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

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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

1. **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).

2. 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 extant 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 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.

INSERT FIGURE 1 ABOUT HERE

A 2x2 matrix has been developed to categorize different BCI technologies for FLE use (Figure 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 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.

INSERT FIGURE 2 ABOUT HERE

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).

Finally, ***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 1 presents the relevant literature on BCI applications, categorized into the identified quadrants in Figure 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).

INSERT TABLE 1 ABOUT HERE

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

This section introduces a conceptual framework (Figure 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 ability 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.

INSERT FIGURE 3 ABOUT HERE

3.1 *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.

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

3.2.1. 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-stressor* (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.*

3.2.2. 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.*

3.2.3. 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.*

4. 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-stressor* (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 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.

INSERT TABLE 2 ABOUT HERE

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, 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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TABLES

Table 1: Selected literature review

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.

Source: The above table was created by the authors.

Table 2: Selected avenues for future research

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?*

Source: The above table was created by the authors.

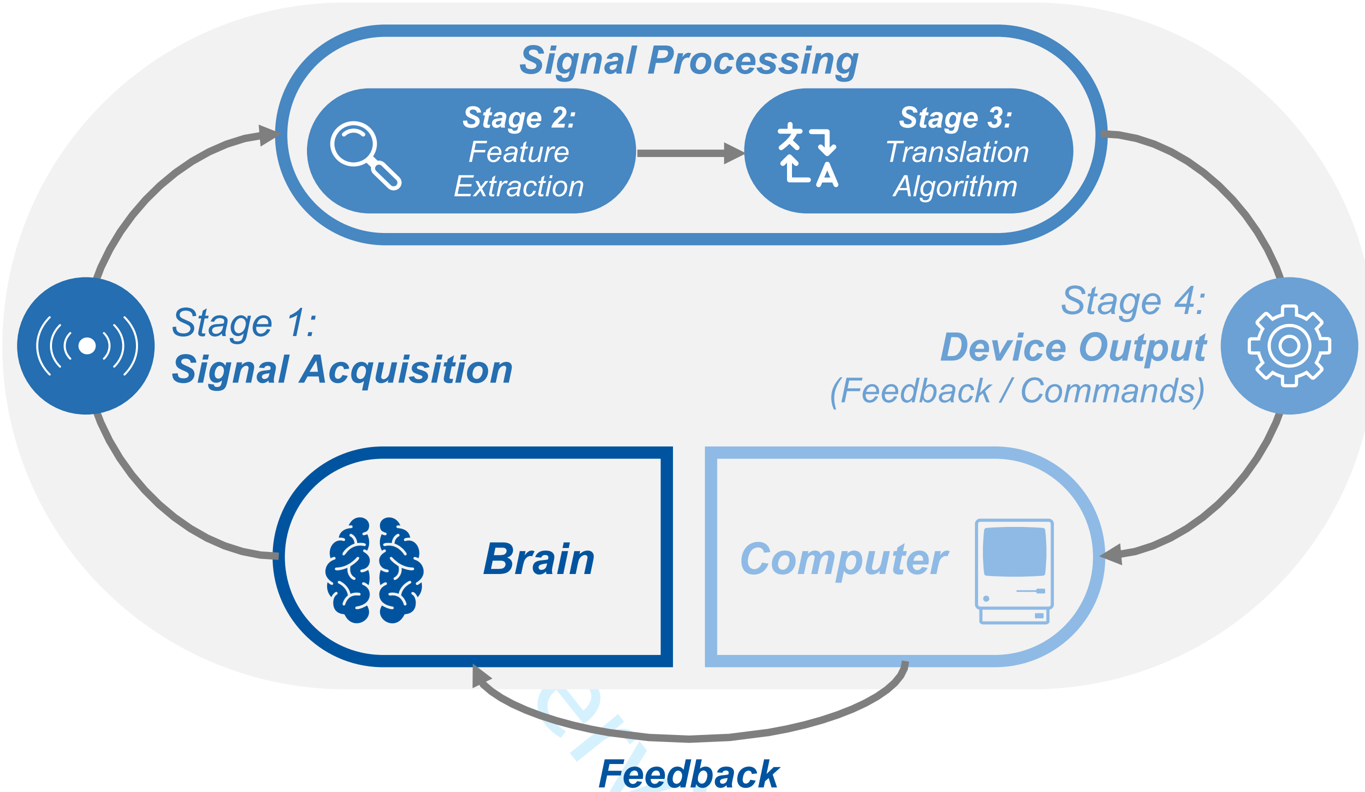

Figure 1: BCI system architecture

Source: The above figure was created by the authors and adapted from Kawala-Sterniuk *et al.* (2021)

