International Journal of Law and Societal Studies
ISSN: 3079-2614
DOI: 10.61424/ijlss
Journal Homepage: www.bluemarkpublishers.com/index.php/IJLSS

IJLSS
BLUEMARK PUBLISHERS

| RESEARCH ARTICLE

When Thought Becomes Tradeable: Legislating Neuroprivacy Frameworks in the Brain-computer Interfaces (BCIs) Commercial Era

Abayomi Ogayemi[1] ✉ Odunayo Oyasiji[2], Adeola Okesiji[3], Ayotunde Omosule[4] and Oluwabiyi Olafimihan[5]
[14]*Independent Researcher, Toronto, Canada*
[23]*Independent Researcher, Calgary, Canada*
[5]*Independent Researcher, Newfoundland and Labrador, Canada*
Corresponding Author: Abayomi Ogayemi, **E-mail**: ogayemiabayomi@gmail.com

| ABSTRACT
Neuralink presents brain-computer interfaces (BCIs), the most innovative technology that enables the brain to communicate with the outside world. The global BCI market size is projected to be 8.7 billion in 2033, upwards of the current 2.1 billion in 2024, due to the brain-computer interfaces (BCIs). These systems are associated with medical and cognitive enhancement benefits but are also accompanied by serious concerns about neuro privacy, i.e., unauthorized inference and commercial use of cognitive data. This study seeks to investigate the regulation of commercial BCIs in addressing the value of neuro privacy rights at Neuralink. The study was based on the systematic literature review (SLR) to examine regulatory approaches to neuroprivacy in BCIs. The three databases used in the review are IEEE Xplore, PubMed and Google Scholar search databases between 2014 and 2025. This research examined eight peer-reviewed articles using a strict selection criterion covering relevance, the quality of the methods, and the publication date, allowing detailed information on the issue of neuro privacy in the BCI era to be drawn. The study used thematic analysis to identify and categorise patterns in the literature regarding neuro privacy, control of cognitive information, and commercial BCI ethics. The results showed the different implications and ethical issues of brain-computer interfaces (BCIs) related to the extraction of cognitive data, neuro privacy safeguards, and the commercialization of neural information. The study shows that commercialization of BCIs is faced with some ethical, legal, and privacy issues, and that firm regulation frameworks are necessary to protect neuroprivacy.

| KEYWORDS

Neuro-privacy, cognitive data, Neuralink, Brain computer interface (BCI), Data security and neuro-rights

| ARTICLE INFORMATION

ACCEPTED: 17 August 2025 **PUBLISHED:** 15 October 2025 **DOI:** 10.61424/ijlss.v2.i1.457

1. Introduction

Brain-computer interfaces (BCIs) are direct communications between the brain and the outside world, eliminating the need for traditional muscular outputs [1]. The idea of brain computer interfaces (BCIs) changed greatly since the time in the 1920s when neuroscientist Hans Berger was the first to use EEG to trace human brain oscillations formed a basis of direct communication with neural signals later. [2]. Invasive BCIs that involve implantation of electrodes within the skull are estimated to develop a total addressable market of USD 94 billion by 2025 [3]. BCI commercial enterprises are quickly entering the market to capitalize on the trend [4]. Neuralink, founded by Elon Musk in 2016, has already raised more than USD 2-5 billion in early 2024 [5, 6]. The company works to enhance the independence of bodily movements for patients with neurological problems and, in the long run, increase human intelligence [7].

Similarly, Kernel was founded by Bryan Johnson in 2016 and launched with an initial investment of USD 100 million of his own money [8]. The company has already created wearable neuroimaging equipment, such as Flux and Flow, which monitor brains in high resolution using the Functional Near-Infrared Spectroscopy (fNIRS) method [9]. BCI has become democratized by pioneers such as NextMind made their Electroencephalography (EEG) headsets accessible approximately USD 399, allowing individuals to have real-time neural control targeted at gaming, smart homes, and neurofeedback [10]. All these ventures are propelling the global BCI market (approximately USD 2-2.1 billion in 2024 to USD 8-8.7 billion in 2033) to growth, with non-invasive systems leading the way [11].

