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Unlocking minds: Psychological roadblocks to the adoption of AI-powered brain–machine interfaces

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Abstract
Brain–machine interfaces (BMIs) are emerging as transformative tools with applications in neuroscience, medicine, and virtual reality. Recent breakthroughs, such as Neuralink's brain implant technology, have showcased the potential to cure neurological diseases and spinal cord injuries. However, as BMIs become more invasive, questions arise about societal acceptance, regulatory challenges, and ethical considerations. This study explores the factors influencing potential users' attitudes and perceptions toward BMIs. We find that performance and effort expectancy, as well as trust and well-being, positively influence behavioral intention to use BMIs. Conversely, the level of invasiveness of BMI technology negatively impacts behavioral intention due to raised privacy concerns and technology fear. These results offer valuable insights for policymakers, healthcare professionals, and technology developers seeking to navigate the challenges and opportunities associated with the adoption of BMIs.

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Keywords
brain–machine interfaces (BMIs), neural implants, neurotechnology, technological adoption, wearable technology, well-being

Introduction

Several once-futuristic technologies have seamlessly integrated into our daily lives, blurring the lines between science fiction and reality (Drew, 2023). Notably, the proliferation of smart devices and wearables allows individuals to enhance their reality by overlaying information onto their real-world experiences. Amid this technological evolution, brain–machine interfaces (BMIs), also known as brain–computer interfaces (BCIs), have emerged as groundbreaking tools with diverse applications in neuroscience, medicine, and virtual reality (VR) (Tang et al., 2023). These innovative interfaces read the brain's activity and translate it into computationally processable information, with bidirectional BMIs even capable of transmitting information back to the brain to modify an individual's mental state. The field of BMIs development and research has experienced significant growth in recent years (Panetta, 2020). This surge in research activity can be attributed in part to the rapid and ongoing advancements in affordable computer hardware and software, as well as an increasing societal recognition of the needs of individuals grappling with severe neuromuscular disorders (Wolpaw, 2007).

The initial impetus for BMIs device development was rooted in the potential to offer novel therapeutic approaches for restoring motor control in severely disabled individuals, including those with spinal cord injuries (Lebedev and Nicolelis, 2006). BMIs are today widely used for healthcare applications such as monitoring (Michael and Michael, 2014), enhancement of medical devices, and other therapeutic purposes (Willett et al., 2023), and hold the potential to restore rapid communication to individuals with paralysis by decoding neural signals associated with attempted speech into text. Companies like Neuralink have taken on the mission to develop assistive technologies that offer restoration of movement and communication capabilities for individuals affected by paralysis-causing injuries or diseases (Drew, 2023). One notable milestone in the field of BMIs occurred on 28 August 2020, when Elon Musk's company, Neuralink, unveiled a significant breakthrough in BMIs technology by showing the successful implantation of a chip, into the brain of a pig (Bellon, 2020). Although some scientists downplayed the event, emphasizing the need for further research, the advances in electrode technology showcased a promising step toward realizing the future vision of curing neurological diseases such as dementia or spinal cord injuries. Besides Neuralink, numerous other companies, including Kernel, Qneuro, NeuroSky, EMOTIV, and even Facebook, are actively working on BMIs, underscoring the technology's current relevance, as evidenced by its inclusion on the 2020 Gartner's hype cycle for emerging technologies (Panetta, 2020). BMIs that not only read brain activity but also actively stimulate specific brain regions through implants (Hilken et al., 2023), and further emphasize the transformative potential of this technology in reshaping the boundaries between humans and technology (Lima et al., 2022).

In all developed countries with sophisticated information systems, containing health costs is a primary consideration, and routine healthcare decisions become much easier for the patients with these kinds of mobile healthcare (mHealth) applications. This trend has likely increased due to the COVID-19 pandemic to provide optimal remote tests and care (Birkmeyer et al., 2021). Scientific, technological, and demographic changes make healthcare a much more complex service to deliver (Berry and Bendapudi, 2007). Given the importance of health behaviors to well-being and health outcomes, BMI-based technologies have great potential in facilitating patient lifestyle and behavior modification through patient education, improved autonomous self-regulation, and perceived competence. On the contrary, while research on BMIs has primarily concentrated on medical applications, there is growing recognition of their future commercial potential, which could ultimately lead to a symbiotic relationship between human intelligence and artificial intelligence (AI), enhancing VR and augmented reality (AR) experiences by allowing users to control games with their thoughts, personalized learning experiences by monitoring cognitive states and adapting content delivery, enabling hands-free control of computers and other devices for increased efficiency, or enhancing the creative process by translating mental imagery directly into digital formats. This could also be used to track and treat medical patient data, and recommend personalized (health) products and services that perfectly fit the consumer needs. Moreover, beyond medical applications, companies have found commercial purposes. BMIs could track personal purchases and marketers then send promotional items personally tailored to their customers. Personalized shopping could be done with recommender systems that suggest healthier food and groceries according to the client's needs, pathologies, and diets measured remotely by the BMIs (Attie and Meyer-Waarden, 2023).

The potential impacts on mHealth hinge greatly on the extensive adoption of this emerging technology within a contemporary consumer-centric society. When referring to the use of BMIs in aiding the fight against chronic diseases in humans, the issue of privacy concerns arises. Since the BMI serves as a virtual personal medical record, all of the patient's medical and contact information is readily available. Should this technology fail to address key issues such as consumer trust, privacy concerns, and technological anxieties, its widespread acceptance could be hindered, resulting in limited profitability and implications for mHealth strategies (Smith, 2007). As technological embodiment progresses toward increasingly invasive devices like those developed by Neuralink, questions arise regarding who will embrace such transformative implants (Hilken et al., 2022).

To ensure successful commercialization, it is imperative to gain insights into people's attitudes and their level of acceptance toward this transformative technology (Laroche and Sadokierski, 1994), even though navigating the path to commercialization poses a complex challenge, characterized by a scarcity of clearly defined strategic approaches (Arias-Oliva et al., 2020). Limited academic evidence exists regarding consumer adoption of BMIs (Lima et al., 2022). So far, only five academic articles have been published in journals, most of which are not within management science. Their primary findings suggest that ease of use, usefulness, and trust are significant predictors of intention to use BMIs, with trust being influenced by technology safety. Concerns about painful procedures and other health-related issues diminish the perceived usefulness of BMIs (Žnidaršič et al., 2021). Furthermore, the limited research indicates that customers remain highly reluctant toward BMIs. An older study (Smith, 2007) reveals that most people lack personal knowledge of BMIs and express significant concerns about identity theft. Many are hesitant to install BMIs for non-medical purposes, such as password activation, banking, and financial transactions, as well as for use by authorities. Interestingly, most people are willing to accept BMIs for medical reasons. While attitudes may have evolved since then, a more recent study (Werber et al., 2018) indicates that reluctance persists, with many considering BMIs primarily for healthcare rather than personal identification, home use, or shopping. Assurance against GPS (Global Positioning System) tracking increases potential users, highlighting the impact of privacy concerns on BMI adoption. The scarcity of empirical research underscores the need for comprehensive studies on attitudes toward BMIs. Neuralink's data collection practices raise questions about whether the data collected qualifies as health data, as it is not primarily recorded for health-related applications (Partridge and Dodds, 2023). This ambiguity surrounding the classification of the data further highlights the complexity of regulatory and ethical considerations in BMIs.

