth. Research on stereotypes about people with disabilities provides some first tentative support for this notion, by revealing that people with disabilities using bionic technologies (e.g., arm or leg prostheses), when labelled as 'cyborgs', are viewed as colder and less competent (Meyer and Asbrock 2018). Evidence from our qualitative interviews further corroborates this conjecturing: "Why does he need this thing? Maybe he's too dumb to manage this himself?" (C8 l. 176). In turn, warmth and competence are widely considered essential cues of interpersonal communication and thus have been consistently linked with service quality inferences (Güntürkün, Haumann and Mikolon 2020; Halkias and Diamantopoulos 2020). We thus posit:

Hypothesis 2: The negative effect of a FLE using a BCI (vs. conventional device) on perceived quality of the service encounter is mediated by reduced perceptions of FLE (a) warmth and (b) competence.

Mitigating the Cyborg Effect: Framing of BCIs' purpose

Considering the potential benefits of BCI use by FLEs, service providers need strategies to effectively integrate BCIs into service encounters while mitigating the anticipated negative impact of the cyborg effect. Prior research suggests that framing the purpose for which a FLE uses a BCI might be such an effective strategy (Castelo, Schmitt and Sarvary 2019; Grewal et al. 2020). For example, Castelo, Schmitt and Sarvary (2019) show that framing the use of human enhancement technology for a social purpose protects users from feeling dehumanized. This theme also emerged in our interviews with customers: "I want to know as a customer, can he make better recommendations by using BCI? Is he more focused on me?" (C14, l. 342). Building on these insights, we propose that framing the purpose of a FLE using a BCI in terms of achieving service personalization rather than efficiency could be an effective framing. That is, rather than emphasizing that a BCI enhances a FLE's abilities to perform tasks more efficiently (Cinel, Valeriani and Poli 2019; Jamil et al. 2021; van Erp, Lotte and Tangermann 2012), service providers might better highlight that BCIs free up mental resources so that the FLE can engage more personally with customers (Cascio and Montealegre 2016; Grewal et al. 2023). For instance, it could be stressed that BCIs allow FLEs to maintain eye contact with customers while simultaneously issuing commands to a computer to check product stock availability.

Improved capabilities to personalize service have consistently shown to improve the outcomes of service encounters (Delcourt et al. 2016; Zablah et al. 2017). For example, FLEs who are perceived to possess higher emotional competencies are better equipped to manage customer emotions effectively, resulting in enhanced outcomes following service failure (Fernandes, Morgado and Rodrigues 2018). Several interviewees noted the potential for improved personalization. Customers mentioned that a FLE could "still hold eye contact [...] and seem more connected to my concerns." (IC13, l. 623), while FLEs welcomed the opportunity to "spend more quality time with the customer." (IF6, l. 163). Furthermore, research indicates that demonstrating empathy and leveraging technology to personalize interactions, such as remembering customer preferences, can significantly improve perceptions of warmth (Danatzis, Karpen and Kleinaltenkamp 2022; Haslam 2006; Longmire and Harrison 2018). Similarly, customers who perceive BCIs as a tool for personalization will likely associate it with heightened competence, as (Huang and Rust 2018) propose that intuitive and empathic intelligences are considered higher-order skills, resulting in customers attributing greater competence to FLEs. We thus posit:

Hypothesis 3: Framing a FLE's use of a BCI in terms of personalization (vs. efficiency) increases customer perceptions of FLE a) warmth and b) competence, and, in turn, perceived quality of the service encounter.

Contextualizing the Cyborg Effect: Service Complexity

Similar to other technologies, the advantages of BCIs will likely vary across different service contexts. We contend that these benefits will be influenced by the complexity of the service, which is defined as the subjectively perceived difficulty in making sense and engaging in the co-creation of a service (Mikolon et al. 2015). As service complexity increases, from simple customer service request towards more complex professional services like financial advice, greater cognitive resources are required from the service interactants (Mikolon et al. 2015) as well as heightened expectations of FLE warmth and competence (He et al. 2019). Therefore, a FLE's use of a BCI might be more understandable for customers in complex service contexts, resulting in a reversal of the cyborg effect. Initial insights from our interviews provide some support for this conjecturing, where customers indicated that they anticipate more benefits in complex services such as financial advice: “But at the bank [interacting with a BCI-enhanced FLE], I could assume that he is more honest, because he has to be honest.” (C1, l. 326)

Importantly, and in line with our argumentation for H3, we anticipate that the reversal of the cyborg effect will occur only if a FLE’s use of a BCI is appropriately framed. Specifically, we expect the cyborg effect to persist if BCI use is framed solely for service efficiency, while it will be weakened or even reversed when BCI use is framed for service personalization. Supporting this conjecture, research indicates that more personalized service can mitigate the negative effects of service complexity (Mikolon et al. 2015). Therefore, we further anticipate that the differential impact of using BCIs (vs. conventional devices) on perceptions of FLE warmth and competence will become more positive as service complexity increases.

Hypothesis 4: The positive effect of framing an FLE’s use of a BCI for personalization (vs. efficiency) on warmth and competence becomes stronger with increasing service complexity.

07.6 Overview of Quantitative Studies

We test our hypotheses in three studies. In Study 2, we seek to establish the cyborg effect (H1) explained by reduced perceptions of warmth and competence (H2) in context of low service complexity (call centre). In Study 3, we aim to replicate the cyborg effect in a field setting and test the framing the BCI use for service personalization (vs. efficiency) as a remedy strategy (H3) in a context of mid-level service complexity (in-store selling). In Study 4, we test the strengthening of this framing effect (H4) in a high complex service setting (financial advice). Finally, we test the hypothesized differences across service settings (H4) through a cross-study analysis and rule out an alternative mediating mechanism through dehumanization of FLEs.

07.6.1 Study 2: Establishing and Explaining the Cyborg Effect

We conducted an experiment to test the hypothesized negative impact of a FLE using a BCI on customers’ perceived quality of the service encounter (H1), as well as the mediation of this effect by warmth and competence (H2).

Method

Research Design: We employed a 2 (FLE technology: BCI vs. Tablet) x 2 (overt vs. covert use of device) between-subjects design. We opted for a tablet as a suitable control condition compared to a BCI due to its established prevalence and familiarity in everyday service interactions (Giebelhausen et al. 2014). We also controlled for overt versus covert use of the BCI, as prior research indicates this might be a relevant driver of how individuals perceive BCIs (Garry and Harwood 2019). Participants entered the lab, sat down in a cubicle, and completed a computer-based survey. We first presented them with a service encounter scenario, in which they contact customer support about the delayed delivery of a pair of Bluetooth headphones they ordered online. We selected this scenario as it reflects a low complexity service encounter (He et al. 2019). Participants were then randomly assigned to one of the four conditions, each involving distinct descriptions and images depicting the FLE. In the control group, participants received a description of how the FLE utilizes a tablet to facilitate the transaction. In the treatment condition, participants read a description of how the BCI facilitates the transaction. In the overt condition, participants read a detailed description of how the BCI augments the FLE's cognitive abilities by interpreting brainwaves and converting them to tablet commands for more efficient customer service. In the covert condition, participants received only a brief description of how BCIs enhance employees to assist customers.

Sample: We recruited 125 participants from a European university in exchange for course credit. We excluded the responses of 4 participants, who indicated that they did not read the instructions carefully. The final sample included 121 responses (M_{Age}=21.62; female = 53.7%).

Measures: After reading about the service encounter, participants completed our survey measures. We measured perceived service interaction quality with a 3-item scale, anchored "1 = Very low" to "7 = Very high", which we adapted from (Lee, Lee and Yoo 2000) (α = 0.82). We measured warmth and competence, respectively, with 1-item scales anchored "1 = Not at all descriptive" to "7 = Extremely descriptive", which we adapted from (Aaker, Garbinsky and Vohs 2012), where participants were asked to indicate the extent to which they thought the FLE was either warm or competent. To account for varying levels of participants' trust in new technology, we incorporated a 3-item technology trust measure (α = 0.70) based on (McKnight et al. 2011).

Results

Manipulation Check: We asked participants on a semantic differential scale whether the FLE solved their issue with either their thoughts or their tablet. Participants who encountered the BCI-equipped FLE indicated that the FLE handled their service inquiry mainly using their thoughts, rather than the handheld tablet (M_{BCI} = 3.183, SD = 1.96 vs. M_{Tablet} = 5.459, SD = 1.53, F = 5.44, $p<0.001$). Thus, the manipulation was successful.

Hypothesis Tests: We first tested a moderated mediation model using the PROCESS macro (Model 7, (Hayes, Montoya and Rockwood 2017) with level of disclosure (overt vs. covert) as a moderator, but did not observe a significant moderating effect. We thus collapsed the conditions to focus on comparing the BCI and control conditions. In support of H1, participants reported a lower perceived quality of the service interaction when the FLE used a BCI rather than a tablet (M_{BCI} = 4.939, SD = 1.119 vs. M_{Tablet} = 5.333, SD = 0.966, F= 4.312 p = 0.04). To test the proposed mediation pathways in H2, we then used the PROCESS macro (Model 4, Hayes, Montoya and Rockwood (2017)) with FLE technology as the independent variable (0=Control;

Table 07.2: Mediation Results

Independent Variables	Study 2			Study 3			Study 4		
	Warmth	Competence	Service Quality	Warmth	Competence	Service Quality	Warmth	Competence	Service Quality
Control	4.525***	5.620***	2.370***	6.044***	5.695***	2.150***	4.764***	4.964***	1.180***
BCI Efficiency	-1.108***	0.053	-0.156	-0.750***	-0.461*	-0.060	-0.257	-0.069	-0.322**
Warmth	-	-	0.233***	-	-	0.411***	-	-	0.269***
Competence	-	-	0.368***	-	-	0.280**	-	-	0.507***
Condition x Warmth	-	-	-0.258	-	-	-0.308	-	-	-0.069
Condition x Competence	-	-	0.020	-	-	-0.129	-	-	-0.035
Total Effect	-	-	-0.394*	-	-	-0.497**	-	-	-0.426**
R^2	0.111	0.000	0.460	0.126	0.047	0.068	0.011	0.001	0.030
MSE	2.503	1.789	0.622	1.000	1.096	0.558	1.542	1.194	0.798
F	14.837***	0.480	33.140***	13.646***	4.698*	32.708***	2.659	0.247	75.053***
BCI Efficiency	-	-	-	5.294***	5.234***	2.296***	4.249***	4.826***	0.779**
BCI Personalization			-	$0.422^{\dagger}$	0.577**	0.098	0.799***	0.377**	0.019
Warmth	-	-	-	-	-	0.455***	-	-	0.359***
Competence	-	-	-	-	-	$0.195^{\dagger}$	-	-	0.505***
Condition x Warmth	-	-	-	-	-	0.192	-	-	0.287
Condition x Competence	-	-	-	-	-	0.113	-	-	0.190
Total Effect	-	-	-	-	-	0.403*	-	-	0.497**
R^2	-	-	-	0.038	0.091	0.505	0.086	0.027	0.548
MSE	-	-	-	1.159	0.849	0.436	1.713	1.267	0.855
F	-	-	-	3.533	9.013**	29.868***	22.631***	6.801**	96.474***
Control	-	-	-	6.044***	5.695***	1.602**	4.506***	4.895***	1.214***
BCI Personalization	-	-	-	-0.328*	0.116	0.054	0.542***	0.308*	-0.264*
Warmth	-	-	-	-	-	0.536***	-	-	0.332***
Competence	-	-	-	-	-	0.242***	-	-	0.503***
Condition x Warmth	-	-	-	-	-	-0.176	-	-	0.180
Condition x Competence	-	-	-	-	-	0.028	-	-	0.155
Total Effect	-	-	-	-	-	-0.094	-	-	0.070
R^2	-	-	-	0.053	0.004	0.476	0.057	0.021	0.452
MSE	-	-	-	0.496	0.881	0.303	1.229	1.101	0.841
F	-	-	-	5.150*	0.362	27.544	14.728***	5.307*	66.854***

1=BCI), service interaction quality as the dependent variable and perceived warmth and competence as parallel mediators. The full regression results are displayed in Table 07.2. Bootstrapping with 5,000 samples and confidence intervals (CIs) for the indirect effects, we found a significant negative indirect effect through warmth (indirect effect = -0.258, BootSE = -0.091, LLCI = -0.459, ULCI = -0.108), but not through competence (indirect effect = -0.258, BootSE = 0.092, LLCI = -0.153, ULCI = 0.210).

Discussion

The results support H1 and offer partial support for H2. We find lower evaluations of service quality when customers interact with a FLE using a BCI rather than a tablet device. We refer to this as the cyborg effect, which denotes a baseline negative effect of deploying BCIs for improving the efficiency of FLEs in service encounters with low complexity. Further, we find evidence for a mediating role of warmth in this effect, but not for competence. A possible explanation could be that the chosen service context does not require as much competence, rendering the perceptual differences in competence by individuals not significant (Gidaković and Zabkar 2021; He et al. 2019). Hence, Study 3 is designed to extend our investigation of the cyborg effect, focusing on how a different framing of a FLE's use of a BCI and higher service complexity influences these evaluations.

07.6.2
Study 3: Mitigating the Cyborg Effect

We sought to test whether the cyborg effect can be mitigated by framing the FLE's use of a BCI in terms of service personalization (vs. efficiency, H3) and by deploying the BCI in a service setting with higher service complexity (H4). We conducted a field-in-a-lab experiment to test these effects in a realistic, yet controlled service encounter between customers and a FLE actor equipped with a functioning BCI device.

Method

Research Design: We randomly assigned participants to one condition in a three-group (BCI framing: efficiency vs. personalization vs. control) between-subjects design that followed a three-phased procedure. In phase 1, participants were seated in computer cubicles and read a short introduction to the service setting, which prompted them to imagine visiting a telecommunication shop to acquire a new smartphone and phone plan. We selected this setting as it reflects a common service encounter (Feine, Morana and Gnewuch 2019) with medium levels of complexity (He et al. 2019). In phase 2, participants were individually escorted to an adjacent room, which contained a store setup of a large national telecommunications provider with promotional materials, phone-mockups, and store design elements (see Web Appendix). A current employee from the service provider acted as the FLE and interacted with participants using the standard service script with questions about their phone and data usage preferences and a presentation of four suggested smartphone and data plan combinations on a laptop.

In the two BCI conditions, the FLE used an Emotiv Epoc X BCI headset to initiate a mental command for displaying the phone plans on the laptop during the interaction. We used the headset's 14-channel EEG capabilities and Emotiv software in combination with a customized developed Python script to detect when the mental command was executed, to trigger the display of the curated phone and data plan as a full-screen image to participants. We opted for this display of preselected phone plans as it closely emulates the procedure observed in the real store, where employees navigate through the database to find the most suitable plans for each customer. In the BCI conditions, this occurred quickly and seamlessly, enabling the FLE to remain focused on the customer (Cascio and Montealegre 2016). Conversely, in the control condition, the FLE open the phone and data plan on a laptop using the keyboard and touchpad.

In the service efficiency framing condition, participants were provided with the same description from Study 2 about how the BCI enhances the abilities of the FLE to provide more efficient service. In the service personalization framing condition, participants read that the BCI reduces the effort for the FLE so that they can better focus on the personal interaction and the customer's needs. Participants read these descriptions in the introduction in phase 1, and the FLE actor briefly repeated these to them in phase 2. Finally, in phase 3, all participants completed a survey about the service encounter.

Sample: We recruited 151 participants from a European university in exchange for course credit. We applied a set of pre-specified criteria and excluded participants from the study if they (a) experienced an interaction where the BCI did not work as intended, (b) did not perform the service encounter with our FLE, or (c) indicated that they did not read the instructions carefully. This resulted in a final sample of 142 responses (Mage=20.99; female = 54.9%).

Measures: We assessed service interaction quality with the same 3-item scale as in Study 1 (α = 0.87). We assessed warmth with a 5-item scale (α = 0.89) adapted from (Choi, Mattila and Bolton 2021), where participants indicated whether the FLE was, for example, caring or friendly. Competence was measured using a 4-item scale (α = 0.82) adapted from (Choi, Mattila and Bolton 2021), where participants rated whether the FLE was, for example, intelligent or organized. We employed these expanded scales in Study 2 to achieve a more comprehensive measurement of warmth and competence. Participants rated both measures on 7-point Likert scales ranging from "1 = Not applicable at all" to "7 = Extremely applicable".

Results

Manipulation Check: We replicated our previous approach by asking participants whether the FLE used their thoughts or a tablet in the encounter. As expected, participants in the BCI conditions indicated that they perceived the FLE to utilize their thoughts, rather than the laptop, to facilitate the service interaction ($M_{BCI(both)}$ = 4.228, SD = 2.006 vs. M_{Laptop} = 5.1, SD = 1.693, F = 6.802, p=0.010). Additionally, we asked participants whether they perceived the FLE offer greater service personalization (vs. efficiency) by evaluating if the FLE held eye contact during the encounter. Insights from our qualitative interviews and established research suggests eye contact as a key indicator for enhanced personal connections between individuals (IC13, l. 623; (Frith and Frith 2012) . We also found this manipulation to be successful ($M_{BCI\ Personalization}$ = 6.555, SD = 0.659 vs. $M_{BCI\ Efficiency}$ = 5.978, SD = 1.277, F = 7.317, p=0.008).

Hypothesis Tests: All regression results are reported in Table 07.2. In further support of H1, we found lower ratings of service quality when the FLE used a BCI framed for service efficiency rather than a laptop ($M_{BCI\ Efficiency}$ = 5.723, SD = 1.057 vs. M_{Laptop} = 6.22, SD = 0.784, F= 6.961 p = 0.01). A parallel mediation analysis (0=Control; 1= BCIEfficiency) with the PROCESS macro (Model 4, Hayes, Montoya and Rockwood (2017)) revealed that this negative effect was explained by reduced perceptions of FLE warmth (indirect effect = -0.308, BootSE = 0.105, LLCI = -0.527, ULCI = -0.121) and competence (indirect effect = -0.129, BootSE = 0.076, LLCI = -0.304, ULCI = -0.008).

We then tested the hypothesized positive impact of framing the FLE's use of the BCI for service personalization (vs. efficiency). In support of H3, we a positive framing effect on service quality ($M_{Efficiency}$ = 5.723, SD = 1.057 vs. $M_{Personalization}$ = 6.126, SD = 0.712, F= 4.549 p = 0.036), and a parallel mediation analysis (0= BCIEfficiency; 1= BCIPersonalization) with the PROCESS macro (Model 4, Hayes, Montoya and Rockwood (2017)) revealed that this effect was explained by increased perceptions of warmth (indirect effect = 0.192, BootSE = 0.106, LLCI = 0.007, ULCI = 0.418) but not competence (indirect effect = 0.113, BootSE = 0.077, LLCI = -0.006, ULCI = 0.288).

Finally, we compared the FLE's use of the BCI for service personalization with the use of a conventional device. We found that the personalization framing resulted in service quality perceptions on par with those of the laptop (M_{Laptop} = 6.220, SD = 0.784 vs. $M_{Personalization}$ = 6.126, SD = 0.712, F= 0.372 p = 0.543). A parallel mediation analysis (0= Control; 1= BCIPersonalization) with the PROCESS macro (Model 4,Hayes, Montoya and Rockwood (2017)), however revealed a significant negative indirect through warmth (indirect effect warmth = -0.176, BootSE = 0.078, LLCI = -0.343 ULCI = -0.027), while no significant mediation effects through competence emerged (indirect effect competence = 0.028, BootSE = 0.049, LLCI = -0.057, ULCI = 0.134).

Discussion

We replicate the cyborg effect in a study with an actual FLE and BCI device (H1). We observe that in service encounters with moderate levels of complexity, such as in-store sales, reduced perceptions of both FLE warmth and competence appear to explain this effect (H2). We also find partial support for H3, whereby framing a FLE's use of a BCI for service personalization (vs. efficiency) enhances the perceived service quality due to heightened perceptions of FLE warmth. Finally, we find evidence suggesting that BCI use framed for service personalization achieves service quality ratings comparable to those of a FLE using a laptop, although the FLE is still perceived as colder, in medium-complexity service contexts. Therefore, we next look into a service setting, in which BCIs might outperform conventional technology.

07.6.3
Study 4: Reversing the Cyborg Effect

Our aim was to test whether the cyborg effect can be reversed when a FLE uses a BCI framed for service personalization in a high-complexity service such as financial advice (H4).