Despite the growing debate on neuro-rights, several research gaps remain that limit a comprehensive understanding and effective regulation. A primary concern is that there is no general agreement on whether and how to legally define and enforce the concept of neuro privacy, in legislatures where cognitive data is not considered particularly sensitive [12]. There is also limited empirical data regarding the methods that commercial BCI companies use to collect, store, or monetize neural data, enabling policymakers to determine practical risks [13]. Moreover, comparative legal analysis is inadequate to comprehend how such rights might be incorporated into the expanses of the law in general [14]. The study fill these gaps through a critique of international regulatory solutions, and an outline of the legal framework based on rights to protect consumer technologies being developed.

The importance of this research lies in its timely contribution to the field of neuro privacy rights, particularly in the current developments in commercial BCI technologies. It formulates some immediate solutions to secure cognitive data against illegal extraction because such commercial BCIs, including Neuralink. This research fills a gap in regulation that lacks sufficient data protection, as existing standards (such as HIPAA and GDPR) less applicable when cognitive data has been acquired outside clinical settings. The purpose of the research was to explore how commercial brain-computer interfaces (Neuralink) can be regulated to protect neuro privacy rights and prevent the unauthorized extraction of cognitive information. The objectives included exploring the role of commercial BCI, such as Neuralink, in cognitively extracting data and analyzing the legal frameworks that safeguard the neuro privacy rights of an individual, as well as recommending the legal means of protecting against the commercial exploitation of cognitive data by BCI technologies.

2. Literature Review

2.1 Neuroprivacy and Cognitive Data

Neuroprivacy is defined as the security of an individual's intellectual and neural information, including brainwave activity, state of mind, intentions, thoughts, and memories [15]. Neuroprivacy has emerged as a serious concern area as brain-computer interfaces (BCIs), such as Neuralink, have gained popularity due to their direct communication with the brain [16]. Houssein et al. (2022) discussed that BCIs have the capability of measuring brain activity and interpreting signals; thus, there is a probability of obtaining details about cognitive data, such as thoughts, emotional states, and intentions [17]. According to Cinel, C., Valeriani, D (2019) study, this information is more personal than any other biometric information, as it can reveal what is going on in a person's mind, which may not have been intended or fabricated [18]. The chances of a hack on cognitive data, which can be used or exploited for actions such as surveillance, increase geometrically as these technologies evolve.

Thus, neuro privacy is necessary not only to protect individual's right to decide about their thoughts but also to prevent abuse in both government and individual spheres [19]. It is necessary to take control over commercial BCIs, such as Neuralink, to maintain the ethical and legal process of extracting cognitive information. However, Kellmeyer (2021) illustrated that BCIs provides unparalleled access to the human mind, governments should develop regulatory frameworks to clearly state how cognitive data must be harvested, utilised, and secured [20]. These rules must ensures the right of users to manage their neural information and prevent its use against business interests, i.e., to target marketing or conduct unauthorised monitoring. Additionally, Naufel and Klein (2020) mentioned that rules should require BCI companies to obtain informed consent from users, ensuring they clearly understand the consequences and risks associated with their data transfer [21]. In addition, organisations need to be transparent about data storage and access sensitive data only to a limited number of users.

2.2 Technological Landscape of BCIs

Neuralink and Kernel are the leaders of technological innovations that are commercial brain-computer interfaces (BCI) aimed at narrowing the bridge between the human brain and other devices [22, 23]. The neural link Elon Musk founded has the purpose of engineering the smooth connection between the brain and the computers and creating implantable devices which could treat neurological disorders and allow direct communication between the mind and machine [24]. Nami et al. (2022) discussed that Kernel also concentrates on non-invasive BCIs, applying sophisticated neurotechnology to scan and get to know the activity in the brain with the implementation covering the medical field, cognitive enhancement or mental health [25]. The two companies are based on an advanced neural interface, a system that interprets the data sent by the brain and decodes it into actions.

The possible applications of these BCIs are vast and this means an opportunity to provide revolutionary functionalities, including cognitive enhancement, memory enhancement, and even communication in individuals with disabilities including paralysis [26]. Although Värbu et al. (2022) elaborated the potential of BCI is enormous, the existing commercial systems have both accuracy-related and invasiveness-related problems, as well as data security issues [27]. As an example, the strategy of Neuralink is the surgical implantation of chips in the brain that causes issues regarding medical risks, ethical concerns, and data privacy related to the acquisition of cognitive information and its storage [16]. However, Martini et al. (2020) pointed out more challenging to decode complex brain activity, and using those methods on a commercial level is still limited due to technological capabilities [28]. Tough control systems and privacy legislation required to eliminate the use of cognitive data to ensure the mental independence of individuals.