While companies like Neuralink are pioneering invasive BCIs with the objective of enhancing communication speed by circumventing sensory bottlenecks (Hilken et al., 2022), it is crucial to acknowledge potential vulnerabilities associated with these technologies that could be targeted by malicious actors to manipulate neural activity (Bernal et al., 2023). Our study thus does a significant contribution to both theoretical and managerial domains within the BMI field. To the best of our knowledge, prior research in this domain has primarily originated from the medical sciences. The literature mostly focuses on medical, technical engineering, and computer science aspects, whereas management science aspects should be relevant to the question of BMI adoption and outcomes (Binyamin and Zafar, 2021). Our first contribution is that we enhance the UTAUT 2 model (Venkatesh et al., 2011), with theories taking into account new factors influencing the intention to use BMIs, including the concepts of well-being (Diener, 1984; Munzel et al., 2018), fear (Fox and Royne, 2018), trust (Pavlou, 2003), and privacy concerns (Hong and Thong, 2013). This extended UTAUT2 model contributes to a better understanding of BMI adoption factors, as even though mHealth and BMIs show a high commercial and medical potential, little is known about their influence on user well-being (Binyamin and Zafar, 2021). In other words, it is unclear whether BMIs lead to technology-mediated transformative experiences by creating smooth human–computer interactions to increase user well-being. Our research, therefore, makes an important contribution, as it explores a nuanced and comprehensive exploration of the direct factors and mediators influencing behavioral intention to use BMIs, providing valuable insights that enrich the literature (Anderson and Ostrom, 2015) on technology adoption surrounding futuristic disruptive technologies. This analysis uncovers multiple (in)direct pathways through which BMIs influence behavioral intention to use, providing a comprehensive understanding of the underlying mechanisms. Hence, the central focus of our research aims to address the following research question: How cognitive and affective factors influence user well-being and adoption of BMI technology? In exploring these inquiries, we seek to shed light on the factors shaping the adoption of this transformative technology, ultimately informing both policy and innovation in the field. These insights can serve as a valuable guide for managers, directing their focus on specific factors when designing communication campaigns aimed at promoting the adoption of BMI technology.

The structure of our research article is as follows: We begin by reviewing the existing literature within the BMI research field. Subsequently, we elucidate our conceptual model and articulate our hypotheses. We then describe the methodology employed in our study. Our findings are presented and discussed, elucidating both theoretical insights and managerial implications. In conclusion, we address the limitations of our research and propose avenues for future investigations, further advancing our understanding of the factors influencing the utilization of BMI technology.

Background

BMIs

BMIs constitute a remarkable communication pathway between the human brain and an external device that operates independently of the brain's conventional output channels, which include peripheral nerves and muscles. Instead of relying on the usual mechanisms involving nerve and muscle-generated movements, BMIs harness recorded brain signals that are then translated into real-time output commands. This functionality empowers the user to control a wide array of devices in the external world, spanning from physical entities like computers, lights, televisions, and wheelchairs to virtual elements such as a cursor on a computer screen (Wolpaw et al., 2000b). Consequently, BMIs emerged as innovative mental prostheses, facilitating communication between computers and disabled individuals, providing a valuable non-muscular communication option utilizing various means such as forehead-attached rods or tooth-embedded keys to enable muscular movements for interaction (Farwell and Donchin, 1988; Lebedev and Nicolelis, 2006; Wolpaw et al., 2000a). For the practical functioning of BMIs, signal acquisition is essential (Leuthardt et al., 2009), which can be achieved through either invasive or noninvasive methods. Invasive techniques involve the direct recording of single-neuron activity using electrodes implanted within the brain, while noninvasive approaches capture signals from the scalp or the brain's surface through radio frequency identification (RFID; Lebedev and Nicolelis, 2006; Wolpaw et al., 2000b). Noninvasive signal recording avoids the need for surgical intervention, but suffers from limited bandwidth due to signal attenuation when passing through brain tissue, bone, and skin, thus impeding its suitability for applications requiring high transmission rates, such as prosthetic control (Lebedev and Nicolelis, 2006; Leuthardt et al., 2009; Wolpaw, 2007; Wolpaw et al., 2000b). The most recent advancements in BMI technology are being pioneered by Musk and Neuralink (2019), who have developed a neurosurgical robot capable of precise electrode insertion into the brain (Musk and Neuralink, 2019).

The promising future development of BMIs hinges on several critical factors, including access to a sufficient number of appropriate and motivated users, which represents a challenge. (Wolpaw et al., 2000a). Moreover, perceived ease of use plays a crucial role, as constant screen availability can complicate the user experience, affecting perceived ease of use (Wolpaw et al., 2000b). For BMIs to gain acceptance among patients, they must mimic the behavior and sensation of the users' own limbs (Lebedev and Nicolelis, 2006). Nevertheless, one of the most significant unanswered questions pertains to the commercial appeal and marketability of BMIs (Schwartz et al., 2006; Wolpaw et al., 2000a). The future will reveal whether adequate commercial interest can successfully navigate the multifaceted challenges associated with BMI development, whether in clinical or non-clinical applications.

Literature on BMI

Limited academic evidence is available concerning consumer acceptance of BMIs (Lima et al., 2022, Table 1). The findings indicate that consumers' attitudes and intentions to use BMIs are positively influenced by factors like perceived ease of use, usefulness, and perceived threat (Žnidaršič et al., 2021). Furthermore, trust in BMI technology is negatively affected by perceived risks, discomfort, and health considerations (Werber et al., 2018). In addition, consumers' health concerns and subjective norms indirectly impact attitudes and intentions through intermediaries such as threat perception, usefulness, and ease of use (Werber et al., 2018; Žnidaršič et al., 2021). Research suggests that a significant portion of the population harbors reservations and concerns regarding BMI usage. Specifically, 67% of individuals lack enthusiasm about using BMIs, with 69% expressing reluctance toward invasive BMIs designed to enhance cognitive abilities. Moreover, a substantial majority (72%) believes that BMIs infringe upon ethical boundaries, while 77% perceive that individuals with BMIs may experience increased productivity in their professions and potentially enhance cognitive capacities.

The main limitations identified across these existing studies on BMIs are significant and encompass various aspects of research methodology, theoretical underpinning, and breadth of analysis. First, the absence of a theoretical framework and the neglect of academic measurement scales hinder the establishment of a solid conceptual basis and standardized metrics for assessing BMI-related phenomena. Second, the lack of comparison between invasive and noninvasive BMIs limits the comprehensiveness of the studies, indicating the importance of conducting comparative analyses to elucidate the strengths and weaknesses of different measurement approaches. Finally, the failure to integrate considerations of privacy risks, well-being, and other relevant factors in BMI research overlooks crucial dimensions that can influence outcomes and implications.

In light of these limitations, our research encompasses a broader scope, integrating multidisciplinary perspectives to comprehensively assess the complexities surrounding BMI and its implications for individuals' trust, technology fears, including privacy concerns, and overall user well-being. From the methodological point of view, our research addresses these gaps by employing rigorous methodologies, incorporating solid theoretical frameworks established measurement scales based on the UTAUT 2 (Venkatesh et al., 2003; Venkatesh et al., 2011), user well-being (Diener, 1984), trust (Pavlou, 2003), risk (Yang et al., 2018), and privacy concerns (Hong and Thong, 2013). We furthermore conduct comparative analyses between (non)invasive BMIs, and integrate perspectives to enhance the depth and breadth of understanding regarding BMI-related phenomena.

Conceptual framework and hypotheses development

Many models and frameworks have been developed to explain the user adoption behaviors of

Table 1. Literature on BMI adoption.