Method

Research Design: We conducted an online experiment that employed the same three-group (BCI framing: efficiency vs. personalization vs. control) between-subjects design as in Study 3. We presented participants with a short introduction to the service setting, which prompted them to imagine contacting a financial advisory firm regarding an investment decision. Existing literature has established financial advisory as a service setting characterized by the high complexity (He et al. 2019; Zhu, Vigren and Söderberg 2024). Within this context, we portrayed the FLE at the financial advisory firm as either wearing a BCI or using a tablet to facilitate the transaction. We used similar descriptions for the two BCI and control conditions as in Study 3, with slight adaptations for this study's context. The FLE then presented participants with various investment options from which they should make their individual investment decision.

Sample: We used the Prolific online panel, known for yielding high-quality response data (Peer et al. 2017), to recruit 386 adult customers from the U.S., Canada, U.K., Ireland, Australia, and New Zealand. By applying a predefined set of criteria, we excluded responses by participants if they (a) failed two or more attention checks, (b) did not complete the full study, or (c) indicated that they did not thoroughly read all instructions. The application of these criteria led to a total of 369 completed questionnaires in the final sample (M_{Age}=37.92; female = 51.2%).

Measures: We evaluated service interaction quality (α = 0.93), warmth (α = 0.95), and competence (α = 0.89) using the same measures as in Study 3. To account for differences in financial literacy, we included a measure of self-assessed financial knowledge (Lind et al. 2020).

Results

Manipulation Check: We followed the approach from our previous studies, asking participants whether the FLE used their thoughts or a tablet to assist them (M_{BCI} = 2.658, SD = 1.817 vs. M_{Tablet} = 5.825, SD = 1.309, F = 301.56, $p<0.001$). To check the success of our BCI framing manipulation (personalization vs. efficiency) in an online setting, we adjusted the measure so that participants rated whether the technology used by the FLE aided personal connection on a 7-point Likert scale ranging from "1 = Strongly disagree" to "7 = Strongly agree" ($M_{Personalization}$ = 5.16, SD = 1.429 vs. $M_{Efficiency}$ = 4.423, SD = 1.301, F = 17.645, p<0.001).

Hypothesis Tests: All regression results are in Table 07.2. We replicate the cyborg effect postulated in H1 ($M_{Efficiency}$ = 4.743, SD = 1.328 vs. M_{Tablet} = 5.169, SD = 1.094, F= 7.628 p = 0.006). However, surprisingly and in contrast to H2, we no longer found any differences in perceptions of FLE warmth or competence when the FLE used a BCI framed for service efficiency rather than a laptop (see Table 07.2). This offers first potential evidence of a weakening of the cyborg effect in high-complexity service settings.

We find support for H3, with higher perceived service quality when the FLE used a BCI framed for service personalization rather than service efficiency ($M_{Personalization}$ = 5.24, SD = 1.364 vs. $M_{Efficiency}$ = 4.743, SD = 1.328, F= 8.261 p = 0.004). Using the PROCESS macro (Model 4, Hayes, Montoya and Rockwood (2017)), we find support for parallel mediation of this effect through heightened perceptions of FLE warmth (indirect effect = 0.287, BootSE = 0.104, LLCI = 0.111, ULCI = 0.515) and competence (indirect effect = 0.19, BootSE = 0.081, LLCI = 0.038, ULCI = 0.354).

Comparing the FLE's use of a BCI for service personalization with the use a conventional device, we again find no significant differences between the conditions (M_{Tablet} = 5.169, SD = 1.093 vs. $M_{Personalization}$ = 5.240, SD = 1.364, F= 0.201 p = 0.655). However, importantly and in support of H4, we find evidence of a reversed cyborg effect on warmth and competence. That is, when the FLE uses a BCI for service personalization rather than a tablet device in a high-complexity service setting, they are perceived as both warmer ($M_{Personalization}$ = 5.05, SD = 1.181 vs. M_{Tablet} = 4.506, SD = 1.035, F= 14.728 p < 0.001) and more competent ($M_{Personalization}$ = 5.203, SD = 1.083 vs. M_{Tablet} = 4.895, SD = 1.016, F= 5.307, p = 0.022). In turn, these reversed effects in favor of the BCI carry through to heightened perceptions of service quality, as indicated by the significant indirect effects (indirect effect warmth = 0.18, BootSE = 0.076, LLCI = 0.056, ULCI = 0.350; indirect effectcompetence = 0.155, BootSE = 0.071, LLCI = 0.022, ULCI = 0.3) obtained in our analysis using the PROCESS macro (Model 4, Hayes, Montoya and Rockwood (2017)).

Discussion

Overall, the results further substantiate our findings from the previous studies for the cyborg effect (H1, H2) and BCI framing effect (H3), while also providing support for our conjecturing in H4. Specifically, we find evidence for a weakening, even reversal, of the cyborg effect and amplification of the BCI framing effect in high-complexity service settings such as financial advice. Framing a FLE's use of a BCI for service personalization seems to pay off in these settings, even when compared to conventional devices such as tablets or laptops, which offers important insights to service providers how and when to equip their FLEs with BCIs.

07.7
Cross-Study Analysis

To formally test observed differences in the cyborg and BCI framing effects across studies, we performed two cross-study analyses. Figure 07.2 depicts the results of both analyses. First, we assessed the cyborg effect by evaluating the results across our three conducted experiments using using the restricted maximum likelihood (REML) method to aggregate our findings, following established procedures in the literature (Goh, Hall and Rosenthal 2016). We calculated the effect size (cohen's d), confidence intervals and variances of effect sizes for each study for the construct service quality comparing conventional devices (e.g. tablet, laptop) with the BCI framed for service efficiency. The overall weighted average effect size was dall = 0.395 (SE=0.094, p<0.0001) and there was no significant heterogeneity among the studies (Q(2) = 0.5803, p=0.748), indicating consistent effect sizes across the included studies. This demonstrates that the negative cyborg effect persists across all studies (and thus levels of service complexity). Next, we assessed BCI framing effect and associated reversing of the cyborg effect from Study 3 (medium service complexity) to Study 4 (high service complexity) when compared against conventional devices. A two-way ANOVA was conducted to examine the effects of the BCI use for personalization vs. control and Study 3 vs. Study 4 on warmth and competence. For warmth, there was a significant interaction effect between the condition and study (B = 0.870, SE = 0.245, p < .001). As shown in Figure 07.2, the two conditions did not significantly differ in Study 3, but in Study 4 the BCI outperformed the conventional device in terms of perceptions of FLE warmth.

07.8
General Discussion

By providing a novel, direct communication link between employees' brains and external devices, BCIs enhance the capabilities of FLEs to offer customers high-quality service at the speed of thought. Meanwhile, consumer-grade BCIs are becoming increasingly available, paving the way for widespread adoption in enhancing frontline service roles. Surprisingly, despite these advancements, empirical investigation into how customers react to FLEs using BCIs is lacking. Previous literature so far solely conceptually investigated this link, leaving a significant gap in our understanding. Therefore, this research aims to explore how customers perceive interactions with BCI-enhanced FLEs and the subsequent impact on service evaluations. To that end, we collect empirical data in a mixed-methods approach. Our qualitative inquiry involved conducting 29 interviews with customers and FLEs to explore themes that influence customer evaluations of interactions with a FLE using a BCI (Study 1). Building on the identified themes and social cognition theory, we quantitatively investigate the impact of BCIs used in customer interactions. We collect both data from real interactions with a FLE using an actual BCI and online experimental data, using diverse samples and service contexts. Potentially overshadowing the potential performance benefits, we identify the 'cyborg effect'

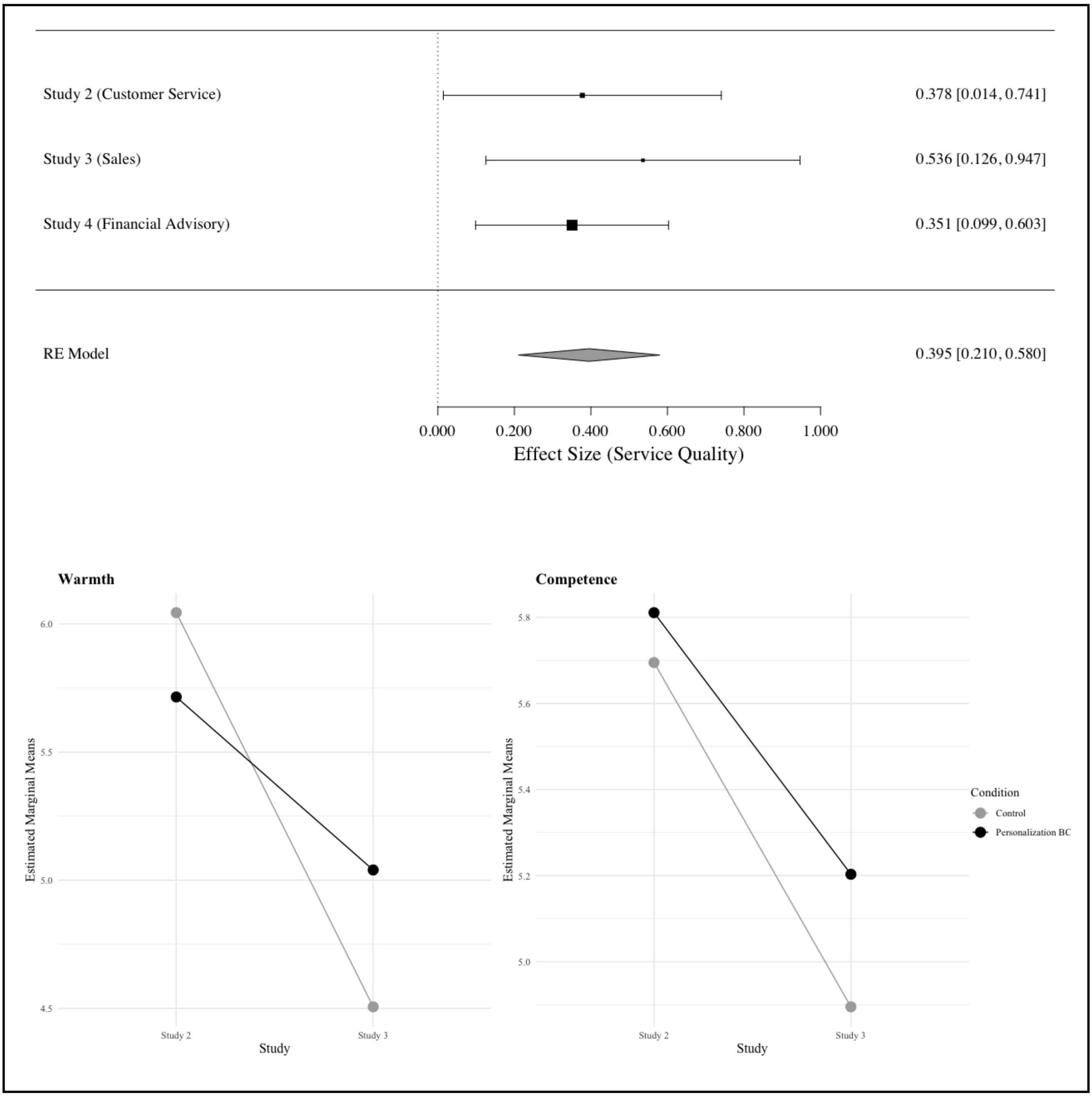

Figure 07.2: Cross-study analyses

by which customer perceive a lower quality of the service interaction when a FLE uses a BCI for improving service efficiency (Study 2). By changing the way in which a FLE's use of the BCI is communicated to customers and framing for service personalization, so that the BCI enables the FLE to be more present for the customer, presents a remedy for the 'cyborg effect' (Study 3). We also find that such framing for service personalization is most effective in more complex service contexts. Here, the cyborg effect is mitigated or even reversed with heightened perceptions of FLE warmth and competence. The following sections detail the main theoretical and managerial contributions of our research.

07.8.1 Theoretical Implications

This research makes several key contributions to the existing literature. First, while there is important conceptual research on customer interactions with BCI-enhanced frontline employees (Garry and Harwood 2019; Grewal et al. 2020), there is a notable lack of empirical evidence into these service encounters. We provide insights from two exploratory qualitative inquiries into how BCIs are perceived by customers and FLEs in service interactions. Our findings reveal both the potential bright and dark sides of BCI adoption. Catalysts for positive experiences include increased service convenience and enhanced frontline employee proficiency. Conversely, inhibitors such as the diminished human connection led to negative outcomes. We further empirically investigate these findings in three experimental studies.

Second, we firmly establish the cyborg effect, which denotes a baseline negative effect of deploying BCI technology for cognitive enhancement of FLEs in service encounters. Our findings demonstrate that the cyborg effect is consistent across various service contexts and diverse samples. This finding is crucial as it highlights and empirically validates the inherent challenges in enhancing the cognitive capabilities of FLEs in service settings, indicating that without addressing customer apprehensions, the significant potential of BCI-enhanced FLEs may be overshadowed by negative perceptions. Moreover, we identify mediators explaining the cyborg effect through the lens of social cognition theory. This theory has been widely utilized to assess customer reactions to human employees (e.g. Wang et al. (2016) and, more recently, robots in frontline roles (e.g. Choi, Mattila and Bolton (2021). We contribute to this body of research by examining the roles of warmth and competence in interactions with BCI-enhanced FLEs, who occupy a position between the extremes of human and robotic entities (Grewal et al. 2020). We find consistent support for warmth as a mediator in explaining the negative impact on service quality evaluations of an encounter. As expected, customers seem to perceive a lack in emotional connection and empathetic interactions with BCI-enhanced FLEs, explaining negative evaluations of interactions. We find some mixed support for competence as a second mediator, indicating that this pathway might depend to some extent on the level of service complexity. Furthermore, this finding may point towards cognitively BCI-enhanced FLEs being able to offset some of the competence deficits observed in robotics research.

Third, we enrich existing literature by identifying critical interventions that can mitigate the negative impacts of the cyborg effect on service evaluations. Our findings reveal that framing the FLE's use of a BCIs for improved service personalization rather than service efficiency can mitigate the cyborg effect. This findings suggest that BCIs positioned for service personalization are perceived more favorably compared to efficiency enhancement by customers, as it aligns with their desire for deep and more personal service interactions (Grewal et al. 2023). Previous research indicates that the potential enhancement of human functions and the closer fusion of human and technology through BCIs are rewarded by customers when higher-order intelligences, such as intuitive and empathic intelligence, are supported by technology (Huang and Rust 2018). This makes the capabilities of human employees unique compared to the more mechanical and analytically perceived roles of robots. In addition, our results underscore the role of service context in mitigating the negative effects of the cyborg effect. We show that for service contexts characterized by higher levels of complexity, framing for service personalization not only mitigates the cyborg effect at moderate levels of complexity, but even reverses it at high levels of complexity. In service encounters such as financial advising, customers appear to perceive BCI-enhanced FLEs as warmer and more competent in these contexts than FLEs using a tablet. Customers reward the role of BCIs in interactions with FLEs as the technology allows them to focus more on the capabilities of human intuition and empathy. Particularly in contexts where the human element of warmth is perceived to be lacking, BCIs overcome previous deficits in warmth and competence, transforming enhanced FLEs to be seen as warmer and more competent.

07.8.2
Managerial Implications

Integrating BCIs in service operations makes a compelling business case. BCI-enhanced FLEs link intuitive and empathetic abilities of human brains directly with computers, enabling a seamless integration of human and artificial intelligence. This holds the potential to enhance the efficiency of employees, while also improving customer outcomes through superior service. This research offers key insights for firms considering adopting BCIs in their service operations.

Our work uncovers that using BCIs for FLE-enhancement can be a double-edged sword in that it can result in the cyborg effect, where customers perceive a negative outcome for interactions with a FLE using a BCI for enhanced service efficiency. Conversely, customers react more favorably when the BCI use is framed for service personalization. This provides an opportunity for a simple yet effective intervention. We recommend that service managers present a brief service script to customers, clearly communicating the benefits of BCI use for service personalization. Our findings indicate that customers explicitly want to be educated on how the device contributes to their service experience. As managers strive to establish an emotional connection with their customers (Kumar and Pansari 2016), BCIs offer a valuable opportunity to achieve this objective. However, developments in consumer-grade devices suggest that emotional enhancement beyond framing, such as improving affective ability or sociability (Baylis and Robert 2004), is possible with BCIs in the near future. These devices can provide employees with real-time feedback on stress levels and suggest interventions to reduce stress during service interactions, ensuring top-quality service for customers. Such emotional enhancement should be communicated in a similar manner by offering explanations to customers to counteract the cyborg effect, strengthening our current findings for future advancements in available technology. Our work also reveals that the service context is crucial when implementing BCI technology in the frontline. In service industries characterized by higher complexity, such as financial advisory, legal or accounting services, emotional enhancements possible through BCIs offer high potential. By counteracting the perceived lack of warmth, BCIs can provide a significant competitive advantage for service managers in these industries by building closer rapport between customers and FLEs. When enhanced FLEs are perceived as warmer and more competent, this dual enhancement can lead to improved service evaluations.

Another important factor for managers to consider is the privacy and ethical implications of using BCI technology in service encounters. Our results indicate that both FLEs and customers have raised concerns about privacy, particularly regarding the sensitive neural data of employees being processed. However, service managers potentially accessing sensitive neural information from employees, which can indicate illnesses (Yuste et al. 2017), attention levels (Bonaci, Calo and Chizeck 2014), and other insights, necessitates the development of clear guidelines for data use. Additionally, FLEs must be explicitly informed about how their brain data is used, as transparency and ethical data practices are crucial for successful BCI implementation, and without them, FLEs may reject the technology entirely (Yuste et al. 2017).

07.8.3
Limitations and Further Research

We acknowledge that this research is subject to several limitations that provide opportunities for further research. First, with regards to the cyborg effect, it is important to recognize that repeated exposure to this technology might alter customer perceptions over time (Bhattacherjee and Premkumar 2004). Despite our realistic setup where we described to customers how BCIs contribute to the service encounter, the initial negative effect might be driven by the novelty of the technology and could diminish with continued exposure. As BCIs are not yet widely established, further research should investigate the impact of repeated interactions on the cyborg effect. Second, while the central focus of our study is on customers' perceptions about interactions with BCI-enhanced FLE, future research could investigate the role of device design. We found that both customers and FLEs commented on the device design, describing the headset as having ”spider-arms” (C9, l. 522), which potentially contributed to the negative outcomes of interacting with cognitively BCI-enhanced FLEs. As we utilized a state-of-the-art headset which requires multiple electrodes to capture good quality neural signals, more developed BCIs in near future may feature more subtle form factor resembling headphones or glasses. Further research could explore the role of device design in shaping customer perceptions of BCI-enhanced FLEs. Third, we find the skill augmentation strategy of firms plays a role in how BCIs impact service interactions. That is, firms can strategically decide whether to hire lower-skilled employees and use BCIs to bring their skills up to a standard in a baseline augmentation approach or a talent enhancement approach, where already highly-skilled employees are enhanced even further. Our findings suggest that firms using a baseline augmentation approach could negatively impact service outcomes, as customers fear that firms "Will hire any numbnut to digitally enhance them to be a somewhat okayish customer service employee." (C15, l. 492). While a talent enhancement approach would be perceived as adding additional value to the service by augmenting employees to provide the best service possible to customers. Additional research could investigate the impact of either strategy on service outcomes for customers in BCI-enhanced FLE interactions. Fourth, although ethical considerations are outside the scope of this investigation, they could also considerably impact on our findings. As sensitive neural data is collected of employees with considerable implications for privacy and data safeguards, we call for further investigation into the ethical frameworks and policies necessary to protect this information. Additionally, understanding how employees accept these technologies and how BCI implementation should be communicated to them is crucial.