2.3 Challenges in Neuroprivacy Protection

Brain-computer interfaces (BCIs), such as Neuralink, are innovative technological developments that allow for the establishment of a direct communication channel between the brain and external devices [29]. There are tremendous possibilities with these systems, including their medical applications, such as the restoration of capabilities and patient computer usage, which may enhance the effect of human-computer interactions [30]. However, Xia et al. (2022) discussed the use of BCIs is associated with numerous issues related to the protection of personal privacy [31]. BCIs can read personal cognitive information, including thoughts, feelings, and intentions, which presents a significant opportunity for serious privacy threats [32]. Although, Quiles Pérez et al. (2021) elaborated that unauthorised user with access to this information may cause a breach of privacy, mainly where cognitive information has been utilised without mutual agreement [32]. Moreover, the threats to individual's autonomy and freedom of will are enormous because of the threat to breach the general systems.

The implications of extracting cognitive data extend beyond societal concerns. Yang and Jiang (2025) highlighted that information collected with the help of BCIs may be used to artificially anticipate or even control decision-making, behaviour, or preferences, thereby infringing on personal rights [33]. The risks increase as the possibility of surveillance also arises; cognitive data may be monitored in real time without the subject's knowledge, allowing for the acquisition of a digital history of thoughts and feelings [34]. As BCIs shift towards a more commercialized lifestyle, privacy rights over neuro privacy take a primacy position [12]. Adequate control would be achieved by establishing robust systems that ensure consent is applied in the collection of data, data safety standards are defined and applied, and cognitive manipulation is avoided. Moreover, as study by Gordon and Seth (2024) suggested that law should address ethical issues, such as whether BCIs can be used to reinforce existing biases or manipulate inner thought processes, as well as establish limits on the use of cognitive information [35]. These problems could be exacerbated by the fact that, without far-reaching safeguards, the evolution of BCIs might occur faster than the safeguards for privacy.

3. Methodology

3.1 Search Strategy

The research employed a systematic literature review (SLR) design as the research methodology to investigate the regulatory responses to neuro privacy issues in commercial BCIs. It involved three academic databases, including IEEE Xplore, PubMed, and Google Scholar, to ensure that it covers all areas of technology, biomedical research, and legal-ethical issues. IEEE Xplore was chosen as the database with the highly-focused content regarding BCI-related innovations. PubMed was selected as the authoritative resource regarding neuroscience research; and Google Scholar used to include as much gray and interdisciplinary literature in the search pool as possible [36]. The search strategy was formulated with the help of Boolean operators, that narrow or broaden the search results, including the following logical connectives AND, OR, and NOT [37]. The keywords were *neuroprivacy, neuro-rights, cognitive data, mental privacy, brain-computer interface,* and *Neuralink*. The search was narrowed using Boolean terms such as "neuroprivacy" OR "mental privacy" AND "brain-computer interface" OR BCI AND "cognitive data" OR "data extraction". The search strategy and results per database are summarized in Table 1 below.

Table 1: Article search strategy

SEARCH METHOD	SEARCH STRATEGY	NO. OF PAPERS
IEEE Xplore	"neuroprivacy" OR "mental privacy" AND "brain-computer interface" OR BCI AND "cognitive data" OR "data extraction"	40
PubMed	"neuroprivacy" OR "mental privacy" AND "brain-computer interface" OR BCI AND "cognitive data" OR "data extraction"	5,837
Google Scholar	"neuroprivacy" OR "mental privacy" AND "brain-computer interface" OR BCI AND "cognitive data" OR "data extraction"	10,600

3.2 Inclusion exclusion Criteria

The research elaborated on inclusion and exclusion criteria, aiming for academic rigour and relevance. The inclusion criterion included peer-reviewed and openly available full-text articles, conference papers, and policy reports published between 2014 and 2025, based on IEEE Xplore, PubMed, and Google Scholar. Relevant literature has explored the topics of neuro privacy, extractive access to cognitive data, and regulatory platforms related to commercial BCIs. This study considers only English language papers for consistency and access to information. The methodologies of the studies considered were given priority to ensure a transparent level of analysis, particularly for primary research and empirical types of approaches. The exclusion criteria eliminated all the articles irrelevant to BCIs or neuro privacy, open-paywall-based papers without free access, and articles lacking methodological transparency. The exclusion criteria included non-English materials, outdated materials (pre-2014), non-academic commentaries, and studies that focused on clinical BCIs without analysing regulation or privacy. Duplicate records and editorial notes had also been eliminated.