Authors	Theoretical framework	Variables	Method/data	Results
Smith (2007)	None	General perceptions about BMI usage applications No academic measurement scales	Noninvasive BMI N = 64, convenience sample, USA Descriptive statistics	Perceived ease of use, perceived usefulness, and threat influence the consumer's attitude and behavioral intention to use BMIs Usage of health IT impacts attitudes that influence behavioral intention to use BMIs Consumers' health concerns, subjective norms, have an indirect impact on attitudes and behavioral intentions through threat, usefulness, and ease of use
Werber et al. (2018)	TAM	TAM variables: Perceived ease of use (PEU), Perceived usefulness (PU), Behavioral intention to use, Perceived trust, Health concerns	Invasive BMI N = 531, convenience sample, Slovenia SEM	PU positively influences intention to use PEU is NS Trust positively, health concerns negatively influence intention to use
Sion (2019)	None	General perceptions about BMI usage applications and impact on cognitive skills and fears No academic measurement scales	Invasive BMI, N = 3,600, USA Descriptive statistics	67% are not enthusiastic and worried 69% do not want invasive BMIs to improve cognitive capacities 72% think BMIs go too far 77% think people will be more productive at their jobs and could increase cognitive capabilities
Žnidarsic et al. (2021a)	TAM	TAM variables: Perceived ease of use (PEU), Perceived usefulness (PU), Behavioral intention to use perceived risk, trust, pain, health concerns	Noninvasive BMI N = 804, convenience sample, Slovenia, Poland SEM	PEU positively influences PU and intention to use Perceived risk, pain, and health concerns negatively influence trust
Žnidarsic et al. (2021b)	None	General perceptions about BMI adoption factors No academic measurement scales	Invasive BMI N = 2,037, Convenience sample, Poland, Croatia, Slovenia, Ukraine, Russia Descriptive statistics	Negative effect on BMI adoption age Positive effect on BMI adoption lost keys and wallets, number of profiles on social media, proportion of credit card purchases
This study	UTAUT2 Trust framework	UTAUT2 variables: effort expectancy, performance expectancy Trust, privacy concerns, technology fear, well-being	Invasive vs non-invasive BMI N = 504, convenience sample, France PROCESS	Performance and effort expectancy, as well as trust and well-being, positively influence behavioral intention to use BMIs The level of invasiveness of BMI technology negatively impacts behavioral intention due to raised privacy concerns and technology fear

new technologies, and these models introduce factors that can affect user intention to use. The most used and predominant models are the technology acceptance model (TAM; Davis, 1989) and the unified theory of acceptance and use of technology (UTAUT1&2) model (Venkatesh et al., 2011) because of their parsimony and power of explication for the intention of usage of new technologies. TAM is based on the theory of reasoned action (Fishbein and Ajzen, 1975), which aims to explain the relationship between perceived usefulness and ease of use of a new technology, and behavioral intentions to use it. An individual's decision to use a particular technology is thus based on (1) the fact of how a person believes that using a new technology is free of effort and (b) the outcomes the individual expects as a result of performing the behavior of usage. For our research we chose UTAUT 2 (Venkatesh et al., 2011) and not TAM (Davis, 1989), since it is more used through a review and consolidation of the constructs of more theories (King and He, 2006). It includes a consolidation of the constructs of different models, such as performance and effort expectancy, to explain the user adoption of new technologies. We have extended UTAUT 2 with the following concepts to adapt it to the BMI context. First, we have used well-being (Diener, 1984), as well-being has become an important asset in marketing strategies and is attracting increased attention in marketing science research (Attié and Meyer-Waarden, 2019; Munzel et al., 2018). Indeed, BMIs aim at improving well-being and physical health (Kalem and Turhan, 2015; Karahoca et al., 2018), and can help monitor health variables. Therefore, the main promise of BMIs is to enhance well-being and provide users with a better quality of life and health. Subsequently, we have added trust (McKnight et al., 2011; Pavlou, 2003), perceived risk (Slovic, 1987), the concept of technology fear (Yang et al., 2018), and privacy concerns (Hong and Thong, 2013). All these variables have been studied and validated in prior research, albeit in different constellations (Attié and Meyer-Waarden, 2019), providing a solid foundation for our adapted TAM in the context of the implanted BMI chip.

Unified theory of acceptance and use of technology

According to Rogers' diffusion of innovation theory established in 1962, the adoption of an innovation by consumers is contingent upon their perception that it offers a distinct benefit compared with existing solutions (Rogers, 1995). UTAUT 2 defines performance expectancy as "the degree to which using a technology will provide benefits to consumers in performing certain activities" (Venkatesh et al., 2011). This concept serves as a precursor to the behavioral intention to use the technology being defined as the psychological factor that determines an individual's inclination to engage in a particular behavior to use a new technology, the most proximal determinant of human social behavior (Venkatesh et al., 2011). Performance expectancy is one of the key factors that influence a person's intention to use a particular technology. BMIs can offer different advantages, increasing the performance of users (e.g. password activation, payment transactions and shopping, social security number and/or driver's license functions, medical management; Werber et al., 2018). Future functions might include enabling users to comprehend and communicate in any language without the necessity of language acquisition. These capabilities give individuals equipped with BMI with a distinctive advantage over those without it, as they can save considerable time, effort, and resources that would otherwise be expended on managing these functions, including language learning endeavors, ultimately leading to improved performance. Consequently, we propose the following hypotheses:

> *H1. Performance expectancy of BMIs has a positive effect on the behavioral intention to use BMIs.*

Effort expectancy is defined as "the degree of ease associated with the consumers' use of the technology," which pertains to the absence of difficulty or effort when employing a new technology (Venkatesh et al., 2011). In UTAUT 2, the impact of effort expectancy on performance expectancy is well established (Venkatesh et al., 2003; Venkatesh et al., 2011), because an individual's belief regarding the potential benefits of new and disruptive (e.g. BMI) technology may be subject to change if they perceive its usage to be arduous or challenging. Thus, the higher the effort expectancy is, the more easily the BMI technology should be used, and the more it should engender a positive experience and capabilities and help users in their daily lives; subsequently, effort expectancy should have a positive impact on performance expectancy (Gao and Bai, 2014). Hence:

H2. Effort expectancy of BMIs has a positive effect on performance expectancy of BMIs.

Well-being

The consumer behavior literature suggests that while utilitarian value, as indicated by effort expectancy and performance expectancy, plays a role in technology adoption, it alone is insufficient (Chitturi et al., 2008; Hsee et al., 2009). In addition to these factors, consumers seek experiences that contribute to their overall well-being, happiness, and other positive emotions when engaging with technology (Sirgy, 2012). There is a growing interest in well-being within academia and transformative marketing research (Sirgy, 2012). Well-being encompasses how consumers perceive their experiences in positive ways through cognitive judgments and affective reactions, independent of objective facts (Medvedev and Landhuis, 2018). Well-being can be linked to physical and mental health (Rozanski and Kubzansky, 2005), positive moods and emotions, and a pleasant affect, all of which refer to positive emotions, life satisfaction, and quality of life (Diener et al., 1985). Factors such as life satisfaction, optimism, and the presence of positive emotions are key indicators used to assess well-being (Diener and Chan, 2011). In the literature, research has identified a significant impact of well-being on consumer decisions regarding the acceptance and use of new disruptive technologies such as smart objects (Attié and Meyer-Waarden, 2019; Meyer-Waarden et al., 2021). In the context of the study of BMIs, individuals might gain new abilities (e.g. comprehending and communicating in any language), thereby inducing well-being linked to physical (e.g. gain of new capacities, healing a disease) and mental health (e.g. positive emotions) by simplifying both their personal and professional life and thus increasing performance expectancy. Thus:

H3. Performance expectancy of BMIs has a positive effect on user well-being.