07.9
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07.9.1
Appendix

Table 07.3: Examples of consumer-grade BCI devices

Device (Company)	Description	Exemplary Use	Price (USD)	Website
Epoc X (Emotiv) ***Used in this research***	Wireless Headset 14-Channel EEG with wet electrodes	• Hands-free control of robot movements • Controlling game actions through mental commands)	$999	www.emotiv.com
GALEA (OpenBCI)	Headset with integrated Virtual Reality device 18-Channel dry electrodes with 4 different BCI sensor technologies	• Precise piloting of drones • Quantification of emotional states in real-time	$25,000	www.galea.co
Muse S (InteraXon)	Wireless Headband 4-Channel EEG with dry electrodes	• Neurofeedback on focus and stress levels for enhanced productivity and improved cognitive function	$399	www.choosemuse.com
NextMind (Snapchat)	Wireless Headset 9-Channel EEG with dry electrodes	• Authentication for device access • Control of smart home devices (e.g. music, lighting)	$399 (developer kit)	www.ar.snap.com
NextSense (Google)	In-Ear Headphone 4-Channel EEG with dry electrodes	• Reveal focus level on task and help refocus based on neural data • Provide auditory nudges to adjust behavior	Unreleased	www.nextsense.io
MW75 Neuro (Neurable)	On-Ear Headphone 12-Channel EEG with dry electrodes	• Optimize wearers performance by suggesting brain breaks when focus wanes • Prevent and detect burnout	$699	www.neurable.io

Figure 07.3: Telecommunication store setup study 3 with BCI-equipped FLE (research assistant)

08

Appendix: Essay II

Wired for Work: Brain-Computer Interfaces' Impact on Frontline Employees' Well-Being

by Alexander Kies, Arne De Keyser, Susana Jaramillo, Jiarui Li, Yihui (Elina) Tang and Ihtesham Ud Din

This essay is accepted for publication at the *Journal of Service Management* (VHB-JOURQUAL3: B). This paper was presented at *Frontiers in Service 2024*.

08.1 Abstract

Purpose – Neurotechnologies such as brain-computer interfaces (BCIs) are rapidly moving out of laboratories and onto frontline employees' (FLEs) heads. BCIs offer thought-controlled device operation and real-time adjustment of work tasks based on employees' mental states, balancing the potential for optimal well-being with the risk of exploitative employee treatment. Despite its profound implications, a considerable gap exists in understanding how BCIs affect FLEs. This article's purpose is to investigate BCIs' impact on FLEs' well-being.

Design/methodology/approach – This article uses a conceptual approach to synthesize interdisciplinary research from service marketing, neurotechnology, and well-being.

Findings – This article highlights the expected impact from BCIs on the work environment and conceptualizes what BCIs entail for the service sector and the different BCI types that may be discerned. Second, a conceptual framework is introduced to explicate BCIs' impact on FLEs' well-being, identifying two mediating factors (i.e., BCI as a stressor versus BCI as a resource) and three categories of moderating factors that influence this relationship. Third, this article identifies areas for future research on this important topic.

Practical implications – Service firms can benefit from integrating BCIs to enhance efficiency and foster a healthy work environment. This article provides managers with an overview of BCI technology and key implementation considerations.

Originality/value – This article pioneers a systematic examination of BCIs as workplace technology, investigating their influence on FLEs' well-being.

Keywords – brain-computer interface; employee well-being; neurotechnology

Paper type – Conceptual Article

08.2 Introduction

"Done well, neurotechnology has extraordinary promise. Done poorly, it could become the most oppressive technology we have ever introduced." (Farahany, 2023a, 11:29).

Neurotechnologies, heralded as the next frontier in service technology, hold the potential to revolutionize human capabilities, advancing us toward superintelligence and optimal well-being (Lima and Belk, 2022). Among these innovations, brain-computer interfaces (BCIs) are emerging as a key technology for enhancing employee well-being (Garry and Harwood, 2019). BCIs comprise technology that creates a direct interface between users' brains and external devices by capturing and interpreting neural signals (Nicolas-Alonso and Gomez-Gil, 2012). These devices can enable thought control of software and robots or monitor employees' cognitive load to recommend breaks for employees experiencing mental fatigue (Liu et al., 2021, Yaacob et al., 2023). For example, Wenco, a Canadian company specializing in technology solutions for the mining industry, introduced SmartCap, a wearable BCI integrated into headwear that measures drivers' brain activity to detect real-time fatigue. When fatigue levels reach critical thresholds, the system provides immediate alerts to drivers and fleet managers, prompting corrective actions. This not only enhances road safety by reducing accidents caused by drowsiness, but also improves operational efficiency by managing fatigue-related risks proactively (Wenco, 2021). With the market projected to grow from USD $2.0 billion in 2020 to USD $6.2 billion by 2030, BCI technology is projected to be particularly impactful in work-related settings, thereby transforming employment environments and FLEs' role therein (UNESCO, 2023, GrandViewResearch, 2022).

As the primary point of contact between firms and customers, frontline employees (FLEs) perform essential boundary-spanning functions (Lages and Piercy, 2012). However, their roles are undergoing significant transformation. Today's increasing labor shortages, continuous adaptation to emerging technologies, and heightened customer expectations have intensified the risk of cognitive overload and emotional exhaustion (Chen et al., 2019, Day et al., 2019). For example, a recent American Psychological Association report about psychological safety in the workplace revealed that 30 percent of FLEs report fair or poor mental health (American Psychological Association, 2024). This growing pressure poses adverse consequences for FLEs' well-being, which is defined as the comprehensive evaluation of one's life satisfaction and the extent to which FLEs experience "optimal psychological functioning" (Ryan and Deci, 2001, p.142). Left unchecked, these strains can culminate and lead to burnout, diminished job performance, and increased turnover, all of which threaten not only FLEs' well-being, but also the firm's long-term success and profitability (Chen et al., 2019).

BCIs are being put forth as one promising solution to help FLEs function better in today's rapidly changing and highly taxing workplace environments (Grewal et al., 2020). Unlike traditional mouse, keyboard, or touchscreen-based interfaces, BCIs allow FLEs to interact with devices solely through their brain activity, eliminating the need for muscular movement (Nicolas-Alonso and Gomez-Gil, 2012). This marks a significant shift toward more seamless and natural engagement with digital environments (Hilken et al., 2022, Vasiljevic and de Miranda, 2020), enabling, among other things, more efficient work processes and a greater emphasis on customers. Workplace BCIs can analyze FLEs' cognitive and affective states, including emotion, relaxation, fatigue, and cognitive workload levels (Saha et al., 2021). By tracking brain activity, BCIs provide users with feedback on their mental states, allowing for real-time analysis and long-term logging to gain detailed insights over time (Zander and Kothe, 2011). For example, air traffic controllers' workplaces can be adjusted based on their current stress levels, such as reduction of visual load by displaying fewer aircraft on the screen or minimizing auditory alerts to prevent distractions from noncritical notifications. This adaptation has been demonstrated to reduce employees' stress levels while increasing operational safety and efficiency (Aricò et al., 2016). Furthermore, BCIs enable users to translate thoughts directly into actions, allowing for direct control over external devices (Kawala-Sterniuk et al., 2021). For example, recent extant studies have investigated how BCIs can improve FLEs' collaboration with (service) robots, enabling direct brain-to-robot communication and continuous task execution without manual interruption (Liu et al., 2021, Coogan and He, 2018, Lee et al., 2022).

Despite the importance of BCI adoption's implications for FLEs and its expected massive impact on many service providers' work environments, scant extant research on this topic exists in the service marketing and service management field. To help guide practitioners with the implementation and adoption of BCIs in the foreseeable future, the authors believe that service scholars need to address this challenge early on proactively. To this end, the present study seeks to (1) conceptualize what BCIs entail, (2) introduce a framework to understand BCIs' impact on FLEs' well-being, and (3) put forth a future research agenda that may inspire future BCI-related work in the service space. Indeed, BCIs are no longer solely a vision for a distant future, as major steps already have been taken to move the technology out of labs and into practical workplace applications. By pursuing this goal, this study addresses calls from marketing and service scholars to explore BCIs' potential and applications, as well as from well-being researchers seeking to understand emerging technologies' impact on FLEs (Subramony et al., 2021, Grewal et al., 2020).

08.3 Setting the Scene: Brain-Computer Interfaces in Service

This article examines BCIs' integration into the workplace, specifically focusing on their effects on FLEs' well-being. Building on ex-

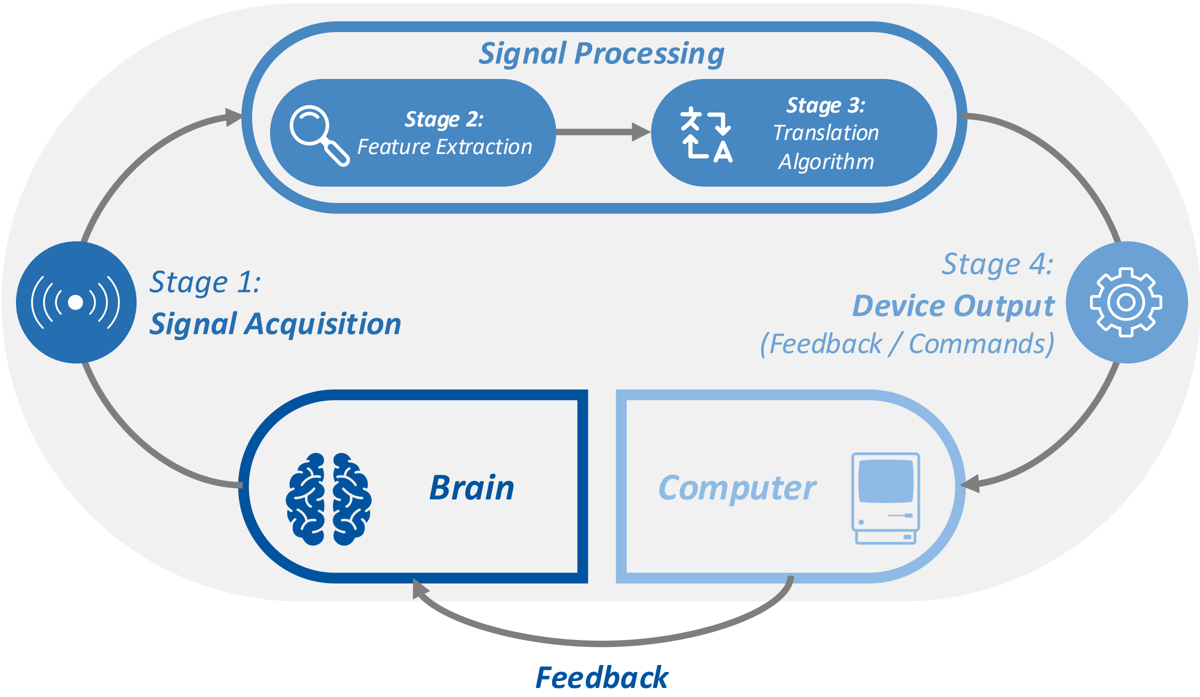

Figure 08.1: BCI system architecture. Source: The figure was created by the author.

tant studies (Kawala-Sterniuk et al., 2021, Nicolas-Alonso and Gomez-Gil, 2012), BCIs have been defined as *a workplace technology that establishes a direct communication link between users' brains and external devices by recording and decoding neural activity*. This definition emphasizes that unlike other (mostly wearable) technologies that measure physiological signals (e.g., smartwatches), BCIs establish a distinct communication channel for unique interaction with devices that is not possible with other wearables (Paluch and Tuzovic, 2019, Vasiljevic and de Miranda, 2020). BCIs, as artificial intelligence systems, recognize patterns in brain signals through a sequential four-stage process (Nicolas-Alonso and Gomez-Gil, 2012, Saha et al., 2021), depicted in Figure 08.1. First, during the signal acquisition stage, brain signals are captured, amplified, and preprocessed to reduce noise and artifacts in the data. Next, during the feature extraction stage, the digital signal is analyzed to distinguish relevant characteristics, such as the user's intent or affective state, from extraneous context. Subsequently, during the feature translation stage, signal features are processed through a translation algorithm that converts the data into readable information for the output device. Finally, during the device output stage, commands from the feature translation algorithm operate the external device or display users' affective state, completing the communication loop.

A 2x2 matrix has been developed to categorize different BCI technologies for FLE use (Figure 08.2). This matrix outlines two key dimensions that categorize different BCI devices, illustrating how these technologies could soon be integrated into service frontlines. The first dimension focuses on signal acquisition modality, distinguishing between

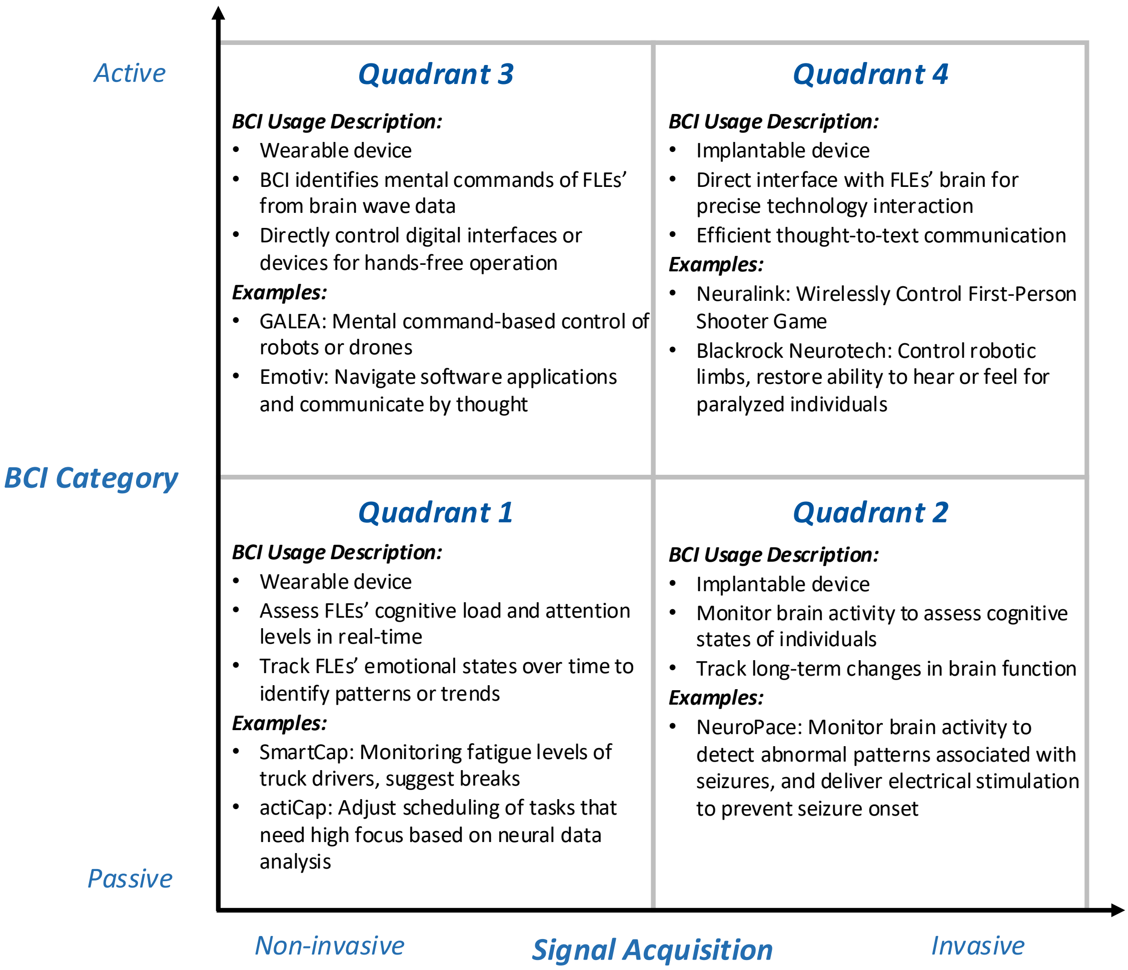

Figure 08.2: BCI typology. Source: The figure was created by the author.

non-invasive (i.e., wearable) and invasive (i.e., implantable) techniques (Nicolas-Alonso and Gomez-Gil, 2012). The second dimension categorizes BCIs based on their approach to capturing and processing brain activity, distinguishing between passive and active BCIs (Kawala-Sterniuk et al., 2021). Notably, active and passive BCIs are distinguished by the way the neural data they collect are processed and used, rather than by the physical device itself. This means that the same BCI hardware can operate in different modes (active, passive, or integrated) based on how it processes and applies the brain activity it measures.

Quadrant 1 represents passive, non-invasive BCIs, which are most prevalent in the market and closest to mainstream adoption in the workplace. Passive BCIs analyze brain signals generated without conscious effort from the FLE, thereby not requiring intentional thought to operate (Aricò et al., 2018). These brain signals typically reflect the FLE's cognitive and affective states, such as emotion, relaxation, fatigue, and cognitive workload levels (Saha et al., 2021). Non-invasive BCIs capture neural information directly from electrodes placed on the scalp, making them the dominant choice in BCI technology due to their sufficient accuracy in detecting and translating brain signals into actionable insights (Aricò et al., 2018). Most companies offering consumer-grade BCI headsets in this quadrant integrate dry EEG sensors into aesthetically appealing devices (Drew, 2023). For example, Neurable incorporates dry EEG sensors into headphones (Takahashi, 2024), while Muse (Hunkin et al., 2021) produces a headband with integrated BCI sensors, both at affordable price points. When deployed as workplace technology, these devices can monitor FLEs' cognitive load and attention levels over time, providing valuable insights or prompting interventions, such as recommending breaks. For example, over 5,000 truck drivers worldwide use BCIs daily in a mining setting to monitor their fatigue levels, with the device suggesting breaks when fatigue is detected (Wenco, 2021). This application outperforms alternatives for detecting fatigue and preventing accidents, highlighting BCI technology's benefits in workplaces (Patel et al., 2022). Furthermore, ActiCap can be used to assess cognitive workload and adapt employee tasks accordingly. For example, in learning contexts, it has been demonstrated that adjusting learning tasks based on analyzed cognitive load significantly enhances learning outcomes and overall task efficiency (Walter et al., 2017, Wascher et al., 2023).

Quadrant 2 encompasses BCIs that are passive and invasive. Invasive BCIs entail surgical implantation of electrodes directly on or in the brain. Invasive BCIs' primary advantage lies in their ability to detect brain signals in high resolution with significantly improved signal-to-noise ratios compared with non-invasive methods (Drew, 2023). However, this approach carries substantial risks due to the associated surgical procedures (Kawala-Sterniuk et al., 2021). Adoption of these BCIs remains limited due to these challenges, as non-invasive options can perform similar tasks without invasive procedures (Saha et al., 2021). The most common applications are in the medical field, in which companies such as Neuropace use these BCIs to detect epileptic seizures accurately and allow individuals to prepare for their onset (Sheng-Fu et al., 2010). Therefore, invasive BCIs' adoption potential in frontline contexts remains minimal for now.

Quadrant 3 represents non-invasive, active BCIs that capture and interpret the user's intentional mental activity (Saha et al., 2021). By imagining hand movements or pre-programming mental commands to execute specified actions, algorithms identify these patterns in neural data. Active BCIs enable users to translate thoughts directly into actions, allowing for direct control over external devices (Kawala-Sterniuk et al., 2021). BCIs in this quadrant allow FLEs to interact seamlessly with technology using only their thoughts, thereby enhancing efficiency and potentially fostering closer social connections with customers. The GALEA BCI headset is one example, allowing for control of (service) robots in collaborative environments through mental commands (Bernal et al., 2022). Furthermore, Emotiv headsets are used to navigate software (e.g., query databases) by thinking about actions (Vasiljevic and de Miranda, 2020).

Quadrant 4 encompasses active and invasive

BCIs. Utilizing technology similar to that of Quadrant 2, these devices capture high-precision signals to detect intentional mental activity reliably (Aricò et al., 2018). Prominent companies working on these BCIs include Blackrock Neurotech and Neuralink, co-founded by Elon Musk (Drew, 2023). Neuralink's short-term goal is to restore function for individuals with motor disabilities, while its ultimate ambition is to integrate this technology for able-bodied individuals, merging human and artificial intelligence to create superintelligence (Reed and McFadden, 2024). Notably, Neuralink implants have demonstrated that monkeys can play the video game Pong wirelessly, and human trials in 2024 demonstrated BCI-enhanced individuals' ability to control a mouse or play first-person shooter video games with the implant (Drew, 2024).

Table 08.1 presents the relevant literature on BCI applications, categorized into the identified quadrants in Figure 08.2. Given that BCI technologies requiring surgical implantation are not expected to be market-ready in the near future, this article focuses on integration of non-invasive BCIs, as represented in Quadrants 1 and 3. Furthermore, non-invasive BCIs have been established widely as a safe technology that does not harm users (Nicolas-Alonso and Gomez-Gil, 2012).