3.3 Selection Process

The study selection was conducted according to the PRISMA guidelines to ensure a robust and systematic review. The first stage of the search was conducted in the three most essential databases: IEEE Xplore (40 records), PubMed (5,837 records), and Google Scholar (10,600 records), yielding a total of 16,477 records. The process continued with the deletion of copy records (3,000). Then, 2,000 records were excluded because they were classified as ineligible using automation tools, and 1,500 records were removed for other reasons. This process resulted in 9,977 refined records that were to be screened. At the screening stage, 7,950 records were excluded based on pre-set specifications, which included inappropriate titles (4,000), unrelated abstracts (2,500), and variants with a high risk of bias (1,450).

Once the removal of these records was done, 2,027 reports were requested to be retrieved. The assessment of eligibility for these reports was conducted, and based on this, 15 reports were selected to proceed with the evaluation. Seven articles were excluded due to the following reasons: publication before 2015 (3), methodological limitations (2), and articles irrelevant to the research question (2). In the end, only 8 studies were found to be included in the review. Such methodology and the openness of the research enabled the inclusion of studies that offered valuable contributions to the subject (Figure 1).

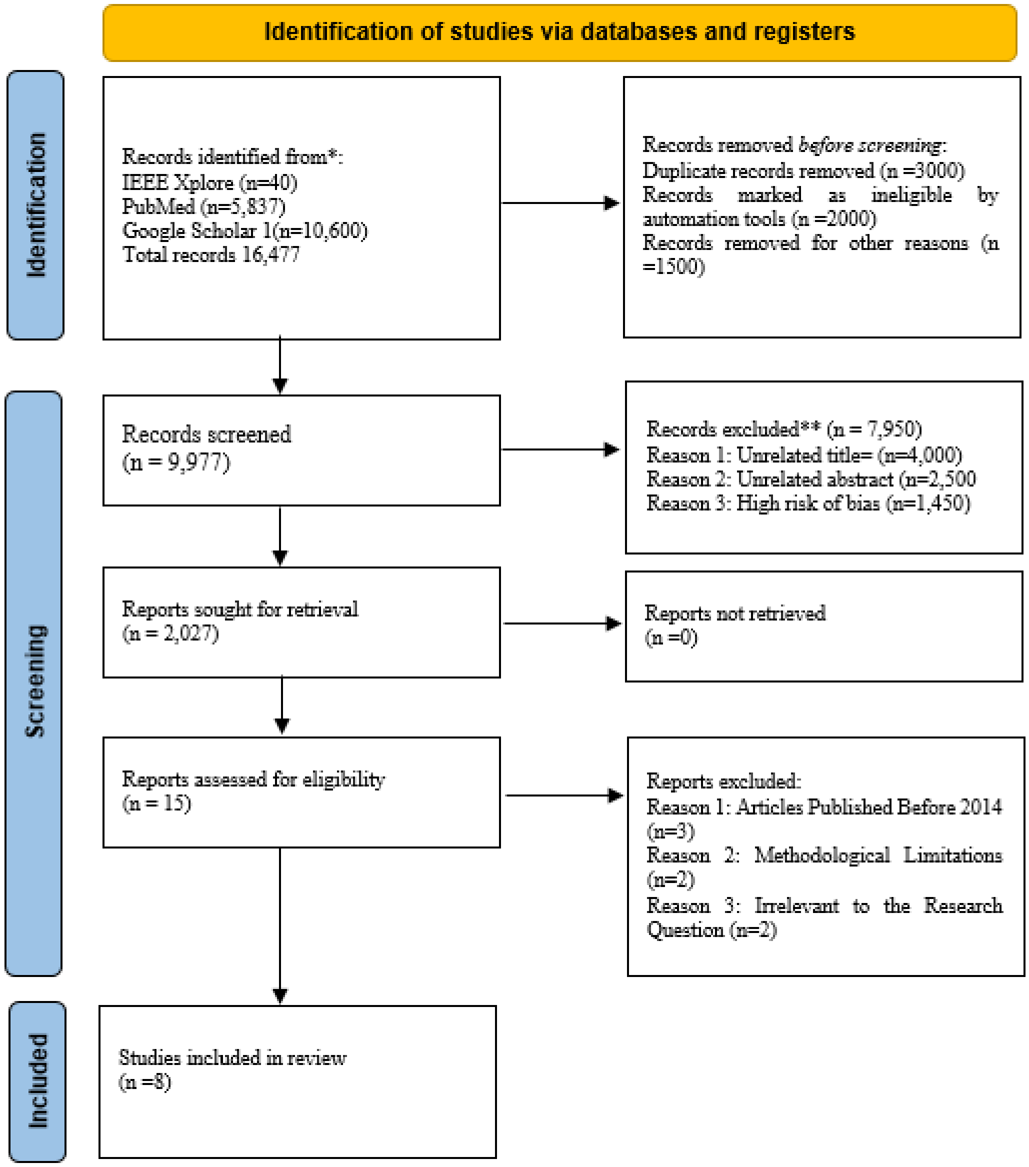

Figure 1: Selection Criteria for the Included Articles

3.4 Quality Assessment

The AMSTAR 2 (A Measurement Tool to Assess Systematic Reviews) checklist was used to evaluate the quality of the included studies in terms of their methodology. This is a systematic assessment tool of reviews based on criteria of rigour, transparency, and reproducibility [38]. The quality of each study was assessed as high, moderate, or low in terms of fulfilling the criteria defined by AMSTAR 2. To achieve a high-quality rating, it was necessary to pass 6-7 of the most essential items, which meant having a good methodological design and minimal bias [39]. Moderate-quality studies involved those that met 4-5 items, and low-quality studies involved those that met 0-3 items. Considering the findings, only a single study could be characterised as of high quality, meaning that it employed a powerful method for assessing neuro privacy, regulatory systems, and cognitive data protection in commercial BCI, such as Neuralink (Table 2).

Table 2: AMSTAR2 checklist