Research indicates that consumers' perceived well-being significantly influences their choices and utilization of technology (Diener and Chan, 2011). By engaging with new technologies like BMIs, consumers' well-being, psychological, and physical health may undergo transformations (Zhong and Mitchell, 2012). These technologies can enhance user capabilities, screen health conditions through automation and sensors, and improve overall health quality (Dhar and Wertenbroch, 2000). BMIs particularly excel in managing situations that demand complex interactions with the environment, which can be challenging for humans. Consequently, BMIs have the potential to elevate user security levels, thereby enhancing both physical and psychological well-being, leading to positive behavioral outcomes. When users perceive a higher level of well-being associated with BMI usage, it tends to augment their positive mental, psychological, and physiological representations of technology use (Davis and Pechmann, 2013). Consequently, an enhancement in well-being following BMI use is expected to strengthen the intention to utilize the technology further. Therefore:

H4. User well-being has a positive effect on behavioral intention to use BMIs.

Trust framework

Consumer decisions regarding technology involve considerations of trust due to the inherent uncertainty surrounding their outcomes (McKnight and Chervany, 2001). Trust encompasses consumers' confidence and reliance on the security, reliability, and integrity of a technology (McKnight et al., 2011). Consequently, trust plays a crucial role in recent models of disruptive technology acceptance (Ostrom et al., 2019), particularly in mitigating uncertainties associated with these innovations (Pavlou, 2003). Numerous studies have underscored the significant impact of trust on shaping intentions to adopt technology (Venkatesh et al., 2011), with trust also being linked to its effects on well-being (Gao and Bai, 2014).

BMIs can undertake repetitive and uncomfortable tasks, thereby supporting users comprehensively in various activities. As a result, BMIs are expected to foster trust by seamlessly integrating into users' daily routines, aiding them in their tasks, and operating efficiently and effectively (Meyer-Waarden et al., 2022). Enhanced trust, in turn, should bolster users' perceptions of performance and effort expectancy, ultimately contributing to their well-being (Meyer-Waarden et al., 2022). Furthermore, when users experience high levels of trust while engaging with technologies like BMIs, they often enter a state of flow, characterized by a sense of well-being that motivates continued usage. For instance, a BMI supporting healthcare could positively impact user trust, and subsequently physical and emotional well-being. Consequently, the use of BMIs is anticipated to provide better support, increase user trust, enhance physical and psychological well-being, and consequently influence intentions to use BMIs positively (Meyer-Waarden et al., 2022). Thus:

H5. Trust in BMIs has a positive effect on user well-being.

H6. Trust in BMIs has a positive effect on behavioral intention to use BMIs.

Invasiveness

BMIs are among the most invasive technologies in terms of bodily intervention. Therefore, perceived risk (Slovic, 1987) stands out as the primary hurdle hindering consumers from expressing an intention to adopt them (van Pinxteren et al., 2019). Invasiveness relates to the extent to which a (BMI) device penetrates the body (Melenhorst et al., 2004). Melenhorst et al. (2004) delineate three dimensions of potential technology invasiveness: physical obtrusion, privacy, and security risk. Physical obtrusion pertains to how the physical presence of a device is perceived by users, encompassing factors such as the device's location within the user's body, its visual appearance, size, and weight. Privacy risk involves the undesired disclosure of private or personal information, which may not necessarily result in misuse. Finally, security risk denotes the intrusion into the technical system, potentially leading to damage or misuse of information, often at the hands of hackers or malicious actors (Melenhorst et al., 2004). These BMI technology-related risks, encompassing concerns such as physical injuries due to potential loss of control, privacy breaches, hacking, data theft, addiction, and ethical considerations, are perceived as significant by approximately 91% of individuals regarding BMI technologies (Smith, 2007). Consequently, factors such as technology fear and privacy concerns hold considerable importance in contemporary TAMs (Ostrom et al., 2019).

Technology fear refers to the apprehension some individuals may experience when faced with using new or unfamiliar technologies (Thatcher and Perrewe, 2002). This fear may stem from perceptions of BMI capabilities, potential errors, or loss of control, leading to negative responses like avoidance or mistrust. Numerous studies have demonstrated that technology fear, particularly stemming from concerns about loss of control, exerts a detrimental effect on trust, as well as adoption and usage of technologies across diverse contexts (Subero-Navarro et al., 2022). Therefore, we hypothesize that health risks associated with BMI usage, and subsequently, technology fear, have the potential to erode trust, consequently diminishing behavioral intentions to utilize the technology (Yang et al., 2018). Hence:

H7. Technology fear due to BMIs has a negative effect on trust into BMIs.

In recent years, the concept of privacy concerns has garnered considerable academic interest, notably fueled by the rapid expansion of information technology and the ubiquitous use of the Internet (Baruh et al., 2017; Lutz et al., 2017). Consumers increasingly desire the ability "to control when, how, and to what extent his or her personal information is communicated to others" (Hong and Thong, 2013: 276), primarily due to the risks associated with cyberstalking, hacking, and unauthorized data usage (Smith et al., 1996). Privacy concerns encompass an individual's apprehension regarding the risks and potential adverse outcomes associated with disclosing personal information (Baruh et al.,

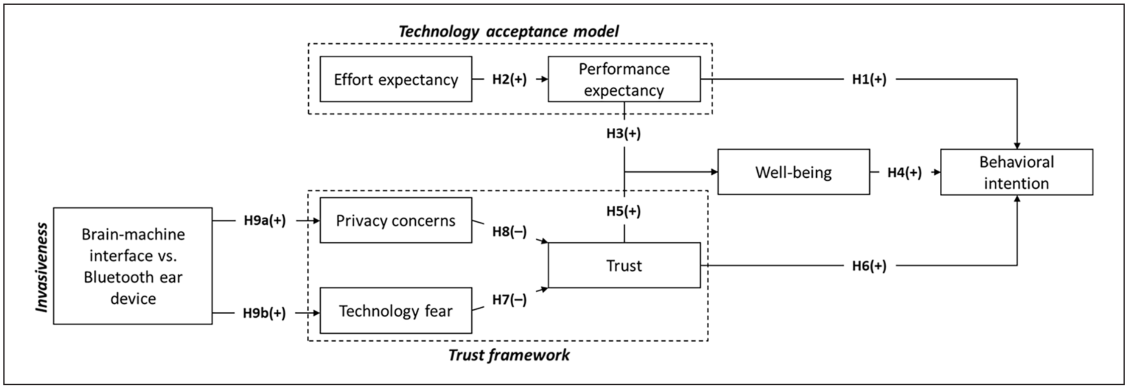

Figure 1. Conceptual model.

2017). Users may harbor anxieties concerning the appropriate collection, storage, and utilization of their personal data by service providers. While studies have underscored the significance of privacy concerns in the acceptance of new information technologies like AI (Attour et al., 2020; Ostrom et al., 2019), notably absent are investigations pertaining to BMIs. These concerns exert a detrimental effect on consumers' technology-related behaviors, influencing trust and adoption. In the context of both invasive and noninvasive BMIs, which necessitate consistent and highly sensitive data collection for operation, privacy concerns emerge as a critical consideration in technology adoption (Hong and Thong, 2013). Consequently, we posit that privacy concerns regarding BMIs adversely impact trust in the technology (Joinson et al., 2010). Therefore:

H8: Privacy concerns due to BMIs have a negative effect on trust in BMIs.