08.4 BCI Integration's Impact on FLEs' Well-Being: A Framework

This section introduces a conceptual framework (Figure 08.3) that helps organize the discussion on how non-invasive BCIs (i.e., wearable) affect FLEs' well-being in the workplace. As a key research priority in service (Ostrom et al., 2015), employee well-being is a fundamental consideration for organizations, with a growing body of literature linking it to critical performance metrics, such as enhanced job satisfaction, increased productivity, and reduced stress (Ter Hoeven and Van Zoonen, 2015, Tuzovic and Kabadayi, 2021, Robertson et al., 2023). This is particularly relevant as FLEs are central to delivering service and interacting directly with customers, making their well-being crucial for maintaining high service standards (Nasr et al., 2014). However, introducing advanced technology such as BCIs alters the organizational frontline's roles and responsibilities (De Keyser et al., 2019). While technology can effectively reduce tedious tasks and make jobs more enjoyable, it can also contribute to increased stress, heightened expectations, and a heavier workload (Day et al., 2010, Day et al., 2019).

FLEs' well-being is a complex, multidimensional concept that lacks a universally accepted definition or framework. Therefore, FLEs' well-being is conceptualized by a broad body of literature encompassing two complementary perspectives: hedonic well-being (i.e., happiness and cognitive/affective evaluation of life) and eudaimonic well-being (i.e., optimal functioning and human growth) (Bartels et al., 2019, Straume and Vittersø, 2012). Hedonic well-being is characterized by leading a good work life that maximizes pleasure and minimizes pain (Sonnentag, 2015), particularly when FLEs achieve their goals. However, eudaimonic well-being entails the abil-

Table 08.1: Selected literature review. Source: The table was created by the author.

Authors	Quadrants 1	2	3	4	Summary of Findings
Alimardani and Hiraki (2020)	x				Review how tracking of users' cognitive and affective state can adapt robot decision making for optimized human-robot collaboration, thereby increasing interactivity and job performance.
Aricò *et al.* (2016)	x				Demonstrate that adaptation of workplaces for air traffic controllers by reducing alerts or visual load on displays effectively reduces mental workload during high-demand situations without interfering with operational tasks.
Hunkin *et al.* (2021)	x				Demonstrate that when individuals receive auditory feedback through a BCI during mindfulness-focused attention meditation, mind wandering is reduced and mindfulness increases.
Jamil *et al.* (2021)	x				Review how BCIs enhance individuals' learning outcomes by adjusting learning content based on mental workload, measuring interest in topics, or increasing focus during critical learning periods.
Telpaz *et al.* (2015)	x				Predict customers' future choices by analyzing brain activity through a BCI while they view binary product options without external instruction to select a product.
Yaacob *et al.* (2023)	x				Review studies focusing on BCI use for real-time fatigue detection and find it feasible to prevent vehicle accidents, workplace errors, and emotional exhaustion.
Sheng-Fu *et al.* (2010)		x			Determine whether epileptic seizures can be detected through a portable BCI with a high detection rate between 92 and 99 percent.
Angrisani *et al.* (2020)			x		Develop an augmented reality headset with an integrated BCI for an industry inspection task and demonstrate the feasibility of inspection through BCIs with relatively high accuracy.
Chen *et al.* (2020)			x		Develop a robotic arm control system using augmented reality and BCIs that can pick up objects. This device demonstrated that users could utilize the system reliably, with a 93.96 percent accuracy rate in object selection.
Coogan and He (2018)			x		Develop routing of BCIs' control signals to gaming applications, virtual reality control, and control of smart home devices, and demonstrate feasibility while giving users additional autonomy during tasks at hand.
Krauledat *et al.* (2008)			x		Demonstrate the ability to control the classical game Pong with a BCI, allowing for quick and precise mental commands to move the paddle without lengthy subject training.
Lee *et al.* (2022)			x		Test the feasibility of users imagining speech that is translated via BCIs for communication with a smart home virtual assistant performing tasks.
Liu *et al.* (2021)			x		Demonstrate that in situations in which workers need to interact with robots, BCIs allow for hands-free control of robots with 90 percent accuracy, which is particularly beneficial when workers' ability to control robots is limited physically.
Zhang *et al.* (2019)			x		Develop mechanisms to interpret BCI data reliably to control a simulated robot to perform tasks or type by recognizing users' intentions as realized through an Internet of Things network with smart home appliances.
Kennedy *et al.* (2000)				x	Describe an invasive procedure that reliably captures brain signals, allowing patients to control the cursor on a computer screen.
Musk and Neuralink (2019)				x	Provide an overview of an invasive, wireless BCI system with the potential ability to control devices through mental commands and present a surgical robot that limits the procedure's invasiveness.
Rapeaux and Constandidou (2021)				x	Review recent advances in implantable BCIs, emphasizing enhanced performance of current technologies and innovations aimed at enabling scalable implementation among individuals.

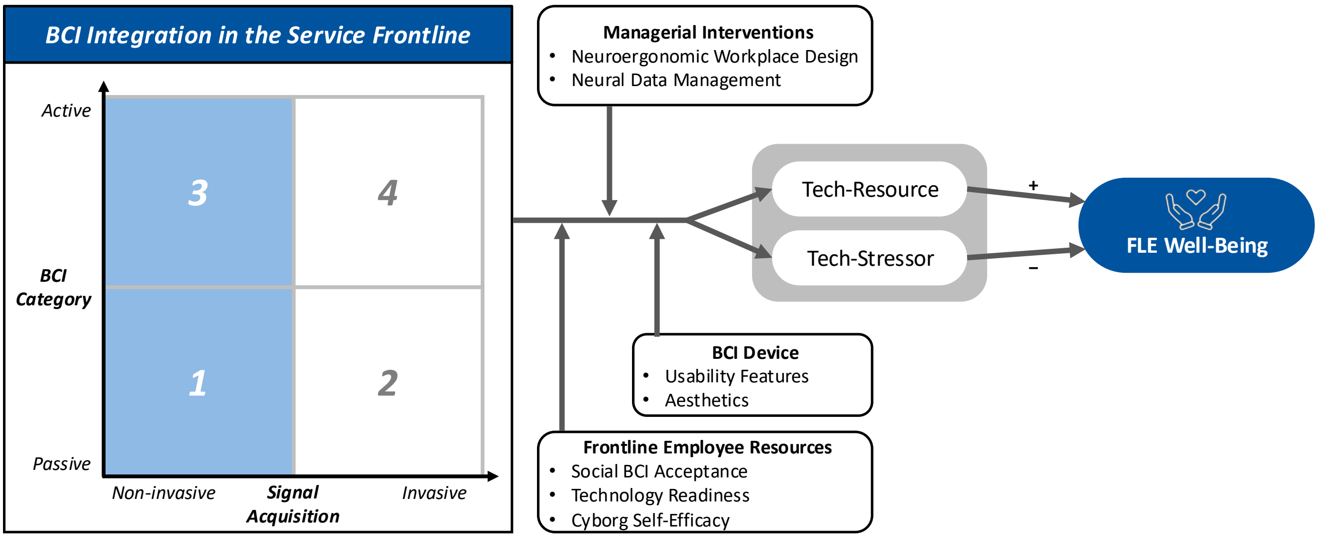

Figure 08.3: Conceptual Framework of BCIs' Impact on FLE Well-being (the shadow indicates this article's focus). Source: The figure was created by the author.

ity to flourish and fulfill one's potential in assigned tasks, reflecting congruence between work activities and deeply held beliefs or values (Bartels et al., 2019, Straume and Vittersø, 2012). In the remainder of this article, the terms hedonic and eudaimonic will be referred to collectively as well-being to simplify the discussion and highlight their combined influence on FLEs. This framework incorporates two mediating factors and three categories of moderating mechanisms to examine BCI introduction's impact on FLEs' well-being. The mediating mechanism focuses on FLEs' perception of BCI technology as either a tech-resource or *tech-stressor*, subsequently impacting FLEs' well-being. Furthermore, the framework theorizes that BCIs' impact on well-being is moderated by FLEs' resources, type of BCI device used, and possible managerial interventions in the workplace.

08.4.1
Using BCIs: BCIs' Mediating Role as Tech-Stressors or Tech-Resources

The conceptualization of BCIs as either *tech-stressors* or *tech-resources* integrates the foundational principles of job demands-resources theory (Demerouti et al., 2001) and the transactional theory of stress (Lazarus and Folkman, 1984) to explore how FLEs respond to the introduction of this technology into their workplaces and its impact on their well-being. As a well-established theoretical foundation, the job demands-resources model has been utilized widely to understand the factors that influence FLEs' well-being (Bakker et al., 2023). At its core, the model posits that every occupation involves elements that can be classified as either job resources or job stressors, each crucial to determining FLEs' well-being (Bakker and Demerouti, 2007, Demerouti et al., 2001). Job demands encompass the physical, social, and organizational aspects of a job that necessitate physical and/or psychological effort, often leading to increased physical and/or psychological costs, such as fatigue and exhaustion (Sonnentag, 2015). These demands are typically challenging in nature and may hinder task accomplishment, potentially resulting in diminished effectiveness, increased work burnout, or more frequent sick leave (Ter Hoeven and Van Zoonen, 2015). However, job resources include the physical, social, or organizational aspects of a job that facilitate achievement of work goals, reduce job demands, and foster personal growth, ultimately enhancing motivation and dedication (Sonnentag, 2015, Bakker and Demerouti, 2007, Day et al., 2010). To sum up, job demands deplete FLE resources and negatively impact well-being, whereas job resources help enhance FLEs' well-being.

Building on this, several extant studies have explored how the job demands-resources model can be integrated with the transactional theory of stress to better understand new workplace technologies' impact on FLEs (Day et al., 2010, Day et al., 2019). The transactional theory of stress posits that stress emerges from the dynamic interaction between the individual and demands imposed by the environment (Lazarus and Folkman, 1984). When new technologies such as BCIs are integrated into the workplace, stress is likely to arise when BCIs are perceived as taxing or exceeding FLEs' available resources (Pratt & Barling, 1988). Therefore, this "*tech-stressor*" mediator has been drawn from both literature streams and refers to situations in which BCIs are perceived as increasing job demands, thereby heightening the physical or psychological effort required from FLEs and contributing to their stress (Penado Abilleira et al., 2021, Tarafdar et al., 2014). Consequently, BCIs can be perceived as a threat in the workplace, leading to a decline in employee well-being (Sonnentag, 2015, Fuglseth and Sørebø, 2014).

The adjacent technostress field has demonstrated extensively the link between technology as a stressor and its negative effects on FLEs' well-being (Ayyagari et al., 2011, Tarafdar et al., 2007, Ragu-Nathan et al., 2008). BCIs similarly can function as *tech-stressors* in several ways. For example, continuous monitoring of cognitive load can function as a form of technological invasion (i.e., "BCI is always watching me'), pressuring FLEs to maintain constant high concentration levels, which can lead to increased stress and reduced well-being (Drew, 2023, Ball, 2010). It also has been suggested that BCIs may cause techno-insecurity (Chiu et al., 2023), in which FLEs fear that technology devalues their contributions (i.e., "BCI is controlling and steering what I do"). Furthermore, BCIs might lead to techno-complexity challenges (Ragu-Nathan et al., 2008), as FLEs must invest significant effort in learning and adapting to these new systems (i.e., "I don't understand what BCI does"). Finally, it has been posited that BCIs could contribute to feelings of techno-overload (Ayyagari et al., 2011), in which data volume overwhelms FLEs (e.g., "BCI gives me too much information"), as well as feelings of techno-uncertainty (Tarafdar et al., 2007), causing decision fatigue and reducing effectiveness.

Conversely, BCI technology also can serve as a "*tech-resource*" that aids task completion, enhances FLEs' motivation, and reduces stress by being perceived as beneficial tools. For example, Emotiv's system helps adapt task scheduling based on cognitive and emotional states, thereby reducing strain and the risk of burnout (Keppler, 2020). Moreover, BCIs can function as cognitive load balancers, redistributing tasks based on FLEs' real-time mental capacity, thereby preventing overload while optimizing performance (Aricò et al., 2016). In other ways, BCIs can function as cognitive aids, alleviating pressure in fast-paced environments. Furthermore, it is anticipated that BCIs might offer personalized, just-in-time training based on an individual's cognitive readiness, helping employees learn and grow without feeling overwhelmed (Walter et al., 2017). Finally, BCIs may boost motivation by delivering real-time feedback on performance, reinforcing positive progress, and increasing job satisfaction (Lechermeier et al., 2020). Thus, the following proposition was posited:

Proposition 1: *The perception of BCI integration as a tech-resource vs. a tech-stressor will mediate its impact on FLEs' well-being. Specifically, perceiving BCIs as tech-resources will enhance FLEs' well-being positively, while perceiving BCIs as tech-stressors will affect FLEs' well-being negatively.*

The transactional model of stress highlights that the perception of technologies, such as BCIs, as *tech-stressors* or *tech-resources* varies between individuals and contexts (Huang and Gursoy, 2024). The same BCI integration might be evaluated differently depending on individual and contextual factors (Truța et al., 2023). The major variables influencing this relationship will be discussed in the following chapter on moderators of this conceptual framework.

08.4.2 Moderators of BCI Integration's Impact on Perception of BCIs as Tech-Resources or Tech-Stressors

Frontline Employee Resources' Moderating Role

FLEs possess or may access distinct social and personal resources that influence how new workplace technology, such as BCIs, shapes the perception of it as either a *tech-resource* or *tech-stressors* (Bakker et al., 2023). This perspective is equally grounded in job demands-resources theory, which underscores both social and personal resources' significance in shaping FLEs' perceptions of technological changes in their workplaces (Xanthopoulou et al., 2007, Xanthopoulou et al., 2013). Social resources refer to the support and resources provided through workplace interactions, which are termed the social BCI acceptance moderator (Hobfoll et al., 2003). Personal resources encompass FLEs' ability to manage demands and challenges, which are termed technology readiness and cyborg self-efficacy moderators (Schaufeli and Taris, 2014).

Social BCI Acceptance. Introducing BCIs as a workplace technology may alter social interactions based on perceived social acceptance of FLEs wearing BCIs in the workplace (Kelly and Gilbert, 2018). Social acceptability involves coworkers and customers drawing on existing knowledge and context cues to evaluate employees using BCIs, with their social reactions (e.g., approval, indifference, exclusion) serving as feedback on these devices' appropriateness in the workplace (Goffman, 2023). Social interactions at work are crucial for FLEs' well-being, as they foster a sense of belonging, support, and collaboration (Sonnentag, 2015). However, BCI-wearing FLEs may alter interactions with peers or customers by creating perceived differences in abilities, which could lead to discomfort or concerns that BCIs give some employees an unfair or unnatural advantage over others (Yuste et al., 2017).

BCI-enhanced FLEs in the workplace may experience less social acceptance, rooted in the uncanny valley concept (Grewal et al., 2020), which suggests that blending human and nonhuman traits, such as integration of BCIs in frontline roles, can evoke feelings of eeriness and discomfort, leading to greater emotional and psychological distance in social interactions (Broadbent, 2017). This notion is supported further by Castelo et al. (2019), who demonstrated that cognitive enhancement of individuals can result in perceptions of dehumanization, with respondents reporting fewer emotional capabilities and a cold, robotic demeanor among enhanced individuals. Reduced social acceptance may disrupt vital interactions between FLEs and their social environments, ultimately leading to the perception of BCIs as *tech-stressors* (Sonnentag, 2015). However, BCI-enhanced FLEs also may experience increased social acceptance due to interactional benefits afforded by the technology (Kumar et al., 2022). For example, BCIs can free up cognitive resources by allowing FLEs to process information simultaneously while interacting with customers or coworkers, thereby reducing distractions that might otherwise divert attention (Grewal et al., 2023, Giebelhausen et al., 2014). This enables FLEs to foster stronger connections and contribute to a more collaborative work environment. Consequently, these enhanced social dynamics may lead to BCIs being perceived as *tech-resources*. Thus, the following proposition was posited:

Proposition 2a: *Higher social acceptance of FLEs using BCIs will lead to BCIs being perceived predominantly as tech-resources, while lower social acceptance will lead to BCIs being perceived dominantly as tech-stressors.*

Technology Readiness. With the implementation of new technologies in the workplace, personal resources are crucial for managing demands and challenges that arise with the introduction of novel technologies such as BCIs (Xanthopoulou et al., 2007, Truța et al., 2023). This study proposes that technology readiness (Blut and Wang, 2020), as a key personal resource, serves as a moderator that influences FLEs' perception of BCIs as either *tech-stressors* or *tech-resources*. Defined as "people's propensity to embrace and use new technologies for accomplishing goals in home life and at work" (Parasuraman, 2000, p. 308), technology readiness suggests that an individual's general mindset toward technology is crucial to their readiness to engage with technological innovations.

Higher technology readiness levels typically are associated with a more positive attitude toward new technology. This makes

FLEs high in technology readiness more likely to view BCIs as tools that can enhance efficiency and ease workloads (Wu et al., 2022). For example, active BCIs require programming and execution of mental commands to interact with technology. FLEs with high technology readiness levels typically would master execution of mental commands more rapidly, enabling them to query databases at the speed of thought, look up information while speaking to customers, or command service robots to perform certain tasks. As a result, it has been suggested that these FLEs likely perceive BCIs as a positive challenge that offers opportunities to adapt work processes through brain signals, thereby viewing them as *tech-resources*. Conversely, individuals with low technology readiness may perceive BCIs as stressors in the workplace, as their ability to understand and adapt to BCI usage exceeds their available resources, resulting in a detrimental impact on well-being and the perception of BCIs as *tech-stressors* (Fuglseth and Sørebø, 2014). This inability to adapt to new technology can lead to anxiety and resistance, as it adds complexity without tangible benefits for employees with low technology readiness (Wang et al., 2018). Thus, the following proposition was posited:

Proposition 2b: *FLEs with higher technology readiness levels are more likely to perceive BCIs as tech-resources predominantly, whereas those with lower technology readiness will perceive BCIs predominantly as tech-stressors.*

Cyborg Self-Efficacy. The introduction of BCIs into the workplace has elicited the term "frontline cyborgs," reflecting the shift toward a state that blends human and robotic attributes (Grewal et al., 2020, Garry and Harwood, 2019). This shift has been proposed to alter FLEs' self-efficacy, defined as FLEs' distinct beliefs in their ability to execute tasks and achieve goals successfully (Bandura, 1982). The introduction of BCIs into their workplaces may enhance or undermine their self-efficacy (Samfira and Paloş, 2021). As a critical personal resource, self-efficacy is linked strongly to FLEs' perception of stress and, therefore, impacts the perception of BCIs as *tech-resources* or *tech-stressors* in the workplace (Karademas and Kalantzi-Azizi, 2004).

When FLEs perceive an enhancement in their competence and ability to handle tasks through BCIs compared with non-enhanced peers, they may experience a sense of being "superhumanized," which would impact their self-efficacy positively (Kies and Paluch, 2023, Bandura, 1982). This perceived increase in capability through BCI affordances can encourage FLEs to undertake more challenging tasks with greater confidence, resulting in higher job satisfaction and performance (Judge and Bono, 2001). Consequently, BCIs would be perceived as *tech-resources*, thereby positively influencing well-being. However, the enhancement of FLEs through BCIs also may cause individuals to feel like they are losing their human qualities and emotional abilities as technology brings them closer to robotic functions. This could lead to a sense of dehumanization (Grewal et al., 2020, Kies and Paluch, 2023), a perspective that can diminish self-efficacy, as human connection is crucial, particularly in frontline roles in which FLEs are central to the service experience (Samfira and Paloş, 2021). Consequently, a dehumanization perspective asserts that BCI-enhanced FLEs' confidence in achieving work outcomes is reduced, leading to the perception of BCIs as *tech-stressors*. Thus, the following proposition was posited:

Proposition 2c: *FLEs who experience a sense of superhumanization through BCI usage (i.e., cyborg self-efficacy) are more likely to perceive BCIs predominantly as tech-resources, while those who feel dehumanized will perceive BCIs predominantly as tech-stressors.*

BCI-Device-Related Factors' Moderating Role

Alongside personal resources, BCIs' characteristics can influence whether FLEs perceive them as *tech-resources* or *tech-stressors* significantly, ultimately impacting their well-being. Drawing on the extensive technology acceptance literature (Davis, 1989, Venkatesh and Davis, 2000), two key moderators have been proposed in the BCI context: (1) usability features, which affect BCI effectiveness and functionality, and (2) aesthetics, which influence user comfort and overall acceptance of the technology.