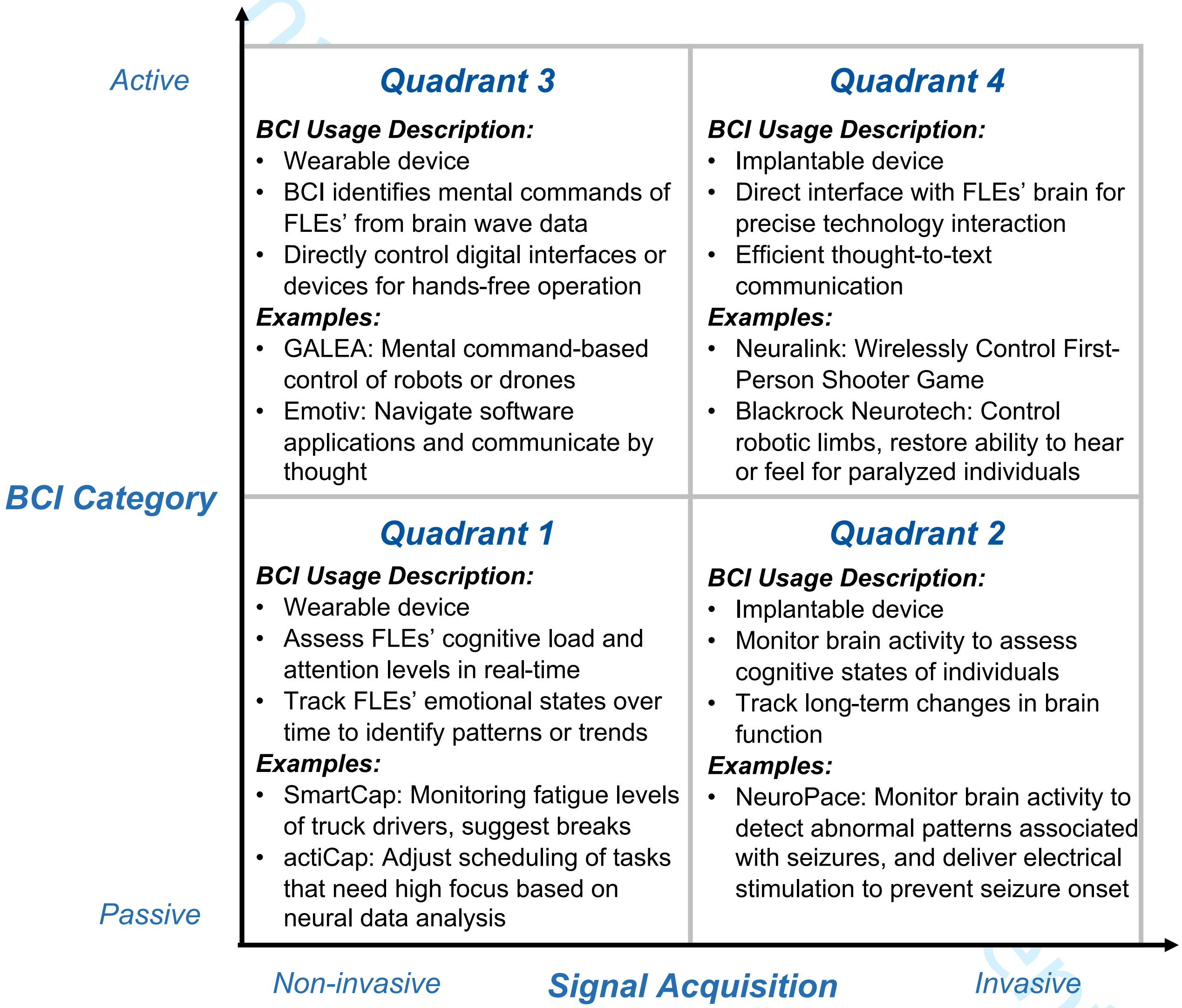

Figure 2: BCI typology

Source: The above figure was created by the authors.

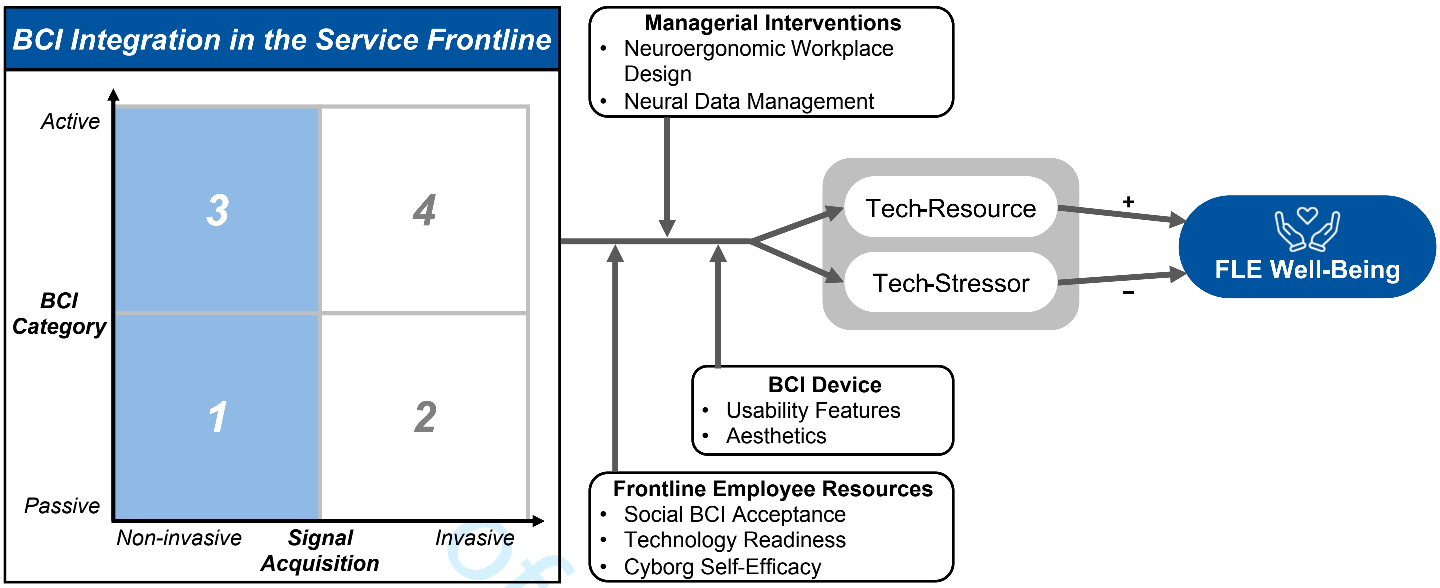

Figure 3: Conceptual Framework of BCIs' Impact on FLE Well-being (the shadow indicates this article's focus)

Source: The above figure was created by the authors.