H9a: Invasiveness of BMIs has a positive impact on privacy concerns due to BMIs.

H9b: Invasiveness through BMIs has a positive impact on technology fear due to BMIs.

Figure 1 represents the conceptual model.

Data and methods

Sample characteristics

We conducted our survey online in France in 2022, gathering responses from a total of 504 participants. Among the respondents, 60.2% were women. The average age of the participants was 29.2 years, with a standard deviation of 12.8 years.

Research design

Studying BMIs like Neuralink is intriguing due to its multifaceted applications across different domains. These interfaces can facilitate real-time translation of thoughts into speech, enhancing communication for those unable to speak (Maiseli et al., 2023). In smart homes, they allow users, particularly those with disabilities, to control their environment using just their thoughts, promoting independence (Maiseli et al., 2023). Health-wise, they offer the potential to restore functions lost to neurological diseases, dramatically improving patient independence and quality of life (Kalinoski, 2024). In addition, they could enhance cognitive processes, expanding human memory and learning capabilities, which could revolutionize education and professional fields (Maiseli et al., 2023).

We employed a between-subject 2 × 4 factorial design, with two levels of invasiveness (invasive BMI and noninvasive Bluetooth ear BMI devices) and four different usage scenarios (i.e. translation, smart home, health, and knowledge) to manipulate and diversify the conditions, thereby enhancing the generalizability of our results. Prior to completing the questionnaire, participants were instructed to view a brief 1-minute video presentation about the diverse applications of BMIs. The participants were randomly assigned to one of the distinct scenarios.

For invasiveness, the first video depicted the BMI chip being surgically implanted in the brain, while the second video showcased the chip being connected via Bluetooth. This approach was employed to assess the impact of the varying degrees of invasiveness associated with the two chip variants on our research model.

Measurement instruments

We adapted existing scales from the literature: effort expectancy (e.g. “I would find it easy to use and set up this technology”) and performance expectancy (e.g. “This technology would be a good assistant in my daily life”) (Venkatesh et al., 2011), trust (e.g. “I think this technology would provide 100% reliable services”) (Morgan and Hunt, 1994), well-being (e.g. “If I lived with this technology, my life quality would be improved to ideal”) (Meyer-Waarden and Cloarec, 2022), behavioral intention to use (e.g. “Looking at its benefits, I intend to live with this technology in the future”) (Venkatesh et al., 2011), privacy concerns (e.g. “I would be concerned about threats to my personal privacy from this technology”) (Hong and Thong, 2013), and perceived technology fear (e.g. “This technology could lead to dangerous side effects due to malfunctions or misuse”) (Lijarcio et al., 2019; Yang et al., 2018).

Data quality

Measurement model. To assess the measurement model, we conducted confirmatory factor analysis with the lavaan package (Rosseel, 2012). The measurement model demonstrates a strong fit, as indicated by the typical fit indices: root mean square error of approximation (RMSEA) = 0.07, comparative fit index (CFI) = 0.93, and Tucker–Lewis index (TLI) = 0.92. Furthermore, the psychometric properties are satisfactory (Tables 2 and 3). The constructs exhibit good reliability, convergent validity (AVE > 0.50), and discriminant validity (HTMT coefficients < 0.85).

Common method bias. To verify common method bias (Podsakoff et al., 2003), we used the *ConMET* package (De Schutter, 2021) in R to test various model configurations by loading items from different constructs onto the same latent variable (Table 4). Each of these configurations resulted in a significantly poorer fit for our measurement model, evident from the substantial increase in the chi-square value (χ^2) with a *p*-value of less than 0.001, as reported in Table 4. Furthermore, we assessed the utility of Harman’s single-factor test (Harman, 1967) and a latent common method variance factor test, but the findings suggested suboptimal or nonsignificant performance in contrast to our measurement model. Our findings suggest that common method bias does not pose a substantial problem in our study.

Post hoc power analysis. To ensure the robustness of our findings, we conducted a series of checks. A post hoc power analysis assessed whether our sample size was sufficient for generating reliable estimates (Moshagen and Erdfelder, 2016). We utilized the *semPower* package (Jobst et al., 2021) to evaluate the statistical power of our analysis. Considering that the RMSEA value is 0.07, the sample size is 504, there are 413 degrees of freedom, and the alpha level is set at 0.05, the calculations demonstrate that our statistical power is highly satisfactory, exceeding 0.99.

Results

Manipulation check

We employed a *t*-test with the *stats* package in R to assess the manipulation check of invasiveness between the invasive BMIs interface and the noninvasive Bluetooth ear device scenarios. The results indicate that respondents perceived a higher level of invasiveness when presented with the invasive BMI scenario ($M_{\text{BMIs}} = 5.54$, $SD = 1.66$) compared with those exposed to the noninvasive Bluetooth ear device scenario ($M_{\text{Bluetooth}} = 5.06$, $SD = 1.70$, $t(502) = -3.17$, $p = 0.002$).

Test of the model

We implemented the model in R using the PROCESS macro (Hayes, 2021) with the following custom syntax:

process(data=df, y=“BI”,”, x=“Invasiveness”,”, m=c(“EE”,”,“PC”,”, “PTF”,”, “PE”,”, “T”,”, “WB”), cov= c(“Age”,”, “Gender”), bmatrix = c(0,1,0,1,0,0,0 ,1,0,0,0,0,1,1,0,0,0,0,0,1,1,0,0,0,0,1,1,1), cmatrix = c(1,1,1,1,1,1,1,1,1,1,1,1,1,1), conf=95)

Table 2. Measurement instruments.

Construct	α	AVE	β
Performance expectancy	0.93	0.78	
PE1 – This technology would be a good assistant in my daily life			0.83
PE2 – This technology would help me save useful time in my daily life			0.89
PE3 – This technology would make my everyday life easier			0.94
PE4 – This technology would increase my efficiency in my daily life			0.87
Effort expectancy	0.79	0.58	
EE1 – I would find it easy to use and set up this technology			0.69
EE2 – I would find it easy to become skillful at using this technology			0.85
EE3 – I would learn quickly how to use this technology			0.74
Technology fear	0.83	0.53	
TF1 – This technology could lead to dangerous side effects due to malfunctions or misuse			0.86
TF2 – This technology may not be completely safe and could represent potential physical risks			0.88
TF3 – This technology would give me the impression that I lose too much control of my brain to technologies			0.72
TF4 – I don't think anyone knows the risk of this technology			0.38
TF5 – I fear this technology could create damages to my brain			0.79
Trust	0.92	0.69	
T1 – I think this technology would provide 100% reliable services			0.83
T2 – I think this technology would not fail me			0.77
T3 – I think this technology would be 100% trustworthy			0.85
T4 – I do trust in the efficacy of this technology			0.81
T5 – I have 100% confidence in this technology			0.88
Well-being	0.90	0.76	
WB1 – If I lived with this technology my life quality would be improved to ideal			0.81
WB2 – If I lived with this technology my feelings of well-being would be improved			0.91
WB3 – If I lived with this technology my feelings of happiness would be improved			0.89
Behavioral intention to use	0.92	0.79	
BI1 – Looking at its benefits, I intend to live with this technology in the future			0.93
BI2 – Looking at its benefits, If I had access to this technology, I intend to live with one in my brain			0.88
BI3 – The probability that I have this technology in the future is . . .			0.86
Privacy concerns	0.95	0.70	
PC1 – I would be concerned about threats to my personal privacy from this technology			0.75
PC2 – I would be afraid to use this technology because cyber pirates could steal my identity and data			0.83
PC3 – I would be afraid to use this technology because cyber pirates might hack into my account			0.78
PC4 – I would be afraid that this technology is collecting too much of my personal data			0.88
PC5 – I would be afraid to use this technology because other people or firms might publish my personal information without my consent			0.87
PC6 – I would be afraid to use this technology because it might insufficiently protect my personal data			0.92
PC7 – I would be afraid to use this technology because it might track and analyze my personal data for personalized offers			.81
PC8 – I would be afraid to use this technology because it might share personal data with other firms for purposes I don't know about			0.87

Notes. PE: performance expectancy; EE: effort expectancy; TF: technology fear; T: trust; WB: well-being; BI: behavioral intention; PC: privacy concern.