Usability features. Building on Ayyagari et al. (2011), usability features include technology usefulness, which refers to ways BCIs enhance job performance; complexity, which addresses whether BCIs can be used effortlessly; and reliability, indicating BCIs' dependability level. Passive BCIs from Quadrant 1 currently offer the highest degree of usability, as consumer-grade devices in this category rely predominantly on dry electrodes that FLEs can wear without any special preparation (Drew, 2023). Unlike wet electrodes, which require frequent rehydration with saline solution during an FLE's shift, dry electrodes reduce the complexity of BCI use (Vasiljevic and de Miranda, 2020). Usefulness in enhancing job performance largely depends on the software connected to the device and how effectively it processes collected data to provide performance benefits. Therefore, current passive BCIs are more likely to be perceived as *tech-resources* due to their relatively high degree of usability (Drew, 2023). However, current devices from Quadrant 3, which are active BCIs, are more complex, as they require extensive training to detect mental commands accurately, potentially leading to fatigue (Saha et al., 2021). Future advancements in machine learning or quantum computing are expected to reduce training times and associated strain significantly (Huang et al., 2022). While these limitations currently contribute to the perception of BCIs as *tech-stressors* due to the high mental effort required, future improvements that enable effortless and instantaneous technology interaction are likely to shift this perception toward BCIs being viewed as *tech-resources*. BCIs also must be reliable in accurately detecting impulses and distinguishing between intentional commands and spontaneous reactions to ensure that FLEs can compose themselves before any actions are executed (Kawala-Sterniuk et al., 2021). As BCI technology emerges from laboratory settings and enters consumer-grade devices, usability is expected to improve with broader adoption.

Thus, the following proposition was posited:

Proposition 3a: *BCIs with higher usability will be perceived predominantly as tech-resources, while those with lower usability will be perceived predominantly as tech-stressors.*

Aesthetics. Successful integration of new technology in the workplace depends not only on usability features, but also on FLEs' aesthetic considerations (Dehghani and Kim, 2019). BCI aesthetics refers to employees' perceptions of the technology's visual and sensory appeal (Shin, 2012). The literature on wearables (e.g., fitness trackers, smartwatches) has established a strong link between wearable devices' compelling visual appeal and positive evaluations of device quality and user enjoyment (Lee, 2022). Furthermore, a pleasing design has been associated with continuous usage intentions, which are important for realizing the benefits that BCIs can offer in the workplace (Dehghani and Kim, 2019). Given that most current BCIs today are worn visibly on FLEs' heads, the technology's aesthetic appeal has been assessed by FLEs themselves, as well as by coworkers and customers. When BCIs are integrated seamlessly into familiar devices––such as headphones, glasses, or headbands––FLEs are more likely to evaluate their aesthetic appeal positively, leading to BCIs being perceived as inconspicuous *tech-resources* (Drew, 2023). However, BCI headsets with multiple visible electrodes that evoke an unfamiliar "spider-like" appearance are more likely to be perceived as *tech-stressors* due to their less-aesthetically-pleasing design. However, it has been proposed that aesthetic appeal diminishes in importance during remote service interactions, in which contact between customers or co-workers does not involve visual contact with FLEs wearing BCIs (De Keyser et al., 2019). In such contexts, FLEs may perceive BCIs less as *tech-stressors* because the devices do not stand out visually in their interactions with others. Finally, as BCIs continue to evolve, the form factor may be reduced to the point at which alterations in FLEs' appearance are no longer visible to others (Grewal et al., 2020, Garry and Harwood, 2019). In such cases, aesthetic appeal's relevance diminishes as the technology becomes seamlessly integrated. Thus, the following proposition was posited:

Proposition 3b: *BCIs with higher aesthetic appeal will be perceived predominantly as tech-resources, while those with lower aesthetic appeal will be perceived predominantly as tech-stressors.*

Managerial Interventions' Moderating Role

FLEs typically exert limited influence over how new technology, such as BCIs, is integrated into their workplaces. In this way, they rely on how management decides to implement these technologies, shaping their perception of BCIs as either *tech-stressors* or *tech-resources* (Day et al., 2010). Accordingly, managerial interventions, which are managers' deliberate actions to modify BCI implementation in the workplace, have been proposed as a moderating mechanism (Brough and O'Driscoll, 2010), in which two critical managerial interventions in the BCI space are considered: (1) neuroergonomic workplace design and (2) neural data management.

Neuroergonomic Workplace Design. Defined as the study of the human brain in relation to work performance, neuroergonomics integrates insights from neuroscience and ergonomics to optimize the design of workplaces, systems, and environments (Mehta and Parasuraman, 2013). Managers can leverage BCIs to design workplaces neuroergonomically, utilizing their functionalities to adjust distribution of work items dynamically based on FLEs' current mental state, influence how these tasks are performed (i.e., mentally commanding software), and tailor feedback to each FLE (Drew, 2023). Managers can make key decisions in designing neuroergonomic workplaces that influence whether FLEs perceive BCIs as *tech-resources* or *tech-stressors*.

When FLEs handle multiple tasks simultaneously, BCIs can adjust relevant information or systems, reduce cognitive overload, and, therefore, enhance perceptions of BCIs as *tech-resources* (Kirchner et al., 2016, Lotte and Roy, 2019). Consider the previous example of air traffic control systems adjusting visual and auditory load based on employees' stress levels (Aricò et al., 2016). Within environments in which safety and security are critical, FLEs may be more inclined toward accepting these adjustments (Pinion et al., 2017). However, using BCIs to decide which tasks to prioritize can take away from FLEs' flexible work environment, in which employees rely on autonomy for motivation and fulfillment (Heer, 2019). System-driven decisions without FLEs' input can create information asymmetries in which employees may feel excluded from key decisions affecting their work, thereby negatively impacting job satisfaction (Duggan et al., 2020). For example, when FLEs derive enjoyment from a particular challenging task, an increased mental workload might lead to unwanted task redistribution, leading to the perception of BCIs as *tech-stressors*. Therefore, it has been posited that FLEs should have a level of control over neuroergonomic adaptations in the workplace, in which shared decision-making with BCIs can foster the perception of the technology as a *tech-resource* (Heer, 2019). This is also relevant to how employees perform tasks with BCI. While active BCIs, which allow for mentally commanding software throughout the workday, can be exhausting for some, others may thrive on the efficiency of thought-based device control.

Managers also can adjust neuroergonomic workplace design through how results from neural data analyses are feedbacked to FLEs (Khakurel et al., 2018). BCIs offer insights into cognitive and emotional states that they cannot access easily otherwise, opening an additional information channel about FLEs' mental state at work (Wascher et al., 2023). Managers can decide whether and how they provide feedback on FLEs' mental state. For example, Neurable offers BCI-integrated headphones that provide users with statistics on periods of focus on a smartphone app (Takahashi, 2024). This information gives employees the option to adjust their work habits based on the neural feedback they receive (Hunkin et al., 2021). As a result, BCIs are more likely to be perceived as *tech-resources*, as they offer useful additional information to

FLEs. Feedback also can be coupled with behavioral adjustments recommended by management based on neuroergonomic analysis (Wascher et al., 2023). For example, BCIs can alert FLEs to take a 15-minute break following a particularly emotionally taxing service encounter. It has been proposed that such interventions, such as alerting truck drivers to signs of fatigue (Wenco, 2021), lead to feedback being perceived as a *tech-resource*, as it can help prevent emotional exhaustion or accidents (Yaacob et al., 2023). BCIs also can detect early signs of burnout and suggest timely interventions to mitigate its onset (Tement et al., 2016). However, managers also can implement real-time feedback to refocus attention when FLEs become distracted (e.g., using their phones), thereby employing it as a motivational tool to redirect their efforts (Farahany, 2023b). Another way firms can integrate BCIs is to quantify FLEs' cognitive performance through regular feedback reports, which then could be discussed and compared across teams. Such feedback's intrusiveness may disrupt workflow and increase counterproductive work behavior, ultimately reducing job satisfaction and motivation (Tomczak et al., 2018). Therefore, this would lead to the perception of BCIs as *tech-stressors*. Thus, the following proposition was posited:

Proposition 4a: *Neuroergonomic workplace adaptations that align with FLEs' preferences and needs will lead to BCIs being perceived predominantly as tech-resources, while misalignment with FLEs' autonomy or preferences will lead to BCIs being perceived predominantly as tech-stressors.*

Neural Data Management. Unlike other workplace technologies that only collect data during specific tasks, BCIs continuously record sensitive neural information without requiring any conscious effort from FLEs (Nicolas-Alonso and Gomez-Gil, 2012). As a result, managers play a crucial role in making decisions about how such sensitive data are handled and processed, which may impact whether BCIs are perceived as *tech-stressors* or *tech-resources*. This connection is supported in the stress literature, which indicates that FLEs experience stress when their personal space and privacy are perceived as being infringed upon (Ayyagari et al., 2011, Day et al., 2010).

Managers are responsible for decisions about how neural data are processed and the extent of access granted to analyze individual FLEs' brain data within an organization. For example, BCI data can reveal medical conditions, such as the early onset of Alzheimer's, that individuals may not be aware of (Yuste et al., 2017). Implementing anonymization or pseudonymization techniques for brain data can limit access to sensitive information, potentially reducing stress and fostering a perception of BCIs as *tech-resources* (Bonaci et al., 2014). (Xia et al., 2022) demonstrated that privacy-preserving processing of neural data is feasible without compromising its functionality.

Furthermore, managerial decisions on how neural data insights are utilized within the company are crucial. While using neural data to adapt workplaces for stress reduction and performance enhancement requires processing, cognitive or emotional exploitation is also a risk, leading to commodification of labor and decreased well-being (Farahany, 2023b). The stress literature has indicated that BCIs are perceived as *tech-stressors* when FLEs feel exploited or surveilled by the technology (Ball, 2010, Day et al., 2010). However, managers can mitigate these negative perceptions by implementing measures such as offering opt-in options, ensuring transparency about how neural data are used, and obtaining informed consent from FLEs (Yuste et al., 2017). Therefore, it has been proposed that effective neural data management, which safeguards FLEs' sensitive information while leveraging BCIs' benefits—such as through neuroergonomic workplace design—will reduce stress and lead to BCIs being perceived as *tech-resources*. Conversely, a lack of transparency or limited information on how intimate FLE data are processed likely will foster skepticism and result in BCIs being perceived as *tech-stressors*. Thus, the following proposition was posited:

Proposition 4b: *Effective neural data management that safeguards FLEs' privacy and ensures transparency will lead to BCIs being perceived predominantly as tech-resources, while a lack of transparency or privacy protection will lead to BCIs being perceived predominantly as tech-stressors.*

08.5

Conclusion, Implications, and Future Research Agenda

This article set out to discuss BCIs' impact on FLEs' well-being, considering the dual nature of this technology as both a contributor (i.e. resource) and potential risk (i.e. stressor) to well-being (Farahany, 2023a). In pursuit of this goal, this article conceptualized what BCIs entail for frontline roles, providing a comprehensive overview of four distinct types of BCIs. Differentiated by BCI category (passive vs. active) and modality of signal acquisition (non-invasive vs. invasive), these types are illustrated with existing and nascent usage examples of BCIs on the service frontline. Due to this conceptualization, the authors predict that non-invasive passive BCIs are primed for immediate integration into frontline roles. Service firms can acquire commercially available devices at a reasonable cost, presenting a significant opportunity to serve customers more efficiently (Grewal et al., 2020, Drew, 2023). Active BCIs, currently limited in their ability to detect complex mental commands reliably, are expected to undergo substantial improvements in the next decade (Maiseli et al., 2023). Building on this overview of BCIs, the authors developed a conceptual framework that focuses on BCI integration's impact on FLEs' well-being, which is influenced by two mediating and three moderating factors.

The authors posited that BCI implementation's impact on FLEs' well-being is mediated by FLEs' perception of the technology as either a *tech-resource* (i.e., dominantly positive impact) or *tech-stressors* (i.e., dominantly negative impact) rooted in job demands-resources theory (Demerouti et al., 2001) and the transactional theory of stress (Lazarus and Folkman, 1984). It has been argued that FLEs' perception of BCIs' purpose in the workplace is instrumental in shaping their assessment of the technology's impact on their well-being. This study's findings suggest that BCIs are more likely to be accepted when integrated to augment or support FLEs in performing their job duties (i.e., increase efficiency), compared with when they are perceived as tools of excessive oversight and monitoring (i.e., increased performance monitoring). FLEs also may perceive identical BCI integrations differently, and their views may not always align with service firms' intentions. Therefore, gaining a better understanding of factors impacting FLEs' perception of BCIs as *tech-stressors* or *tech-resources* is important.

To this end, three categories of moderators were delineated. Yet, each leaves much room for empirical research on BCI acceptance and usage in the service space. The authors detail a series of future research questions in Table 08.2. First, this study identified FLE resources as a moderator category impacting BCI implementation and FLEs' perception of BCIs as *tech-resources* or *tech-stressors*. These resources are described as personal and social factors that affect the perception of BCIs in the workplace (Bakker and Demerouti, 2017). It has been proposed that BCIs change the perception of self and others during interactions through technological enhancement, posing important implications for whether BCIs are perceived as *tech-resources* or *tech-stressors*. Future research should delve into the nature of these changes in interactions and how BCIs should be designed to support employees' well-being. Second, this study identified BCI usability and device design as a second important set of moderators. Usability is relevant (Ayyagari et al., 2011) and is expected to be likely well-evaluated when passive BCIs are introduced in the workplace, as adaptations or benefits do not require conscious effort from users, unlike active BCIs. Furthermore, BCI design is undergoing changes toward smaller form factors, making these devices less intrusive and visible, which may position them as *tech-resources* (Dehghani and Kim, 2019, Drew, 2023). Exploring how these factors influence FLE acceptance will provide greater clarity on the role of design, determine whether interactions are affected when BCIs are not visible, and assess the impact of training time on FLEs' perceptions of active BCIs. Third, the authors identified managerial interventions as a third moderating force explaining firms' impact on concrete decisions regarding how BCIs are implemented in the workplace. Neuroergonomic approaches present a valuable opportunity to adapt to workplaces, enhancing FLE efficiency while preserving cognitive and emotional resources. Further research should explore the role of autonomy and clarify the potential well-being benefits these approaches may offer. Additionally, when BCIs are introduced on the frontline, firms process sensitive data, which may lead FLEs to perceive BCIs as *tech-stressors* if informed consent is not properly obtained. Research is needed to clarify the role of anonymizing user data and how FLEs need to be informed to mitigate these concerns.

At a higher level, service organizations will face significant ethical and legal challenges when implementing BCIs in the workplace. While not the central focus on the articles,

Table 08.2: Selected avenues for future research. Source: The table was created by the author.

Research Area		Research Avenues
FLE Resources	1.	Social dynamics can change when new technology is introduced in the workplace (Day *et al.*, 2010). Active BCIs allow for seamless control of devices in the background. *Does this shift the focus from technology in service interactions to human connections? If present, how can potential perceptions of FLEs as "uncanny" be overcome and reduce the feeling of eeriness?*
	2.	FLEs' increased technology readiness is connected with perceiving BCIs as *tech-resources* (Wu *et al.*, 2022). *However, as passive BCIs are simply worn by FLEs, does technology readiness matter for passive BCIs? Does the reduced adoption hurdle lead to increased adoption of BCIs across all demographics? Are active BCIs perceived as tech-stressors, as they require training in mental commands?*
	3.	Extant research suggests that BCIs can impact FLEs' self-efficacy by either making them feel dehumanized or superhumanized through the technology (Kies and Paluch, 2023; Grewal *et al.*, 2020). *How does the self-perception of being superhumanized affect FLEs' performance? Does this help perceive BCIs as tech-resources? However, FLEs can feel dehumanized. How does dehumanization impact work performance and job satisfaction? Does feeling dehumanized through technology help in high-pressure environments in which emotional detachment can be beneficial* (Sonnentag *et al.*, 2010)*?*
	4.	*How should FLEs communicate the use of BCIs to customers? Do BCIs introduced on the frontline raise customer expectations and, therefore, function as tech-stressors? What implications does this pose for service failure?*
BCI Device	5.	BCI technology's visibility has been demonstrated to lead to increased customer acceptance (Grewal *et al.*, 2020). *However, does this hold true for FLEs, or would FLEs' prefer invisible or unobtrusive BCIs? And if so, why? Does making the device less visible than, e.g., a headset lead to increased adoption intentions among FLEs?*
	6.	Aesthetically pleasing device designs play an important role in appreciation levels and attitudes toward new technology (Shin, 2012). *Do sleek, futuristic designs help FLEs adopt BCIs, or do they expect integration into common, everyday devices? What comfort level do FLEs expect to consider BCIs tech-resources?*
	7.	Non-invasive BCIs generally are viewed as safe to use, with extant research indicating no significant adverse health effects (Nicolas-Alonso and Gomez-Gil, 2012). *How must firms communicate health and safety implications effectively to ensure that FLEs feel secure and confident about using BCIs?*
	8.	BCIs' usability, particularly active BCIs that require training mental commands, is a key factor in their adoption. *What are acceptable training times for FLEs to perceive BCIs as tech-resources and not tech-stressors? Do other factors (e.g., complexity, service industry) influence acceptable training time?*
Managerial Interventions *Neuroergonomic Workplace Design*	9.	Adapting the workplace based on algorithmic decisions has been demonstrated to decrease autonomy and agency over tasks among FLEs (Duggan *et al.*, 2020). *How does adapting tasks based on FLEs' own neural data impact autonomy and agency perceptions? What is the level of agency over neuroergonomic workplace design required for positive impact on FLEs' well-being? Extant research from, e.g., coworking with robots has suggested that some level of agency is strongly preferred (Heer et al., 2019)*
	10.	Neuroergonomic workplace design can adjust screen layouts, next tasks, and individual break scheduling (Lotte and Roy, 2019). *Would these adaptations increase FLEs' productivity and job satisfaction, or would these changes lead to a decrease in motivation and well-being as positive, challenging tasks are allocated elsewhere?*
	11.	By collecting and analyzing neural data, FLEs' cognitive and mental states open a novel information channel for them (Hunkin *et al.*, 2021). *Would giving FLEs insights into their mental and emotional states improve their well-being? How do FLEs utilize such data when made available to them? What is the longitudinal impact when FLEs can track their health and well-being (i.e., prevent burnout)?*
	12.	Feedback on FLEs' cognitive and emotional state can be helpful as a motivational tool, but also lead to counterproductive work behavior (i.e., actions opposed to firms' interest, e.g., absenteeism). *What is the optimal frequency and feedback method, and how should it be communicated to FLEs to function as a motivational tool? What types of feedback are deemed acceptable and what feedback should managers refrain from providing to FLEs?*
Neural Data Management	13.	Sensible neural data can be anonymized or pseudonymized to limit firms' access to FLEs' neural data (Xia *et al.*, 2022). *Does implementing privacy-preserving technologies (i.e., on device data management, anonymization) impact FLEs' perception of BCIs as tech-stressors or tech-resources? To what extent does this mitigate concerns related to surveillance and control of FLEs? Transparency about data processing is an important factor in technology adoption, so how can protection measures be communicated to FLEs transparently?*
	14.	Informed consent is a critical component of BCI deployment, particularly at the frontline service level, where FLEs' neural data are collected and processed (Yuste *et al.*, 2017). *What are the most effective methods for communicating neural data usage complexities, and how can these approaches be designed to ensure informed decision-making? Can an opt-in approach be a viable solution?*
	15.	*Does the level of trust toward the firm regarding responsible data handling lead to perceiving BCIs as tech-stressors or tech-resources?*

the authors do want to highlight its relevance. From a legal perspective, use of BCI technology is governed by AI regulations, such as the EU AI Act, which became effective in 2024 (European Commission, 2024, European Commission, 2021). Within this act, service firms are permitted to integrate BCI technology but must secure FLEs' informed consent and avoid manipulative practices. While processing FLEs' emotional states is restricted heavily, exceptions exist for safety-related purposes, such as monitoring fatigue. Neuroergonomic workplace design is permissible but is subject to regulatory safeguards designed to protect FLEs' sensitive neural data. Similar developments are occurring globally, with the "AI Bill of Rights" in the United States and the "AI Law" in China (The White House, 2022, Yang, 2024), though the EU AI Act provides detailed guidelines on BCI utilization (Steindl, 2024). Other significant ethical challenges related to BCI technology in the workplace include autonomy, human rights, and social inequality. For further reading, the following research is recommended: Yuste et al. (2017), Burwell et al. (2017), Kreitmair (2019). Key future research questions include how firms can navigate emerging regulatory frameworks, such as the EU AI Act, while upholding ethical practices in managing neural data. Given the complexity of this data, it is crucial to determine how firms can ensure that FLEs fully understand and provide informed consent to BCI usage. Additionally, it is essential to assess whether existing regulations offer adequate protection for employees' cognitive privacy. Also, further investigation is necessary to identify best practices for balancing BCIs' performance-enhancing potential with employees' rights to autonomy and freedom from surveillance. Firms must consider how to prevent the misuse of sensitive neural data and to what extent FLEs should control the data collected from their brain activity. Moreover, research should explore how transparency in data usage can foster trust between employees and organizations, mitigating fears of exploitation or misuse. Finally, as BCIs become more widespread, it will also be important to study their long-term impact on workplace equality. Research should address whether disparities could arise if access to BCI technology or the ability to adapt to it varies across different demographic groups. Finally, ethical inquiries should examine whether BCIs enhance or erode human dignity and autonomy in the workplace, and how firms can ensure that their implementation supports, rather than undermines, these fundamental principles.