Study Title	Clarity of Research Question	Design Appropriateness	Population & Intervention Description	Comprehensive Outcome Measures	Effect Size & Significance	Bias & Limitations	Funding /Conflicts Disclosed	Score (Max: 7)
Effectiveness of a Personalized Brain-Computer Interface System for Cognitive Training in Healthy Elderly: A Randomized Controlled Trial	1	1	1	1	1	1	0	6
Brain-Computer Interface (BCI) Researcher Perspectives on Neural Data Ownership and Privacy	1	1	1	1	1	0	1	6
Open Multi-Session and Multitask EEG Cognitive Dataset for Passive Brain-Computer Interface Applications	1	1	1	1	1	1	0	6
A Cognitive Brain–Computer Interface Monitoring Sustained Attentional Variations During a Continuous Task	1	1	1	1	1	1	0	6
Evaluation of Commercial Brain–Computer Interfaces in Real and Virtual World Environment: A Pilot Study	1	1	1	1	1	1	0	6
Do Publics Share Experts' Concerns about Brain–Computer Interfaces? A Trinational Survey on the Ethics of Neural Technology	1	1	1	1	1	1	1	7
Optimising non-invasive brain-computer interface systems for free communication between naïve human participants	1	1	1	1	1	1	1	7
Natural brain-information interfaces: Recommending information by relevance inferred from human brain signals	1	1	1	1	1	1	0	6

3.5 Data Analysis

The research used thematic analysis to compare and summarise results based on the chosen literature. This qualitative procedure enabled to identify, and classify frequent patterns related to the issues of neuro privacy, control of cognitive data, and the ethical aspects of commercial BCIs. Thematic analysis has been justified due to its applicability in the use of interdisciplinary data, encompassing legal, and biomedical sources. It enabled the systematic coding of concepts, including consent, surveillance, data ownership, and neuro-rights, to be compared using different methodologies [40]. The strategy provided consistency and richness to the ways of seeking answers to the questions of how various sources discuss the emerging issues of regulations in the field of brain-computer interface technologies.

4. Results

4.1 Study Selection and Outcomes

All the studies described in this review focus on investigating the use and effects of brain-computer interfaces (BCIs) in various cognitive domains. The research article by Yeo et al. (2018) focused on measuring the efficacy of an individual neurofeedback cognitive training system-BRAINMEM to enhance cognition in older adults. The randomised controlled trial demonstrated that the overall marks did not show significant changes in cognitive performance, males showed an improvement in delayed memory and language scores, while on the other hand, the female population did not exhibit any significant changes [41].