Our model (Figure 2) accounts for 63% of the variance in behavioral intention. H1 finds support as performance expectancy significantly and positively impacts behavioral intention to use BMIs ($b=0.09$, $p<0.001$). H2 is supported, indicating that effort expectancy significantly and positively influences performance expectancy ($b=0.41$, $p<0.001$). In addition, H3 is supported as performance expectancy significantly and positively affects well-being ($b=0.26$, $p<0.001$), while H4 is supported with well-being significantly and positively impacting behavioral intention to use BMIs ($b=0.53$, $p<0.001$). Moreover, H5 demonstrates support as trust significantly and positively influences well-being ($b=0.28$, $p<0.001$), and H6 indicates trust significantly and positively affects behavioral intention to use BMIs ($b=0.19$, $p<0.001$). Furthermore, H7 is supported, showing that technology fear significantly and negatively influences trust ($b=-0.40$, $p<0.001$), and H8 is supported with privacy concerns significantly and negatively influencing trust

Table 3. HTMT coefficients.

	PE	EE	TF	T	WB	BI	PC
PE	–						
EE	0.40	–					
TF	0.20	0.43	–				
T	0.42	0.56	0.48	–			
WB	0.72	0.48	0.41	0.68	–		
BI	0.65	0.51	0.44	0.67	0.82	–	
PC	0.11	0.25	0.58	0.38	0.27	0.29	–

Notes. PE: performance expectancy; EE: effort expectancy; TF: technology fear; T: trust; WB: well-being; BI: behavioral intention to use; PC: privacy concern.

Table 4. Common method bias.

	Chisq	*df*	*CFI*	*RMSEA*	*SRMR*	*Chisqbydf*	*Chisq.Diff*
Proposed model	1,317.348	413	0.931	0.066	0.054	3.19	
EE and PE	1,809.307	419	0.893	0.081	0.089	4.318	491.96***
EE and T	1,655.081	419	0.905	0.077	0.063	3.95	337.733***
EE and WB	1,717.1	419	0.901	0.078	0.066	4.098	399.752***
EE and BI	1,687.748	419	0.903	0.078	0.064	4.028	370.4***
EE and PC	1,908.582	419	0.886	0.084	0.106	4.555	591.235***
EE and PTF	1,796.681	419	0.894	0.081	0.082	4.288	479.334***
PE and T	2,838.405	419	0.815	0.107	0.082	6.774	1,521.058***
PE and WB	2,019.593	419	0.877	0.087	0.075	4.82	702.245***
PE and BI	2,253.816	419	0.859	0.093	0.082	5.379	936.468***
PE and PC	3,316.744	419	0.778	0.117	0.156	7.916	1,999.396***
PE and PTF	2,649.413	419	0.829	0.103	0.145	6.323	1,332.065***
T and WB	2,013.223	419	0.878	0.087	0.068	4.805	695.875***
T and BI	2,034.984	419	0.876	0.087	0.064	4.857	717.636***
T and PC	3,052.139	419	0.798	0.112	0.15	7.284	1,734.791***
T and PTF	2,239.749	419	0.861	0.093	0.084	5.345	922.401***
WB and BI	1,577.905	419	0.911	0.074	0.055	3.766	260.558***
WB and PC	2,719.396	419	0.824	0.104	0.15	6.49	1,402.048***
WB and PTF	2,401.265	419	0.848	0.097	0.099	5.731	1,083.917***
BI and PC	2,807.712	419	0.817	0.106	0.149	6.701	1,490.364***
BI and PTF	2,336.287	419	0.853	0.095	0.097	5.576	1,018.94***
PC and PTF	2,225.997	419	0.862	0.093	0.091	5.313	908.65***
Harman's One Factor	7,669.604	434	0.446	0.182	0.164	17.672	6,352.257***
Latent CMV fixed	1,316.997	412	0.931	0.066	0.054	3.197	0.35

Notes. PE: performance expectancy; EE: effort expectancy; PTF: technology fear; T: trust; WB: well-being; BI: behavioral intention to use; PC: privacy concern; CMV: common method variance; ***$p < 0.001$.

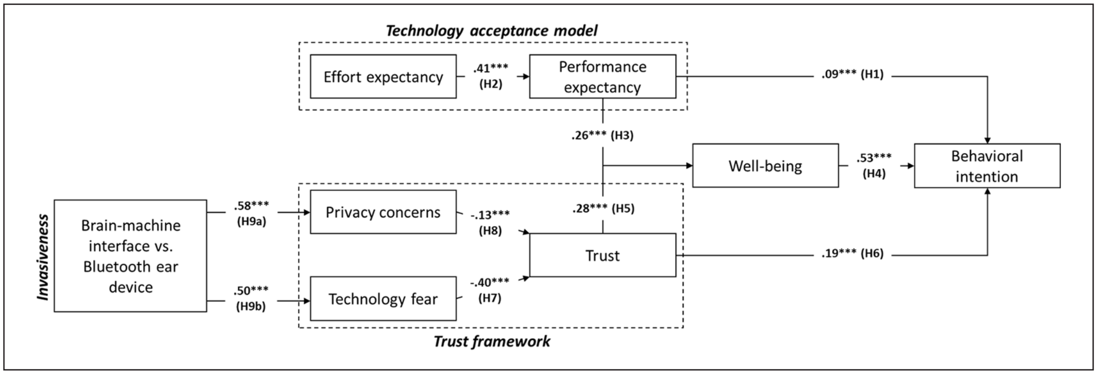

Figure 2. PROCESS results.

Table 5. Indirect effects.

	Effect	BootSE	95% CI	
			Lower	Upper
Total	–0.0901	0.0230	–0.1388	–0.0485
BMIs → TF → T → BI	–0.0366	0.0112	–0.0611	–0.0178
BMIs → TF → T → WB → BI	–0.0292	0.0087	–0.0487	–0.0143
BMIs → PC → T → BI	–0.0135	0.0068	–0.0293	–0.0031
BMIs → PC → T → WB → BI	–0.0108	0.0053	–0.0230	–0.0025

Notes. TF: technology fear; T: trust; WB: well-being; BI: behavioral intention to use; PC: privacy concern; BMIs: brain–machine interfaces.

(b=–0.13, p < 0.001). Finally, H9a finds support as invasiveness significantly and positively influences privacy concerns (b=0.58, p < 0.001), and H9b is supported, indicating that invasiveness significantly and positively influences technology fear (b=0.50, p < 0.001).