This conceptual study, while offering valuable insights, also has limitations. This article focuses on non-invasive BCIs, which offer practical short-term solutions, but may overlook invasive BCIs' potential to transform FLEs' well-being, thereby limiting the findings' generalizability. The proposed 2x2 matrix focuses on clear distinctions between active and passive BCIs, but hybrid BCIs, which integrate functionalities from both, potentially offer a broader range of applications. While the authors believe that the separate findings related to well-being are still applicable to hybrid BCIs, hybrids' unique potential has not been explored fully. Finally, the conceptual framework lacks empirical validation, which is to be expected at this stage, and the authors strongly encourage further testing of the propositions as well as the additional future research questions put forth in the article.

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09

Appendix: Essay III

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

by Alexander Kies and Stefanie Paluch

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09.1 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

09.2 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*bnin*2022, *itisprojectedtoreach*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-RQ 1: *How does the interaction setting impact user-evaluations of BCI technology?*

Sub-RQ 2: *How does the interaction setting impact user-evaluations of BCI technology?*

Sub-RQ 3: *To what extent does the level of BCI functionality shape user perceptions?*

Sub-RQ 4: *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.

09.3 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

Table 09.1: Examples of Consumer-Grade BCIs

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

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 09.1.

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.

09.4
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 (Mage =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 (Mage =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.

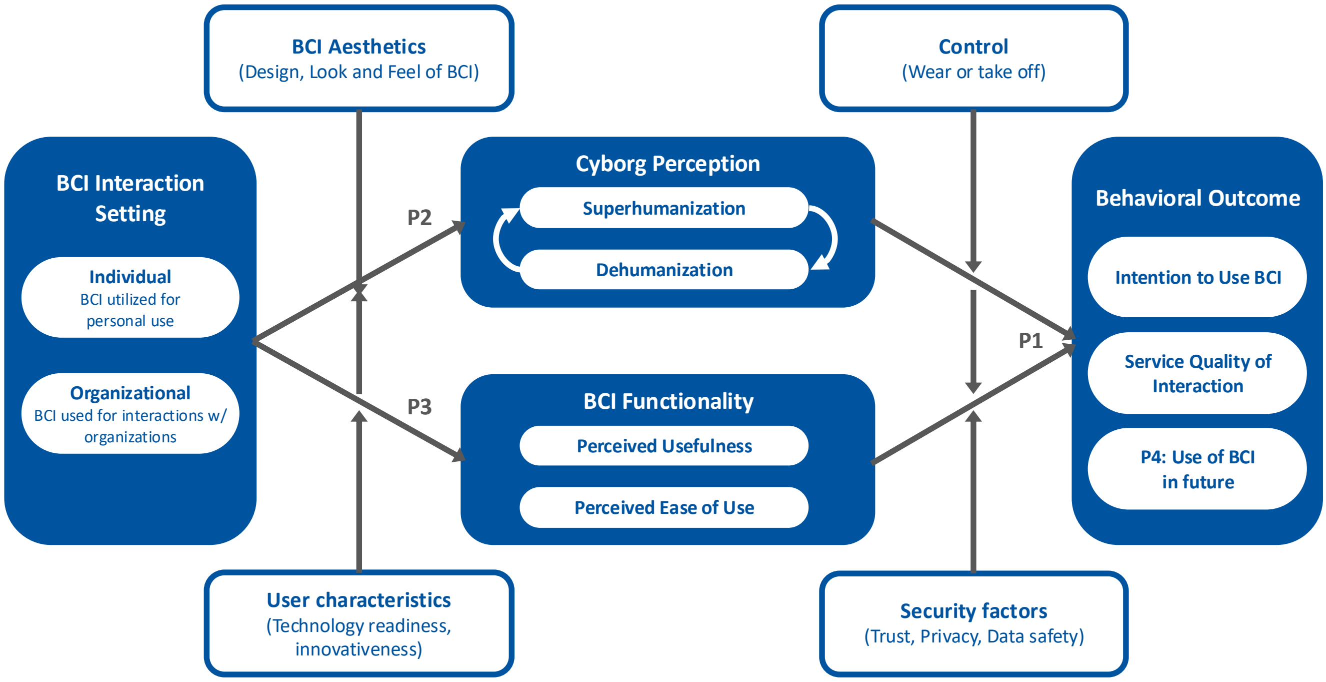

Figure 09.1: Proposed Research Model

09.5
Results of the Qualitative Study

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.

09.6
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.

09.7
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10

Appendix: Essay IV

Beyond Words: The Future of Metaverse Communication Through Brain-Computer Interfaces

by Alexander Kies and Stefanie Paluch

This essay is currently being prepared for submission to a special issue in *Internet Research* (7.9 5-year Impact Factor).

10.1 Abstract

The evolution of Brain-Computer Interfaces (BCIs) from specialized medical tools to mainstream market technologies marks a pivotal transition, where the ability to communicate with individuals and technology through thought is becoming a reality. BCIs stand to offer an unprecedented level of immersion and technological embodiment in the metaverse by granting users the ability to gain insights into their mental state, directly manipulate reality-enhanced environments, or receive communication seamlessly without the need for peripheral technology. This development holds the potential to foster deeper social connections and shared experiences, thus enhancing individuals' well-being. Although there is a substantial body of research on the technical aspects of BCI technology, there is a noticeable gap in the literature on the transformative potential BCIs hold for communication within the metaverse. Therefore, this paper sets out to (1) delineate a comprehensive definition of neuroimaging and neurostimulation BCIs for communication, (2) establish a conceptual framework rooted in actor-network theory that details enhanced communication affordances through the use of BCIs, and (3) discuss the ethical implications of mainstream market BCI technologies and areas for future research. This paper systematically explores the role of BCIs as a novel communication technology in the metaverse, delving into their impact on individual well-being.

10.2 Introduction

In the rapidly changing landscape of modern technology, communication is experiencing a profound transformation. Central to this revolution are Brain-Computer Interfaces (BCIs), which are defined as communication and control technologies that enable users to send (receive) messages and commands to (from) external devices by detecting and interpreting their brain activity, which involves no muscular stimulation or speech (Lotte and Roy, 2019, Nicolas-Alonso and Gomez-Gil, 2012). These BCIs extend the communication affordances of users by providing insights into mental states, the capability to communicate with technology through thoughts, and the ability to receive communication from others (Drew, 2024, Hilken et al., 2022). A novel medium for communication emerges, enhancing well-being by allowing individuals to share emotional experiences and enabling of effortless and rapid exchange of communications, deepening connections and mutual understanding (Zander et al., 2010). This is particularly relevant in the metaverse, where the blending of physical and virtual worlds demands greater technological embodiment (Rubo et al., 2021). For example, in collaborative gaming, brain-to-brain communication enables innovative telepathic gaming techniques that can foster deeper social connections with fellow players (Vasiljevic and de Miranda, 2020; Semertzidis et al., 2023). Additionally, BCIs can communicate cognitive and emotional states to modify reality-enhanced environments. For instance, the application Inter-Dream analyzes an individual's brain activity and adjusts the virtual reality environment accordingly to support physiological processes that promote healthy sleep, resulting in reported increases in mindfulness and relaxation (Semertzidis et al., 2023). Moreover, this application can be adapted to customize game dynamics or job tasks based on the user's current mental capacity to manage these activities (Fang et al., 2021, Aricò et al., 2016).

By 2030, the BCI market is projected to reach a valuation of USD 6.2 billion from USD $2.0 billion in 2020 (GrandViewResearch, 2022). This forecast casts little doubt that BCIs, as communication mediums, are more than just speculative prospects for the far-off future. While initially created to assist individuals with physical disabilities in communicating through spellers and controlling electronic wheelchairs (Kawala-Sterniuk et al., 2021), the advent of consumer-grade devices marks a shift towards enhancing interpersonal communication and engagement in the metaverse. Considerable progress has already been made in transitioning this technology from research environments to a tangible part of individuals' daily lives. For example, OpenBCI has introduced a VR headset integrated with BCI technology, enabling seamless interaction within the metaverse. This innovative BCI headset has showcased its capabilities, notably controlling a drone during a TED talk, demonstrating its practical applications beyond virtual environments (Houser, 2024). Another notable example is NextMind, a company acquired by Snapchat, which has shown the capability to adjust music and control objects within a reality-enhanced environment (Heater, 2022). Moreover, major technology firms such as Neuralink, co-founded by Elon Musk, have made significant strides by demonstrating the first human implant of a BCI, enabling an individual to play games such as chess purely through mind control (Drew, 2023, Drew, 2024).

Taken together, these developments highlight the capacity of BCIs to establish a new communication channel, independent of traditional speech or muscle-based pathways. However, while much research has been devoted to technical advancements (Kawala-Sterniuk et al., 2021), there remains a significant gap in understanding the impact of these changes on communication dynamics and practices (Hilken et al., 2022). As BCIs gain popularity among consumers, it becomes imperative for communication and marketing scholars to understand their potential and ethical implications. Therefore, this paper seeks to investigate how BCIs change the communication affordances of users in the metaverse by building on actor-network theory and details how these changes affect the well-being of individuals. Thus, the contribution of this paper is to: (1) synthesize the existing literature on BCIs and provide a definition and overview of BCI as communication technology, detailing the functionality of neuroimaging and neurostimulation uses. (2) develop a conceptual framework for BCI-enhanced communication along four dimensions, discussing the impact of BCI-enhanced interaction for self-communication, BCI-to-BCI, BCI to the metaverse, and one-sided BCI communication. Building on this basis, we highlight the ethical implications arising from the use of BCI-enhanced communication, emphasizing their possible adverse effects on individual well-being. Furthermore, we propose a research agenda that aligns with the dimensions outlined in our conceptual framework, aiming to investigate these critical issues further.

10.3 Brain-Computer Interfaces' Impact on Communication Pathways

Brain-Computer Interfaces are seen as the next evolution of AR and VR, offering enhanced communication in augmented environments through deeper technological embodiment (Palmer, 2021, Hilken et al., 2022). Building on extant studies (Kawala-Sterniuk et al., 2021, Nicolas-Alonso and Gomez-Gil, 2012), BCIs have been defined as *a technology that establishes a direct communication link between users' brains and external devices by recording and decoding neural activity*. This definition emphasizes that unlike other (mostly wearable) technologies that measure physiological signals (e.g., smartwatches), BCIs establish a distinct communication channel for unique interaction with devices that is not possible with other wearables (Paluch and Tuzovic, 2019, Vasiljevic and de Miranda, 2020). Unlike conventional communication methods, where individuals rely on muscle movements or speech, BCIs create a direct pathway for communication between the brain and external devices – or vice versa leading to bidirectional interaction (Jiang et al., 2019, Nicolas-Alonso and Gomez-Gil, 2012). Figure 010.1 depicts a BCI system, which will guide the discussion for this chapter. It is important to note that the scope of this research focuses on non-invasive (i.e. wearable) technologies alone, as invasive (i.e. implantable) BCI technologies requiring surgical implantation are not expected to be market-ready in the near future (Nicolas-Alonso and Gomez-Gil, 2012).

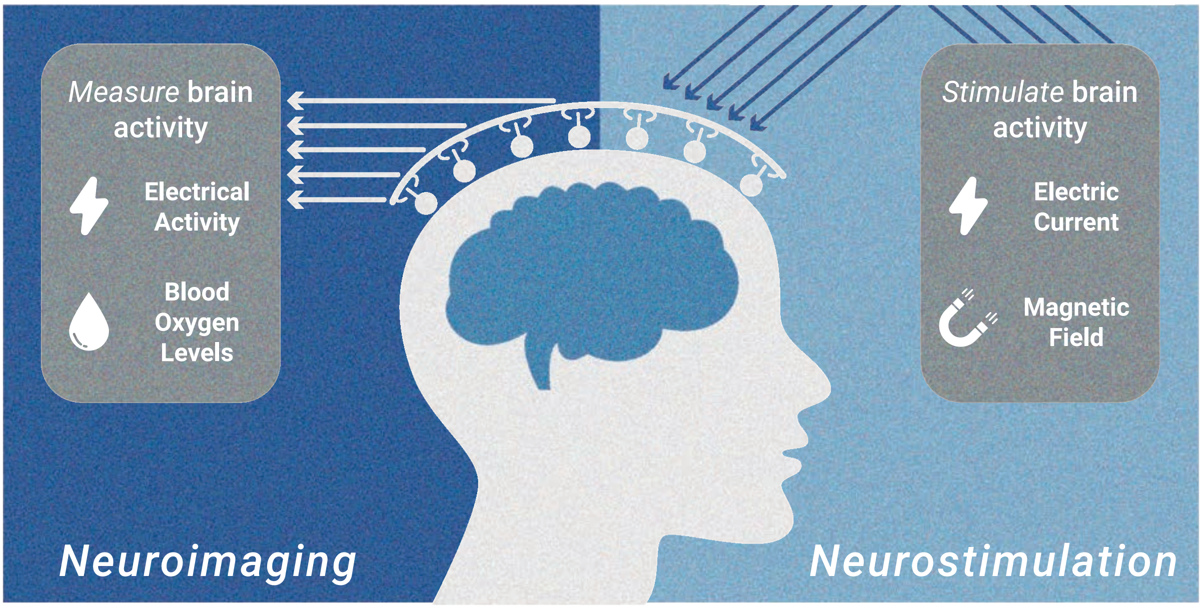

Figure 010.1: Neuroimaging and neurostimulation

10.3.1 Neuroimaging

Neuroimaging refers to a communication technology, depicted on left side of Figure 010.1, that measures individuals' brain activity and allows for "neuro-to-digital" communication, where the user's neural activity is converted into a response within the digital environment (Hilken et al., 2022). Unlike traditional mouse, keyboard, or touchscreen-based interfaces, these BCIs allow users to interact with devices solely through their brain activity, eliminating the need for muscular movement (Kawala-Sterniuk et al., 2021). This marks a significant shift toward more seamless and natural engagement with digital environments (Hilken et al., 2022, Vasiljevic and de Miranda, 2020). By tracking brain activity, neuroimaging BCIs provide users with feedback on their mental states, allowing for real-time analysis and long-term logging to gain detailed insights over time (Zander and Kothe, 2011). Most prevalent neuroimaging technologies rely on capturing electrical activity (e.g. EEG) or blood oxygen levels (eg. fNIRS), which can be seamlessly integrated with reality-enhancing technology (Drew, 2023, Dubois et al., 2024). For example, the OpenBCI Galea headset integrates BCI technology with a VR headset, to allow its users to control drones through mental commands (Bernal et al., 2022). Table 010.1 depicts further examples of consumer-grade neuroimaging BCIs. BCIs used for neuroimaging process data in a four-step process (Kawala-Sterniuk et al., 2021): First, during signal acquisition, brain signals are captured, amplified, and preprocessed to reduce

Table 010.1: Examples of Consumer-grade BCI Devices for Neuroimaging and Neurostimulation

Device (Company)	Description	Communication Examples	Price (USD)
		Neuroimaging BCIs	
Axon-R (Cognixion)	Integrated BCI & AR device Sensor technology: EEG, ECG, EMG, EOG	• Thought-to-speech interface • GPT-enhanced AR headset for rapid communication	$25,000
Epoc X (Emotiv)	BCI headset Sensor technology: EEG	• Insight on cognitive and affective states to user • Control and interact with games e.g. first-person shooter	$999
GALEA (OpenBCI)	Integrated BCI & VR device Sensor technology: EEG, EMG, EOG, EDA, PPG, Eye tracking	• Hands-free interaction with games in virtual reality • Control drones or robots • Adjust reality-enhanced environment to mental state	$25,000
NextMind (Snap AR)	BCI for integrated use with VR/AR devices Sensor technology: EEG	• Control technology by visual focus • Adjust music, lighting by controlling smart home	$399 (Dev Kit)
		Neurostimulation BCIs	
CloudTMS machine	Transcranial Magnetic Stimulation	• Receive communication by magnetically stimulating brain regions	$64,995
LIFTiD	Transcranial direct current stimulation (tDCS)	• Receive communication by electric stimulation • Increase focus and concentration	$159
Xen (Neuvana)	Vagus nerve stimulation through headphones	• Receive communication by electric micropulses • Increased calmness and focus	$449
		Brain-to-Brain BCIs	
PsiNet	Measure neural activity via EEG as input Stimulate neural activity via transcranial electric stimulation (tES)	• Strengthen sense of connection • Distribute mental workload • Control over others state of mind	N/A

noise and artifacts. Next, in feature extraction, the signal is analyzed to isolate relevant characteristics, such as user intent or affective state. Then, in feature translation, a translation algorithm converts these features into readable output. Finally, during device output, the translated commands operate the external device or display the user's affective state, completing the communication loop.

This "neuro-to-digital" information can subsequently be processed in an active (i.e. mentally controlling technology) or passive (i.e. assessing mental state) manner (Drew, 2023). Passive BCIs analyze brain signals generated without conscious effort from the user, thereby not requiring intentional thought to operate (Aricò et al., 2018). These brain signals typically reflect the user's cognitive and affective states, such as emotion, relaxation, fatigue, and cognitive workload levels (Saha et al., 2021). For example, users can track their focus and engagement during learning tasks, pinpointing optimal learning conditions and times, thereby boosting their educational performance (Galway et al., 2015, Jamil et al., 2021). Additionally, monitoring emotional states can elevate one's awareness of emotions, assisting in more effective emotion management and possibly leading to enhanced mental health (Steinert and Friedrich, 2020). In gaming contexts, passive BCIs can modify game dynamics, difficulty levels, and narrative elements based on the player's emotional responses and engagement, creating a more personalized and immersive experience (Vasiljevic and de Miranda, 2020).

Active BCIs on the other hand capture and interpret the user's intentional mental activity (Saha et al., 2021). By imagining hand movements or pre-programming mental commands to execute specified actions, algorithms identify these patterns in neural data. The advantage of active BCI lies in its ability to facilitate hands-free interactions, freeing users from the constraints of physical controllers (Drew, 2023). For example, recent studies have investigated how BCIs can improve users' collaboration with (service) robots, enabling direct brain-to-robot communication and continuous task execution without manual interruption (Liu et al., 2021, Coogan and He, 2018, Lee et al., 2022). Moreover, active BCIs allow users to communicate directly with others in the metaverse by converting thoughts into text, circumventing traditional input methods (Nicolas-Alonso and Gomez-Gil, 2012). Additional applications include artistic creation in virtual environments, where users can transform their brainwaves and intentions into visual art, expanding the realm of creative expression (Nijholt et al., 2018).

10.3.2 Neurostimulation

BCIs' functionality can be further extended by neurostimulation, which refers to BCIs' modifying or influencing brain activity in response to input from the digital environment, depicted on the right side of Figure 010.1 (Hilken et al., 2022). Such stimulation may be experienced as sensory information on grip strengths of prosthetics (Klaes et al., 2014), modulation of emotional states (Widge et al., 2014) or olfactory feedback from virtual reality environments (Hilken et al., 2022). Applying neurostimulation is possible through non-invasive options using small electrical or magnetic pulses. Two of the most prominent neurostimulation technologies are transcranial direct current stimulation (tDCS) and transcranial magnetic stimulation (TMS) (Dayan, 2012). tDCS delivers a low electrical current to the brain via electrodes placed on the scalp, while TMS stimulates the brain by generating a brief, high-intensity magnetic field that affects the brain tissue beneath the skull (Hallett, 2007, Nitsche et al., 2008). Both technologies, initially explored in medical contexts, are considered generally safe and have become available for consumer purchase (Wexler, 2018). However, compared to neuroimaging BCIs, consumer-grade neurostimulation is still in its relative infancy (Hildt, 2019).

Incorporating neurostimulation into BCIs extends their functionality by enabling bidirectional communication, wherein “digital-to-neural” interactions become feasible (Hilken et al., 2022). Users equipped with such BCIs can not only receive inputs from digital environments or other individuals but also actively transmit information through their mental commands. This communication affordance can therefore facilitate direct interaction between two or more individuals through brain-to-brain interfaces (Grau et al., 2014). Such interfaces enable the exchange of thoughts, sensory experiences, and motor commands between users, bypassing traditional communication channels (Kerous and Liarokapis, 2017, Nitsche et al., 2008, Wexler, 2020). For example, brain-to-brain interfaces let people work together by sharing information directly between their brains. Thus, individuals can collaborate and make shared decisions without using traditional forms of communication like speaking or writing (Jiang et al., 2019). Moreover, users of neurostimulation BCIs can receive communication from digital (service) environments through tactile feedback, such as that provided by virtual reality settings, thereby enhancing their sense of immersion (Racat and Plotkina, 2023). Additionally, these BCIs can facilitate the transfer of emotional states from the environment to the user, enabling them to experience emotional responses directly through neural stimulation (Maksimenko et al., 2018, Valle, 2022, Widge et al., 2014). Table 010.1 presents a research-grade brain-to-brain interface that makes use of bidirectional communication.

Neurostimulation is an emerging field that facilitates stimulation of brain regions (Hallett, 2007). While neuroimaging technologies have become more widespread in consumer-grade devices (Drew, 2023), applications for neurostimulation have achieved significant milestones, slowly advancing the technology for use beyond laboratory settings (Wexler, 2020). Both neuroimaging and neurostimulation aspects of BCI technology have the versatility to be used independently or in an integrated manner. Examples of both applications using consumer-grade technology are available in Table 010.1.

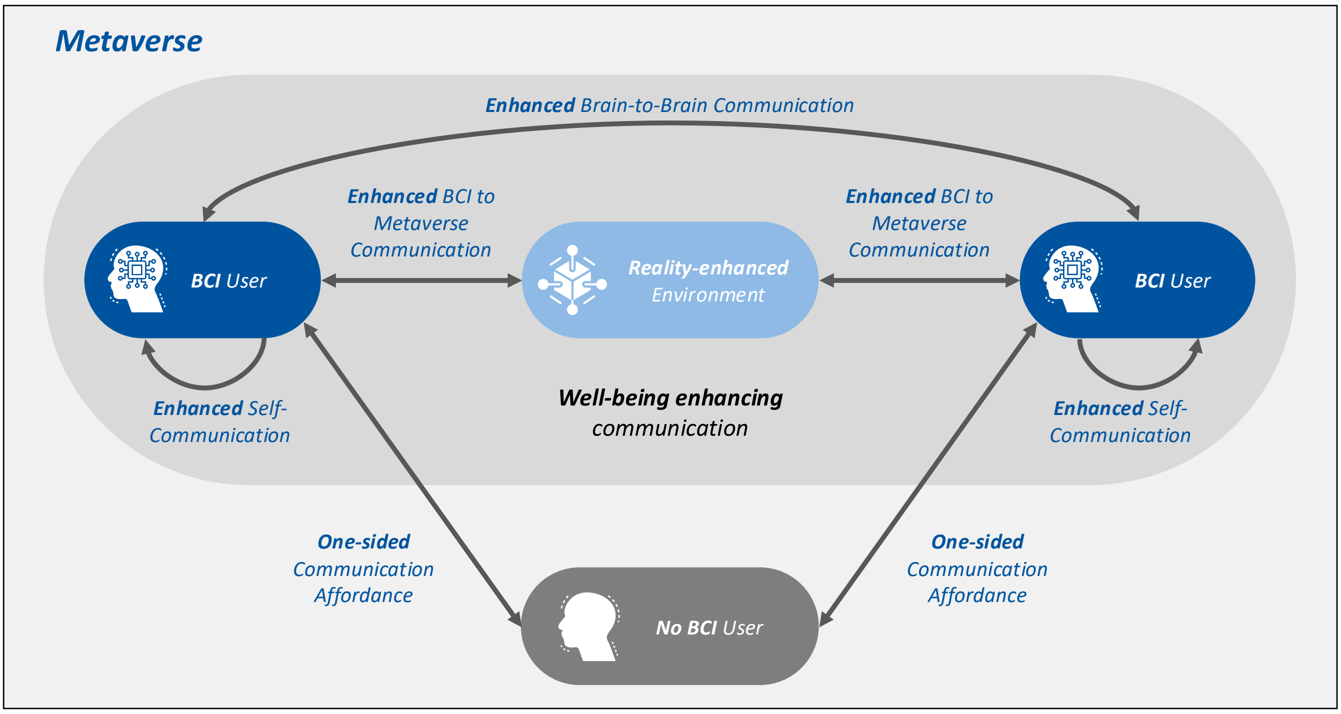

Figure 010.2: Conceptual Framework: The Metaverse-BCI-Communication Model

10.4 BCI Communication Model in Metaverse

This section presents a conceptual framework (Figure 010.2) that organizes the discussion on how neuroimaging and neurostimulation BCIs influence communication affordances and user well-being. A key research priority in Human-Computer Interaction (HCI) for emerging technologies like BCIs is understanding how users engage with digital interfaces to optimize their well-being through these interactions (van Erp and Toet, 2015, Yoon and Kim, 2022, Mekler and Hornbæk, 2019).

The concept of users' well-being is inherently complex and lacks a universally agreed-upon definition or framework. As a result, we adopt a comprehensive perspective from existing literature that distinguishes between two complementary dimensions: hedonic well-being and eudaimonic well-being (Bartels et al., 2019, Straume and Vittersø, 2012). Hedonic well-being emphasizes a life filled with pleasure and the minimization of pain (Sonnentag, 2015), particularly in the context of communication, where positive experiences are prioritized. In contrast, eudaimonic well-being focuses on achieving personal growth and realizing one's full potential, which is deeply rooted in the alignment between one's communication abilities and core values (Bartels et al., 2019, Straume and Vittersø, 2012). To simplify the discussion, we use the term "well-being" to refer to both hedonic and eudaimonic aspects, underscoring their combined influence on users' experiences and outcomes.

The conceptual foundation for identifying emerging communication pathways through BCIs in this paper is grounded in Actor-Network Theory (ANT), which is well-suited for analyzing complex relationships in human-technology interactions (Latour, 2007, Tatnall, 2003, Waldherr, 2019). In this context, ANT conceptualizes both human (e.g., users) and non-human entities (e.g., BCIs, digital environments) as actors within a network, where their roles and relationships continuously shape communication dynamics and outcomes (Latour, 2007). This perspective allows us to view BCIs as active participants that not only transmit information but also mediate, transform, and influence how human actors communicate and perceive interactions in these enhanced environments.

This paper identifies three key actors emerging from BCI-enhanced communication, which are depicted in Figure 010.2. The first are BCI-enhanced users, who employ integrated neuroimaging and neurostimulation devices to interact with their environment. The second are regular users, not equipped with BCI technology, leading to an asymmetry in information depth that affects communication dynamics. The third actor is a non-human entity: the reality-enhanced environment within a metaverse context, which can adapt itself or transmit communications directly to individuals. These actors form a network that creates four novel communication pathways shaped by BCI-enhanced interactions: (a) the impact when both parties in an interaction employ BCIs, (b) interactions to or from the metaverse, (c) the effect of BCI on self-communication, and (d) interactions in one-sided BCI for communication. The following sections will explore these pathways in detail, highlighting the unique impact of BCI technology on communication dynamics.

10.4.1 Enhanced BCI-to-BCI Communication

Enhancing BCI-to-BCI communication involves the integration of BCIs to enrich interactions between two or more indivuduals using BCIs. This enables bidirectional communication within virtual environments, allowing for a more immersive and interactive experience by directly transmitting thoughts, emotions, and sensory perceptions between users (Jiang et al., 2019, Wolpaw et al., 2002).

From a technical perspective, enhanced BCI-to-BCI communication hinges on two pivotal mechanisms. Firstly, neuroimaging allows users to simultaneously influence the shared virtual environment, facilitating a dynamic and interactive experience (Zander et al., 2010). Secondly, the integration of neuroimaging and neurostimulation enables the bidirectional flow of information, allowing for the transmission and reception of data in a manner that integrates users' experiences and actions in real time (Wexler, 2020). Leveraging the combination of neurostimulation and neuroenhancement unlocks the true potential of BCIs within the metaverse by integrating humans into shared experiences, beyond mere interaction (Semertzidis et al., 2023). Such direct and nuanced exchange of mental states not only deepens the level of empathy and understanding among participants but can also significantly contribute to enhanced social well-being and social connectedness within the metaverse

(Keyes, 1998, Semertzidis et al., 2023).

By transcending language barriers and traditional input device limitations, BCI-to-BCI communication can impact how individuals exchange information in the metaverse. For example, individuals can form a "social network" of interconnected brains (Jiang et al., 2019). Existing research has demonstrated the feasibility of working together on a task by senders encoding signals through neuroimaging and receivers correctly interpreting this information by receiving information via neurostimulation to execute a task. Receivers could even discern when to trust the received signal and when it was not reliable (Jiang et al., 2019, Rao et al., 2014). Enhanced communication and interaction within teams have been linked to improved task satisfaction and overall well-being, highlighting the importance of effective collaboration (Sonnentag, 2015). BCI-to-BCI communication further enables the dynamic adjustment of tasks and virtual environments based on real-time neuroimaging insights from individuals engaged in them (Ma et al., 2022). By tailoring tasks to the current mental states and cognitive loads of participants, this approach enables the sharing of cognitive responsibilities, leveraging individual strengths in real-time (Grau et al., 2014). This results in more enjoyable and efficient interactions within virtually enhanced spaces, optimizing both individual and collective experiences. An example of this collaborative communication is the art installation "Hivemind", where two individuals communicate by translating brain activities into flashing lights, which then influence the other's brain rhythms similar to a conversation until a synchronized state is achieved (Nijholt et al., 2018).

Furthermore, BCI-to-BCI communication enhances the non-verbal sharing of emotions in the metaverse, making it easier to express and understand feelings without self-formulation (Widge et al., 2014). This leads to a more vivid sharing of positive moments and a deeper, communal experience of negative emotions, thus positively enhancing well-being (Semertzidis et al., 2020). For example, neuroimaging technologies enable the rough extraction of visual experiences from BCI users, leading to a dynamic adjustment of reality-enhanced environments based on imagined or actual visual information (Singh et al., 2023). This allows individuals to share significant moments or dreams, enhancing social connections (Rahman, 2021). Adding to this, a study by Semertzidis et al. (2020) has investigated the impact of Brain-to-Brain emotion sharing. Socially close individuals wore a neuroimaging and neurostimulation device and shared their emotions over multiple days. Participants were able to increase their emotional competence and improve their ability to regulate them. Furthermore, a study by Fang et al. (2021) explored the effects of telepathic interaction through Brain-to-Brain communication in gaming. Participants reported feeling a stronger social bond and a sense of presence with each other, even when physically separated. The findings also point to new possibilities in gaming, highlighting how BCI technology can open up innovative ways of connecting and interacting within virtual spaces (Vasiljevic and de Miranda, 2020).

However, BCI-to-BCI communication could have negative impacts on well-being. Due to the continuous, unfiltered sharing of thoughts and emotions, communicators could perceive this added channel to induce emotional overload and blurred personal boundaries (Kreitmair, 2019, Wexler, 2018). As this omnipresent connection might hinder personal privacy and the ability to withhold communication, this could potentially harm interpersonal dynamics by "oversharing" (Drew, 2023). Research also raises concerns about the loss of individuality and agency, as the complex flow of information in brain networks makes it challenging to discern personal thoughts from those of the collective, complicating individual decision-making within these interconnected networks (Yuste et al., 2017).

10.4.2 Enhanced BCI to Metaverse Communication

Integrating BCI technology within reality-enhanced environments can significantly enhance communication affordances. That is, the novel forms of interaction and control enable highly personalized and immersive activities, which can lead to more enjoyable experiences (Hilken et al., 2017). BCI communication can promote mental health and inclusivity and empower users by providing them with thought-based control and interaction within the metaverse, thereby positively impacting their well-being (Coogan and He, 2018, Rahman, 2021). This enhanced communication with reality-enhanced environments evolves the user's role from controlling the environment to integrating within it, establishing a symbiotic relationship where both the user and the environment exchange signals. This integration transforms the user and metaverse into an assemblage, emphasizing collaboration and the extension of the human body as central to communication (Hoffman and Novak, 2018, Semertzidis et al., 2023).

A central development in enhancing well-being within a reality-enhanced environment is the application of neuroergonomics, which allows for automatic customization based on their current mental capacity and priorities (Dehais et al., 2020, Mehta and Parasuraman, 2013, Wascher et al., 2023). Through the use of neuroimaging techniques, environments can be dynamically tailored to users' cognitive and affective states (Dehais et al., 2020). For example, air traffic controllers' workplaces can be adjusted based on their current stress levels, such as reduction of visual load by displaying fewer aircraft on the screen or minimizing auditory alerts to prevent distractions from noncritical notifications. This adaptation has been demonstrated to reduce employees' stress levels while increasing operational safety and efficiency (Aricò et al., 2016). Adapting the virtually enhanced workspace based on users' communication of their own state has been shown to improve job satisfaction and work performance, thereby enhancing well-being (Martinez et al., 2022, Sonnentag, 2015). Transforming these principles for gaming, BCI technology can tailor reality-enhanced environments by customizing scenery, game difficulty, and tasks. Adapting the environment to align with the user's preferences, creates a more immersive and enjoyable user experience, positively contributing to (hedonic) well-being (Vasiljevic and de Miranda, 2020). For example, an avatar in reality-enhanced settings can morph in response to the user's current emotions or visually represent intense emotional states, such as anger visually representing the user as a wolf (Liu et al., 2010). Amores et al. (2016) presented a proof-of-concept demonstrating how BCI users can adapt 3D environment, when they are in a state of focus, to increase mindfulness and better concentration.

The integration within the BCI-metaverse assemblage facilitates seamless and hands-free communication with (virtual) robots or bodily extensions. This enables users to collaborate with robots in a cooperative manner, where users can control their actions, and in turn, the (virtual) robots adjust their working pace to match the human users in a bidirectional approach (Chen et al., 2020, Liu et al., 2021). This can lead to improvements in well-being through personalized and enhanced communication in user-robot interactions. Furthermore, interacting within reality-enhanced contexts via BCI holds profound implications for accessibility and individual well-being, as physical limitations no longer hinder interactions, ensuring that everyone can potentially engage fully and equally in metaverse space (Nicolas-Alonso and Gomez-Gil, 2012). Moreover, communication in transcends traditional language barriers, enabling more inclusive and versatile interactions within reality-enhanced settings (Semertzidis et al., 2023). Moreover, neuroimaging technologies allow for the anticipation of users' preferences before they are consciously made (Telpaz et al., 2015). Through the metaverse's capacity to "read" users' minds, it can preemptively understand preferences and decisions, facilitating a form of "magical" communication. Here, the environment automatically adjusts by predicting the next desired control or change, potentially enhancing well-being by creating a seamlessly intuitive and personalized experience (Fang et al., 2021).

Employing neurostimulation technologies can enrich communication by introducing an additional feedback channel from reality-enhanced environments to users. This reverses the traditionally established dynamics of environment control where the user controls the environment, potentially leading to a more enjoyable and immersive experience (Semertzidis et al., 2023). This extends the scope of sensory engagement beyond the conventional auditory and visual information transmitted, enhancing tangibility through the incorporation of transmitting haptic feedback, weight perception, temperature variation, taste, or smell back to the user (Valle et al., 2024). For example, in digital-to-neural communication, the metaverse can initiate muscular movements in the user to affect cognitive and emotional processes within the brain (Moulier et al., 2016, Hallett, 2007). Leveraging this communication pathway, immersive games can be innovatively designed by placing computer-to-brain interactions at the heart of immersive gaming experiences.

However, the integration of a reality-enhanced environment into BCI user communication can also have adverse effects on well-being. As communication becomes richer and more immersive, it may lead to social isolation with technology replacing human interaction (Burwell et al., 2017, Kreitmair, 2019). Engaging with this sophisticated setup could result in technostress, where individuals feel overwhelmed by the need to learn and use advanced technology extensively (Ayyagari et al., 2011). Especially since current neuroimaging and neurostimulation technologies require extensive training and elaborate setups, to function as intended (Vasiljevic and de Miranda, 2020). Additionally, insights from AR and VR research on addiction suggest a risk of dependency on BCIs in the metaverse, leading to mental illness, aggression, or sleep problems (Merkx and Nawijn, 2021).

10.4.3 Enhanced Self-Communication

Enhanced self-communication refers to the improved internal communication for individuals using BCIs, enabled by deeper insights into their cognitive and emotional states (Kawala-Sterniuk et al., 2021, Aricò et al., 2016). This enhancement arises from establishing a communication channel that automatically captures information, thus enhancing the flow of information without demanding extra effort from the user (Zander et al., 2010). Consistently, enhanced insight and modulation of one's cognitive and emotional states have been linked to increased subjective well-being and life satisfaction, presenting a compelling case for the positive impact of BCIs on self-communication (Hixon and Swann, 1993, Lyke, 2009, Moulier et al., 2016). The most notable technologies for self-communication include passive BCIs and neurostimulation devices.

Insights gained from monitoring cognitive states, such as focus and attention over long-term settings, have been demonstrated to positively influence well-being (Zander and Kothe, 2011). Tracking focus during tasks can enhance efficiency by pinpointing the most productive times for task engagement (Ienca et al., 2018). Additionally, suggesting breaks upon reaching cognitive load limits has been shown to bolster cognitive outcomes and support mental health (Lotte and Roy, 2019). By monitoring states and offering the ability to intervene, BCI-supported introspection can lead to reduced instances of burnout and exhaustion, thereby effectively preventing adverse health outcomes (Yaacob et al., 2023). In learning contexts, monitoring concentration and focus has proven to enhance individuals' learning outcomes, leading to superior academic achievement (Galway et al., 2015, Jamil et al., 2021). Integrating these approaches, particularly in the context of neurostimulation, can positively impact individual well-being. Stimulating specific brain regions with electrical or magnetic signals has been shown to facilitate improved learning, which in turn fosters a greater sense of achievement, enhanced career opportunities, and intellectual development (Dayan, 2012). For instance, the application of an electrical current can specifically target and stimulate brain regions associated with mathematical abilities. When used in conjunction with training, this method leads to improvements that persist over time (Cohen Kadosh et al., 2010).

Reflecting on the role of emotional insight in self-communication, the ability to understand and manage emotions is vital for everyday life. Utilizing BCIs to monitor emotions can aid in addressing social challenges and safeguarding both mental and physical health, thereby significantly enhancing well-being (Huang and Rust, 2018, Huang et al., 2023). Advanced BCIs can identify and potentially regulate emotions, distinguishing between pathological emotional patterns that deviate from an individual's norm and their typical emotional responses (Widge et al., 2014). This allows to detect changes early, facilitating personalized emotional management and support, which can significantly improve an individual's quality of life. Furthermore, they provide strategies for enhancing these emotional states. Given the complexity and often elusive nature of emotions, BCIs provide insights into genuine emotional expression. For example, when participants were given information about their affective state through BCIs, many appreciated the additional stream of information that quantifies their experience and current emotional state, which has been shown to enhance individuals' well-being (Hassib et al., 2017, Lyke, 2009). This capability can also assist individuals in better adapting to their environments, resulting in enhancements in their daily lives and contributing to improved emotional health. Additionally, neurostimulation can positively influence the way emotions are processed and experienced. For instance, studies indicate that stimulating specific brain regions can alter emotional processing without affecting mood directly (Moulier et al., 2016). This approach can be used to enhance the processing of positive stimuli while minimizing attention to negative ones, such as anger. It offers users the potential to either mitigate these negative feelings or obstruct their processing altogether (Mondino et al., 2015).