Mediation analysis

The mediation analysis (5,000 bootstrap samples; Table 5) revealed several indirect effects of the independent variable (BMIs) on the dependent variable (behavioral intention to use BMIs) through various mediator variables (technology fear, trust, well-being, effort expectancy, performance expectancy). Specifically, the total indirect effect of BMIs on behavioral intention to use BMIs was –0.0901 (BootSE=0.0230, 95% CI=[–0.1388, –0.0485]). Individual indirect effects were observed as follows: (1) BMIs had an indirect effect on behavioral intention to use through the path BMIs → technology fear → trust → behavioral intention to use with an effect of –0.0366 (BootSE=0.0112, 95% CI=[–0.0611, –0.0178]); (2) BMIs had an indirect effect on behavioral intention to use through the path BMIs → technology fear → trust → well-being → behavioral intention to use with an effect of –0.0292 (BootSE=0.0087, 95% CI=[–0.0487, –0.0143]); (3) BMIs had an indirect effect on behavioral intention to use through the path BMIs → privacy concerns → trust → behavioral intention to use with an effect of –0.0135 (BootSE=0.0068, 95% CI=[–0.0293, –0.0031]); (4) BMIs had an indirect effect on behavioral intention to use through the path BMIs → privacy concerns → trust → well-being → behavioral intention to use with an effect of –0.0108 (BootSE=0.0053, 95% CI=[–0.0230, –0.0025]). These findings provide insights into the multiple pathways through which BMIs influence behavioral intention to use in the mediation model.

Robustness check

To ensure our results are consistent across different contexts, we retested the model by controlling for four scenarios: translation, smart home, health, and knowledge, with health as the reference category. The results, which are detailed below, remained consistent, thereby affirming their robustness and generalizability.

Our model accounts for 64% of the variance in behavioral intention. H1 finds support as performance expectancy significantly and positively impacts behavioral intention to use BMIs ($b = 0.06$, $p < 0.01$). H2 is supported, indicating that effort expectancy significantly and positively influences performance expectancy ($b = 0.46$, $p < 0.001$). In addition, H3 is supported as performance expectancy significantly and positively affects well-being ($b = 0.28$, $p < 0.001$), while H4 is supported with well-being significantly and positively impacting behavioral intention to use BMIs ($b = 0.56$, $p < 0.001$). Moreover, H5 demonstrates support as trust significantly and positively influences well-being ($b = 0.25$, $p < 0.001$), and H6 indicates trust significantly and positively affects behavioral intention to use BMIs ($b = 0.21$, $p < 0.001$). Furthermore, H7 is supported, showing that technology fear significantly and negatively influences trust ($b = –0.36$, $p < 0.001$), and H8 is supported with privacy concerns significantly and negatively influencing trust ($b = –0.14$, $p < 0.001$). Finally, H9a finds support as invasiveness significantly and positively influences privacy concerns ($b = 0.59$, $p < 0.01$), and H9b is supported, indicating that invasiveness significantly and positively influences technology fear ($b = 0.50$, $p < 0.001$).

Discussion and contributions

Discussion of the results

First, the positive influence of performance expectancy on behavioral intention aligns with existing research, indicating that individuals are more inclined to intend to use a technology when they perceive it as beneficial (Venkatesh et al., 2011; Drew, 2023; Tang et al., 2023). One notable finding in our study is the significant impact of performance expectancy of BMIs on well-being, providing empirical evidence for the idea that users' perceived utility and benefits significantly contribute to their overall well-being (Drew, 2023; Tang et al., 2023). This corresponds with the previous transformative marketing literature highlighting the importance of user well-being experience and performance expectancy in the adoption of cutting-edge technologies (Meyer-Waarden and Cloarec, 2022).

Moreover, our results demonstrate the pivotal role of trust in shaping both well-being and behavioral intention to use BMIs. Trust has long been recognized as a fundamental factor in technology adoption (Hilken et al., 2022), and our findings reinforce this concept by showing that higher levels of trust are associated with improved well-being and a greater likelihood of adopting BMIs. Conversely, the adverse effects of privacy concerns and technology fear on trust underscore the critical necessity of addressing privacy (Malhotra et al., 2004; Martin and Murphy, 2017) and security issues (Roca et al., 2009; Slovic, 1987) in the development and deployment of futuristic technologies (Bernal et al., 2023). Our findings offer empirical support for previous literature emphasizing the importance of trust-building strategies in technology adoption contexts.

Furthermore, our analysis delves into the intricate relationships between BMIs, their mediators (e.g. technology fear, trust, well-being, effort-, and performance expectancy), and behavioral intention to use. There are multiple pathways through which BMIs influence behavioral intention to use. For instance, the pathway through performance expectancy and trust (McKnight et al., 2011; Meyer-Waarden and Cloarec, 2022) illustrates that when individuals perceive BMIs as beneficial and trustworthy, they are more inclined to intend to use them. Similarly, the mediation through technology fear and trust underscores the role of trust-building in mitigating the negative impact of technology fear on behavioral intention (Slovic, 1987), further emphasizing the significance of trust in adopting futuristic technologies (Hilken et al., 2022).

Finally, building on Hermann et al. (2024), BMIs share similarities with AI, particularly in serving vulnerable consumers. They both prioritize adaptability and personalization, with AI customizing interactions based on user contexts, mirroring BMIs' interpretation of neurological data for appropriate responses. In addition, AI's focus on accessibility aligns with BMIs' aim to enhance the quality of life for people with disabilities, using similar analytical tools to understand user intentions. Ethical considerations surrounding AI deployment (Cloarec et al., 2023), such as privacy and inequality, are relevant to BMI development, emphasizing the need for a responsible framework to guide both fields toward effective and ethical technologies.

Theoretical contributions

Our study does a significant theoretical contribution within the BMI field in management and marketing science. To the best of our knowledge, prior research has primarily been done in the medical sciences and no study has been done in management science (Binyamin and Zafar, 2021). Our findings carry substantial implications for the literature within the swiftly evolving domain of disruptive technologies, particularly BMIs. BMIs have prominently featured at the forefront of technological progressions, offering diverse applications across fields such as neuroscience, medicine, but also commercial applications, such as CRM with personalization, smart homes, and cyber security (Tang et al., 2023). In an era where smart devices and BMIs blur the lines between science fiction and reality (Drew, 2023), comprehending the factors that shape individuals' behavioral intentions toward these technologies is paramount. Our study illuminates this complex landscape, shedding light on the intricate interplay of variables that influence the adoption of BMIs.

Our first theoretical contribution is that we enhance the UTAUT 2 model (Venkatesh et al. 2011) with theories taking into account new mediating factors influencing the intention to use BMIs: transformative marketing theory with user well-being and perceived risk and trust theory (McKnight et al., 2011), privacy calculus theory, including the concepts of well-being (Cloarec et al., 2022, 2024b; Attié and Meyer-Waarden, 2019; Diener, 1984; Meyer-Waarden et al., 2021; Munzel et al., 2018), technology fear (Fox and Royne, 2018; Yang et al., 2018), trust (Gao and Bai, 2014; Ha and Stoel, 2009; Pavlou, 2003), and privacy concerns (Hong and Thong, 2013). This extended UTAUT2 model contributes to a better understanding of BMI acceptance factors, as even though mHealth and BMIs show a high commercial and medical potential, little is known about their influence on user well-being (Binyamin and Zafar, 2021). We thus enrich the broader IS literature on technology adoption surrounding futuristic disruptive technologies BMIs, leading to technology-mediated transformative experiences by creating smooth human–computer interactions to increase user well-being. Our research, therefore, makes an important contribution, as it explores for the first time a nuanced and comprehensive exploration of the direct factors (e.g. performance and effort expectancy) and mediators (e.g. technology fear, trust, well-being) influencing behavioral intention to use BMIs, providing valuable insights that enrich the IS and transformative marketing literature (Anderson and Ostrom, 2015; Sirgy, 2012). This analysis uncovers multiple (in)direct pathways through which BMIs influence behavioral intention to use, providing a comprehensive understanding of the underlying mechanisms.