Nevertheless, self-communication might also result in adverse effects. Treating inherently human attributes as quantifiable metrics could diminish individual well-being, as stereotypes regarding desirable cognitive or emotional states may emerge from external influences (Steinert and Friedrich, 2020). Additional concerns include the potential for individuals using BCIs to be perceived as socially isolated or ostracized by those not utilizing such technology, negatively affecting social well-being. Furthermore, while BCIs can offer positive health benefits, they might also prompt excessive scrutiny of mental states or contribute to a loss of personal identity (Yuste et al., 2017).

10.4.4 One-sided BCI Communication

In one-sided BCI communication, the interaction dynamic shifts depending on whether the sender or receiver is equipped with a BCI. If the sender uses a BCI, they can enhance the communication by transmitting complex data like intentions, emotions, and cognitive states, offering a richer context to the receiver (Zander et al., 2010). Conversely, when the receiver uses a BCI, they are positioned to understand nuanced inputs through neuroimaging or neurostimulation, enriching their reception of the communication in reality-enhanced settings, provided the sender transmits BCI-compatible information. While BCI technologies enhance communication capabilities, an imbalance in these interactions can lead to issues. Research indicates that disparities in communication depth may harm relationships, creating power imbalances and complicating the interpretation of social cues (Ruben et al., 2021). As a result, the social well-being of individuals can potentially decrease, even when communication depth is increased (Rahman, 2021).

The adaptation of a shared reality-enhanced environment for communication serves as a beneficial addition, offering an extra channel to convey emotional or cognitive experiences, thereby elevating well-being through enhanced sharing and experiencing a sense of togetherness (Keyes, 1998). This arrangement can promote empathy among non-BCI users and lead to closer connections (Semertzidis et al., 2023). Similarly, in the context of neurostimulation, the sender's ability to convey richer information to a receiver capable of receiving neurostimulation enhances communication, facilitating more effective and nuanced exchanges (Wexler, 2018). Existing literature has established a clear connection between enhanced technological embodiment and the sharing of emotions, leading to an improvement in the social well-being of individuals (Flavián et al., 2021). For instance, one-sided BCI interactions can play a pivotal role in enhancing learning processes, where a BCI-enabled sender can modify the environment to optimize learning outcomes, and the BCI-receiving party benefits from neurostimulation or targeted information, ensuring effective learning through direct feedback (Galway et al., 2015, Jamil et al., 2021).

However, there are also potential negative implications for social well-being due to the asymmetrical nature of one-sided communication. For instance, the use of BCI technology by one party in communication can result in distraction and a diminished focus on individuals without BCI enhancements, potentially sidelining their contributions and presence (Ruben et al., 2021). The disparity in communication capabilities between BCI-enhanced users and others within reality-enhanced interactions can create a power imbalance, potentially straining relationships. When only one participant in the interaction can effortlessly modify reality-enhanced environments or be influenced by them, it grants this individual disproportionate control over the situation. Such power imbalances in communication have been demonstrated to lead to disengagement, frustration, or loss of self-esteem (Lam and Xu, 2019, Kreitmair, 2019). Furthermore, the potential delay experienced by the non-BCI partner, who must rely on traditional input methods, could induce feelings of frustration, or lead to the exclusion of the non-BCI communication partner. The unequal ability to share emotional or cognitive states might further strain communication (Zander et al., 2010). Moreover, the perception of BCI-enhanced communication partners could result in them being seen as less human than others. Castelo et al. (2019) explored how individuals with abilities that surpass typical human capacities, such as enhanced communication through or with BCIs, are perceived as being dehumanized. This phenomenon could foster stereotyping and the exclusion of individuals who utilize BCI for communication within reality-enhanced environments (Grewal et al., 2020). Another dimension of inequality in reality-enhanced communication is the widening of the digital divide. Individuals without BCI enhancements face disadvantages in educational opportunities, employment prospects, and social connections due to the lack of richness and depth in their communication capabilities.

10.5 Ethical Implications

The advent of BCIs within reality-enhanced communication contexts blurs the boundaries between humans and machines, paving the way for potential integration with technology in the metaverse. BCIs introduce a groundbreaking channel of communication that can enhance the messages transmitted and broaden the bandwidth of signals received, either by other BCI users or from the reality-enhanced environment the user is in (Wolpaw et al., 2002). However, as BCI technology interfaces directly with the human brain, it introduces a myriad of ethical considerations surrounding the application of neuroimaging and neurostimulation technologies (Kreitmair, 2019). Unlike other communications via speech or mouse and keyboard, brain waves can only be controlled to a certain extent by the user. This offers a deeper insight into the user's internal state compared to other biometric technologies, such as eye-tracking or facial recognition, that can deduce levels of concentration or emotional states, albeit with lower depth and precision (Kawala-Sterniuk et al., 2021). To safeguard the well-being of users using communication via BCIs, it is crucial to address emerging ethical concerns. Consequently, we draw upon established literature to review the ethical concerns associated with direct-to-consumer BCIs across dimensions of privacy & consent, agency & identity, safety, responsibility, and justice (Burwell et al., 2017, Kreitmair, 2019, Lima and Belk, 2022, Steinert and Friedrich, 2020, Vlek et al., 2012, Wexler and Thibault, 2018, Yuste et al., 2017, O'Brolchain and Gordijn, 2014). We have compiled a comprehensive overview of the primary ethical challenges related to communication within the Metaverse via BCIs, including definitions, examples, and references, presented in Table 010.2.

Privacy & Consent. Utilizing BCIs for communication in reality-enhanced environments introduces new potential breaches of user privacy, which makes measures for data protection important. That is, brain activity represents most private information that was previously inaccessible through other methods of communication, where individuals have a large degree of control over verbal or muscular communication shared with others (Hilken et al., 2022). As BCIs collect both unintentional and intentional brain activity, analyzing the data by parties without explicit consent to do so, can reveal psychological traits, attitudes toward others, and potential health issues like onset dementia (Yuste et al., 2017). When data is shared without consent to healthcare providers, ad-

Table 010.2: Ethical Implications for BCI in reality-enhanced communication

Ethical Implication	Definition	Examples	Example Literature
Privacy & Consent	Right of individuals to control access to collection, use and sharing of their personal neural data and ensure voluntary agreement to participate in BCI communications in metaverse	• Psychological traits, attitude towards others, health issues disclosed without consent • (Workplace) discrimination based on cognitive and affective brain activity	Yuste et al. (2017)
Agency & Identity	Ability of individuals to act independently and make free choices based on user-directed action and expressing thoughts and personalities in the metaverse	• Manipulating decisions by predicting choices before they are made • Modification of brain activity can lead to self-estrangement • Increased agency for individuals with physical disabilities	Vlek et al. (2014)
Safety	Measures and practices to prevent physical and psychological harm to individuals using BCIs to communicate in the metaverse	• Generally safe to use, neurostimulation can lead to small risks to physical well-being • Hacking BCIs could lead to physical harm	Ienca et al. (2018)
Responsibility	Changes in the level of legal and moral responsibility of actions, when communication and interactions in the metaverse are executed by thought control	• Increased responsibility due to information increase • Decreased responsibility when acting on subconscious brain activity	O'Brolchain et al. (2014)
Justice	Fair and equal benefit distribution of BCI communication affordances to all members of society	• High cost could lead to unequal division of communication benefits • Shared use, public funding	Kreitmair (2019)

vertisers, or workplaces, individuals could face discrimination based on how focused they are at their jobs or how healthy their brain activity is, thus negatively impacting individuals' well-being (Kreitmair, 2019). Covertly collecting sensible information can also increase users' perceived vulnerability (Aguirre et al., 2015). To safeguard user privacy and prevent misuse, consumer BCI devices should implement an opt-in solution for sharing data with third parties, where explicit consent is required to process data outside the device (Yuste et al., 2017). Another effective method to protect brain signal data is to encrypt signals, which has been shown to effectively prevent the identification of individual brain wave patterns of others (Agarwal et al., 2019). Furthermore, regulatory bodies have taken initial steps to outline which data collected from BCIs can be processed and for what purposes, aiming to guide companies in the responsible handling of sensitive information. Moreover, obtaining consent for communication via neurostimulation is a crucial issue. Given that stimulating the brain of a BCI-wearing communication partner, whether through metaverse or by other individuals, can influence their affective and emotional state, there are inherent risks associated with nonconsensual brain stimulation (Dayan, 2012). This raises concerns about personal agency and identity as well, which we will discuss later in this section. Therefore, employing stimulation for communication necessitates processes for consent for receiving brain-stimulating communication every time it is transmitted.

Agency & Identity. Communicating within the metaverse through BCIs raises ethical considerations regarding individual agency and identity – two facets deeply interconnected with navigating self-perception and social environments, thus playing a crucial role for well-being (Vlek et al., 2012). Looking at neuroimaging technologies, on the one hand, can have a significant impact on individuals' sense of agency by interpreting the BCI user's brain activity. For example, BCIs can detect that the user is about to make a decision and prompt changes to the reality-enhanced environment that could influence this decision (Telpaz et al., 2015). This opens the possibility for manipulation of users' decisions e.g. in marketing communications, to induce them to make a different decision for products or services of competing firms, thereby undermining user agency. However, neuroimaging also enhances communication and self-expression by providing additional avenues for individuals to authentically present their self and identity within metaverse environments (Ienca et al., 2018). Additionally, neuroimaging BCIs can significantly enhance agency for individuals with disabilities, by providing novel means of communication that bypass physical limitations, significantly enhancing their well-being (Nicolas-Alonso and Gomez-Gil, 2012). For example, someone with motor neuron disease could interact and adjust metaverse environments, engage in social communication, or control their digital avatar seamlessly, without the constraints of established interaction devices like a joystick, keyboard, or mouse. On the other hand, neurostimulation BCIs can blur the line between user-directed action and technology-induced behavior. The ability of users to receive communication from reality-enhanced environments and others within shared spaces carries the risk of compromising authentic communication and self-expression, as it allows for the modification of the emotional and cognitive states of users to some degree (Jotterand and Giordano, 2011). Research in neurostimulation has produced mixed findings, with some individuals reporting feelings of "self-estrangement" due to a perceived loss of control over their emotional states or actions, thereby undermining their sense of self. Individuals reported having difficulty assessing, whether their communications to others are their authentic selves or induced by technology (Zuk et al., 2018). However, interconnected brain-to-brain communication within the metaverse can also redistribute the sense of agency among participants, potentially leading to enhanced collaborative experiences, where traditional boundaries of personal autonomy are redefined (Semertzidis et al., 2023). Findings from BCI-to-BCI communication studies suggest that agency can be collectively experienced among users, indicating that it is not solely located within an individual's brain but can be distributed among various agents within the system, leading to a shared sense of agency.

Safety. Ensuring the safety of users in the context of neuroimaging and neurostimulation stands as a critical ethical concern. As communication technologies evolve, their development must prioritize the physical and psychological well-being of individuals (Ienca et al., 2018). Neuroimaging technologies, which monitor brain activity through non-invasive methods such as detecting changes in electrical activity or blood flow, are generally regarded as safe based on their strong safety record in clinical and research settings (Kawala-Sterniuk et al., 2021). They merely read and interpret brain activity without intervening and therefore pose minimal to no physical risks to the well-being of their users. Neurostimulation technologies on the other hand are also generally considered safe to use, yet they present more direct concerns for the physical well-being of users (Rossi et al., 2009). The use of electronic stimulation can result in contact dermatitis or skin burns, while magnetic stimulation can increase the risk of stimulation-induced seizures (Wexler, 2018). These risks to well-being are largely dependent on stimulation parameters. More concerning, however, are the serious health risks that could emerge if malicious actors were to hack these BCIs, escalating stimulation beyond safe thresholds. Such misuse could lead to severe outcomes, including loss of consciousness, posing significant health hazards. Consequently, certifications and safeguards need to be established that e.g. manipulated games in metaverse communication cannot cause harmful overstimulation in individuals. Additionally, there is a need for long-term studies to comprehensively understand the effects of prolonged and continuous use of neurostimulation devices (Kreitmair, 2019). BCI technology also affects psychological well-being and safety. Engaging in virtual environments and receiving neurostimulation could lead to psychological dependency in altering the mental or cognitive states of users, with some individuals needing the stimulation to effectively focus or regulate their emotions (Burwell et al., 2017). As levels of immersion increase with BCI in reality-enhanced settings, individuals might also encounter difficulties in distinguishing between real and virtual environments (Rubo et al., 2021).

Responsibility. Employing BCI technology for communication, especially with its capability to transmit communications and actions at the speed of thought, significantly impacts the legal and moral responsibilities within the metaverse (Vlek et al., 2012). In communications or interactions, where e.g. inner subconscious thoughts lead to the adaption of metaverse environments where individuals may have difficulty questioning the ownership of their actions (Burwell et al., 2017). For instance, if an angry impulse results in harmful communication with others or leads to the destruction of digital twins by transferring this impulse from the metaverse to real-world environments, a reconsideration of responsibility attribution arises (Steinert and Friedrich, 2020). This is especially relevant when current inefficiencies in muscle or speech-based communication provide a buffer for reflection and behavioral adjustment, which is bypassed in instant thought-to-action translations. Similarly, this applies to the unintentional transmission of inner thoughts to others who should not be aware of this message (Wolpaw et al., 2002). Consequently, there is an argument that individual responsibility for actions might be reduced, as subconscious actions complicate attribution as not every action is explicitly consented to (O'Brolchain and Gordijn, 2014). This issue becomes particularly relevant in contexts like joint decision-making in metaverse games, where brain-to-brain communication via BCI distributes tasks and agency among various participants and makes clear attribution difficult (Fang et al., 2021). However, responsibility could also increase due to increased communication affordances and the ability to regulate cognitive and affective states. Individuals would gain a higher volume of information that can be transmitted and received (O'Brolchain and Gordijn, 2014). Consider air traffic controllers who fail to adjust virtual screens by their mental capacity, potentially leading to a greater attribution of responsibility in the event of accidents or errors. While BCI-enhanced individuals gain a higher degree of control over their environment, thus assuming more responsibility, this could adversely affect well-being if the increased load of information and responsibility heightens perceptions of technostress (Ayyagari et al., 2011).

Justice. As enriched communication in the metaverse via BCIs offers communication affordances, these benefits need to be distributed fairly and equally among all individuals in a society to secure a positive well-being impact (Kreitmair, 2019). Given that BCIs offer improvements for communication, interaction, mental health management, and educational outcome improvements, these benefits must be distributed equally to foster a just society. Currently, the relatively high cost of BCI technology and accompanying reality-enhancing devices restricts access to advanced communication features to a privileged few (Lima and Belk, 2022). With only a few individuals having access to this technology, the social divide could widen, given that only affluent individuals can amplify their abilities to levels beyond what is considered 'normal' (Burwell et al., 2017). As neurotechnologies in the metaverse become more widespread, their integration into everyday functioning might soon be considered the norm, thereby emphasizing access to BCI as an ethical requirement in the future. Improving access for more could involve the shared use of devices, including in publicly funded spaces, to extend benefits to more individuals. Additionally, costs could be reduced through increased adoption, as observed with consumer-neuroimaging and -neurostimulation technologies, which are becoming more accessible at lower prices (Drew, 2023).

10.6 Research Agenda

To achieve the goal of enhancing communication affordances through BCIs in the metaverse, research must focus on how BCI technology can be most effectively and responsibly utilized to improve interpersonal and intertechnological communication and interaction. Given that this field is still in its infancy, there are exciting opportunities for impactful research. Therefore, we propose a research agenda, depicted in Table 010.3, outlining key directions across the four communication pathways delineated within our conceptual framework. Additionally, we have thoroughly examined the ethical considerations prompted by this development and have integrated key concerns into our agenda. However, the research agenda is not intended to be exhaustive but aims to provide a comprehensive overview of the key areas of focus.

Brain-to-brain interaction through BCIs plays a crucial role in communication, as it can surpass the traditional language barrier and enrich the exchange by directly transmitting and influencing intentions and emotions (Nicolas-Alonso and Gomez-Gil, 2012). This invites inquiries into the potential benefits of social connections as well as the negative consequences of oversharing emotional states. Additionally, further research could explore the implications of shared decision-making on allocating individual responsibility within these collaborative contexts. Investigations into BCI-to-metaverse communication should delve into the design of protective measures necessary when technology directly stimulates the user's brain, ensuring safeguards to defend against unauthorized manipulation. Additionally, research should examine how consent mechanisms in BCI communication can be structured to maintain the autonomy and privacy of neural data processing. Future studies on enhanced self-communication should explore the long-term consequences of accessible cognitive and emotional state information, particularly

Table 010.3: Research Agenda

Topic	Research Opportunity / Questions
Enhanced BCI-to-BCI Communication	How does the shared virtual environment facilitated by enhanced BCI-to-BCI communication contribute to the formation of deeper social connections and understanding among users?
	How does real-time adjustment of tasks and environments based on neuroimaging insights from users engaged in BCI-to-BCI communication enhance collective and individual experiences?
	What potential negative impacts could arise from continuous, unfiltered BCI-to-BCI communication, such as emotional overload or blurred personal boundaries, and how can these be mitigated?
	What are the implications of distributed agency in BCI-to-BCI communication for personal identity and the perception of self, especially when actions or decisions are influenced by collective neural inputs?
	How does the use of BCI technology for instantaneous thought-to-action communication in the metaverse challenge traditional notions of legal and moral responsibility?
Enhanced BCI to Metaverse Communication	What are the implications of employing neurostimulation technologies to introduce additional feedback channels from the environment to users, and how does this enrich the sensory engagement?
	How effective are opt-in solutions and signal encryption in protecting user privacy and preventing misuse of brain signal data collected by consumer BCI devices?
	Considering the potential influence of neurostimulation on an individual's affective and emotional state, what consent mechanisms need to be established for communication via neurostimulation in BCIs?
	What measures need to be implemented to ensure that users are not in danger from neuroimaging and neurostimulation? How does this need to be communicated to users effectively?
Enhanced Self-Communication	In what ways can long-term monitoring of cognitive states, such as focus and attention through BCIs, contribute to individual well-being and productivity? And how does this influence individual's adoption decisions?
	How do individuals perceive the quantification of their emotional and cognitive states through BCIs, and what effect does this have on their well-being and emotional health?
	What strategies can be implemented to reduce users' perceived vulnerability and safeguard against the covert collection of sensitive information through BCIs?
	In what ways can increased levels of immersion through BCI in reality-enhanced settings impact users' ability to distinguish between real and virtual environments, and what are the implications for their psychological well-being?
One-Sided BCI Communication	What are the implications of communication imbalances created by one-sided BCI usage for the interpretation of social cues and the maintenance of power equilibrium in relationships?
	What strategies can mitigate the frustration or exclusion experienced by non-BCI partners due to communication delays or the inability to modify reality-enhanced environments?
	How can BCI technology be developed and distributed to ensure fair and equal access to its communication affordances for all?
	In what ways can shared use of BCI devices in publicly funded spaces, such as libraries or community centers, contribute to democratizing access to advanced communication and mental health management tools?

focusing on the potential adverse effects of continuous self-quantification. Additionally, research should examine how communication via BCIs in the metaverse affects the ability to differentiate between real and virtual worlds when interaction is mediated through BCIs. Finally, research on one-sided BCI communication should delve into how unequal access to technology influences power imbalances, communication delays, and a diminished richness in interactions.

10.7 Conclusion

Given the potential of BCI technology to enrich communication and interaction within the metaverse, there is a clear need to examine its impact and implications comprehensively. To this end, we adopted a multidisciplinary approach, integrating literature streams from communication, neurotechnology, and reality-enhancing technologies, to define and conceptualize communication affordances BCI technology offers in the metaverse, as well as its significant effects on individual well-being. We conclude that the potential role of BCI in enhancing interpersonal interactions and relationships is profound, illustrating how BCIs serve as innovative mediums for communication and empathy. By challenging the notion of computers and humans as distinct entities, the advent of BCI suggests a more intimate integration with technology, fostering a shared experience among users, enriched by the context and feedback within the metaverse. This integration not only bridges the gap between human cognition and digital expression but also introduces a new era of interconnectedness and mutual understanding. As the field of market ready BCIs is still emerging, with neuroimaging devices becoming increasingly accessible and neurostimulation devices gradually entering the market, we delve into the ethical considerations that arise. We acknowledge the significance of these implications and, along the dimensions of our conceptual framework, identify critical research areas necessary to facilitate a responsible adoption of this technology.

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