Managerial and policy implications

In exploring the factors shaping the acceptance of BMI technology, our research aims to provide valuable insights for both policy and management stakeholders. These insights can be instrumental in guiding communication campaigns and decision-making processes in the field. Here are some managerial and policy recommendations based on our findings: first, our research underscores the significant influence of performance expectancy on user well-being. Therefore, managers in technology companies should prioritize user experience and perceived utility in the design and development of BMI products. By focusing on enhancing user satisfaction and perceived benefits, companies can create more user-centric and successful BMI products. Second, firms should emphasize the benefits of performance expectancy and user well-being to assist consumers in making informed decisions about BMI adoption. Clear communication about how BMI technology enhances users' well-being and performance can help alleviate concerns and promote acceptance. This can be achieved by emphasizing the tangible health benefits that the technology offers. For instance, BMI technology can monitor and enhance mental health by tracking brain activity to identify early signs of stress and anxiety. Proactive measures can then be taken based on these data, as evidenced by clinical trials showing significant reductions in stress levels among regular users. By presenting such concrete health benefits, users are reassured of the positive impact on their well-being. Third, trust plays a pivotal role in shaping users' perceptions and intentions toward BMI technology. Therefore, companies should prioritize transparent communication (Cloarec, al., 2024a) about technology risks to underscore the importance of trust. Clear and honest communication about data privacy policies and security measures can enhance the credibility and reliability of BMI products and services.

For policy our research also offers valuable insights: first, policymakers should use our research findings to devise regulations and guidelines that foster responsible development and deployment of BMI technology. By understanding the factors influencing BMI adoption, policymakers can implement measures to ensure ethical and safe deployment of these technologies. Second, our research highlights the adverse influence of privacy concerns and technology fear on trust toward BMI technology. Policymakers should prioritize addressing these privacy concerns by implementing robust privacy regulations and security measures to reduce perceived technology risks. By addressing these issues, policymakers can create an environment conducive to safe and ethical BMI adoption. Third, policymakers can focus on strategies to cultivate trust in BMI technologies among the public. This may include initiatives to educate the public about the benefits and safety measures of BMI technology, as well as promoting transparency and accountability among technology companies.

By implementing these recommendations, both managers and policymakers can contribute to the responsible development and adoption of BMI technology, ensuring its benefits are realized while addressing potential risks and concerns.

Limitations and future research directions

This study has several limitations that should be considered when exploring future research directions, particularly as investigations into BMIs are rare and in a nascent state. There is a need for extensive research, especially regarding ethical considerations. First, a key limitation lies in the study's exclusive focus on samples coming from the French population. While the research offers valuable insights into the acceptance of BMI technology within France, it does not consider the potential variations in attitudes and behaviors across different cultural, demographic, or geographical groups, thus limiting the generalizability of the results beyond this specific context. Future studies should aim to broaden the scope of investigation to diverse cultural, demographic, and geographical groups (e.g. multiple countries or regions), to explore cultural-specific variations in attitudes and behaviors toward BMI technology across different populations. In addition, research could explore the role of cultural values (e.g. individualism–collectivism; masculinity–feminity; power distance, and uncertainty avoidance (Hofstede, 1993).

Second, the data collected in this study primarily consist of declarative information obtained through surveys and questionnaires. While declarative data provide valuable insights into consumers' stated opinions and intentions regarding BMI technology, it doesn't directly measure their actual behaviors or experiences with such devices. Consequently, there may be a discrepancy between what participants express in surveys and their reactions in real-life situations, potentially affecting the accuracy of the findings and their ability to predict real-world consumer behavior. Based on this limitation, future research directions could include mixed-methods approaches, by conducting longitudinal field studies in real-world settings where BMI technology is really being used or tested that combine qualitative methods, such as interviews or focus groups, with quantitative surveys and questionnaires. As BMIs are still in early development and not widely available in consumer or health markets, employing wearable technology or other similar tracking devices could monitor participants' actual usage of similar technology in their daily lives. This approach offers objective data on usage patterns, validating self-reported behaviors from surveys. By tracking actual usage patterns, researchers can better understand how consumer perceptions evolve and whether they align with initial intentions expressed in surveys. Observing consumers' interactions with the technology in real-world settings provides more accurate insights compared with surveys. Longitudinal studies following participants over time allow observation of changes in behavior and attitudes toward BMI technology. By adopting these future research directions, scholars can address the limitations of relying solely on declarative data and enhance our understanding of consumer behavior toward BMI technology in real-world contexts.

Considering their nascent status, the legal, regulatory, and ethical dimensions surrounding BMIs are continuously evolving. The ethical issues in the use of BMIs are complex and wide-ranging, including human dignity, non-instrumentalization, privacy, data theft, non-discrimination, informed consent, equity, the precautionary principle, and value conflicts. Health risks due to invasive BMIs implanted in the human body are other ethical issues. On the contrary, BMIs could be used for cancer treatment. Our study did not incorporate all these ethical considerations regarding (non)invasive BMIs, representing a significant limitation. Future regulatory developments may significantly influence consumer acceptance, a factor not fully explored in our study and warranting further investigation. Therefore, it is crucial for future research to incorporate ethical considerations outlined by the National Commission for the Protection of Human Subjects of Biomedical and Behavioral Research into biomedical and behavioral studies involving human subjects. Future studies should prioritize integrating ethical considerations into research methodologies, particularly concerning the development, implementation, and usage of BMIs. Future research should thus delve into understanding consumer resistance and skepticism toward BMI technology. Investigating the reasons behind consumer reluctance (next to technology fear and privacy concerns) to adopt BMIs can provide valuable insights into the barriers hindering technology acceptance.

Another important research direction involves examining consumer autonomy and individuals' rights to reject BMI technology. Researchers should investigate the ethical implications of BMI adoption, considering individual autonomy and consumer rights, next to the factors we analyzed (e.g. privacy concerns, technology security). By acknowledging and respecting individuals' rights to make informed choices about BMI technology, researchers can contribute to the development of ethical guidelines and policies that protect consumer rights. Furthermore, researchers should explore ways to integrate ethical considerations into the design and development of BMI technology. This could involve incorporating features that prioritize user autonomy, such as opt-in/opt-out mechanisms for data collection, transparent privacy policies, and user-controlled settings (Cloarec, 2020, 2022). In addition, researchers could investigate the impact of ethical design principles on consumer perceptions and acceptance of BMI technology. By designing technologies that respect and uphold consumer rights, researchers can promote responsible technology development and foster trust among users. Future research could also focus on developing effective communication strategies to address consumer skepticism and promote informed consumer autonomy decision-making regarding BMI technology adoption. Researchers could explore the role of message framing, and persuasive techniques in shaping consumer perceptions of BMI technology.

These research directions include ensuring informed consent, safeguarding participant privacy, and addressing potential risks and benefits associated with BMI technology. To investigate how evolving regulations and legal frameworks impact consumer acceptance of BMIs could involve longitudinal studies tracking changes in public perception and acceptance of ethical considerations surrounding BMIs as well as in consumer attitudes and behaviors in response to regulatory changes in different jurisdictions. This extensive research should engage stakeholders, including policymakers, industry professionals, healthcare providers, and advocacy groups, in discussions about ethical considerations related to BMI technology.

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