In the study by Naufel and Klein (2017), focused on the views of BCI researchers regarding the ownership and privacy of neural data. Their survey of 122 researchers yielded results indicating that most researchers conformed to the idea that participants must have access to raw neural data, and the fear of participants selling their data was also raised [21]. According to a study by Hinss et al. (2023), a dataset of passive BCIs to track cognitive states, including workload and vigilance, has been introduced. The outcomes revealed that the difficulty of tasks had a significant impact on mental workload [42]. In their research, Gaume et al. (2019) have developed a cognitive BCI for the daily, widespread task of sustained visual attention, achieving accuracy results of 75% and 85% at 5-second and 30-second epoch lengths, respectively [43].

A study conducted by Vourvopoulos and Liarokapis (2014) assessed the level of adaptation among users of brain-controlled systems and found that individuals adapted easily to navigate the robot in both real and virtual settings [44]. Matthew et al. (2020) examined discomfort with BCIs and revealed a moderate level, particularly in areas such as hacking and loss of autonomy [45]. Renton et al. (2019) tested the use of a non-invasive BCI speller, allowing its users to communicate freely, and found that it was slower at information transfer compared to cued typing [46]. Finally, the Manuel et al. (2016) study addressed the question of whether brain signals could provide ten times more predictions about word relevance in experiments involving reading [47]. All these studies are helpful in their own right and provide inclusive information on the various functions of BCIs and the ethical issues entailed.

4.2 Study Characteristics

The articles reviewed the different applications of brain-computer interface (BCIs) in thinking, the privacy of neural data, and the recommendations for information. A study conducted by Si Ning Yeo et al. (2018) examined the usefulness of a personalized Brain-Computer Interface (BCI) system, BRAINMEM, to be used in cognitive training in older individuals between the ages 60-80. A randomized controlled trial using 227 subjects was carried out by assigning randomly 227 subjects to either an intervention group. The overall outcome did not indicate many cognitive changes, but in males, a significant effect was indicated, especially on the delayed memory and language scores [41]. The study by Naufel and Eran Klein (2017) examines 122 BCI researchers in a questionnaire based on their views on the concept of neural data ownership and privacy. The survey received the ideas about which participant's raw neural data should be available at the end of the studies, and which participants' raw neural data should be usable as a donation or sale. The results indicated that 58% of the researchers believed that the participants should have access to their information, and some raised their concerns that the raw data could not be valid and could be misused by the participants [21].

Hinss et al. (2023) study emphasised the COG-BCI dataset dedicated to the research of passive BCIs to track such mental states as workload and vigilance. The goal was to provide an open source set of EEG data on which to develop pBCIs and a total of four tasks (MATB, N-Back, PVT, and Flanker) were run during three sessions. The data set was confirmed through subjective, behavioral and physiological measures to calculate mental load. The findings indicated the cross session differences in the EEG signals, and that the dataset was susceptible to the mental workload estimation with more than 85 percent accuracy. [42]. The research by Antoine Gaume et al. (2019) dealt with using a continuous performance task (CPT) to determine sustained attention in 14 participants. With reference to the data collected using EEG signals, the study concluded that theta, gamma, beta, and alpha power could predict cognitive load with the accuracy of between 75% and 85%. The limitation was the noise of data and other external distractions of execution of work [43].

Vourvopoulos and Fotis Liarokapis (2014) compared the two robotic prototypes in terms of their adaptability in user systems and discovered that there was rapid adaptation of the participant particularly those having the previous know-how of gaming [44]. In addition, Sample et al. (2020) recruited 1,403 individuals of Canada, Spain, and Germany states to evaluate the issues of individuals within the country concerning the BCIs, with a greater focus on the problems of hacking, privacy, and the threat to autonomy in the context of the BCI usage [45]. Renton et al. (2019) assessed a BCI speller interface in 17 naive participants in terms of the ability to optimize the system and facilitate free communication. Although the typing speed is lower than in cued tests, there were improvements in typing speed associated with high classification accuracy of participants and this implies that the system can be used in free communication [46]. Manuel et al. (2016) discussed a brain-information interface to recommend information depending on brain signals and concluded that the use of EEG signals allowed to predict the relevance of words in comparison with random feedback [47]. This study the increasing opportunities of BCIs not only including usage inside control interface but also inside information retrieval have been highlighted (Table 3).

Table 3: *Eligible articles*

Study Title	Author(s)	Year	Aim	Methodology	Participants	Findings/Results
Effectiveness of a Personalized Brain-Computer Interface System for Cognitive Training in Healthy Elderly: A Randomized Controlled Trial	Si Ning Yeo et al.	2018	To explore the effectiveness of personalized neurofeedback cognitive training using BRAINMEM in improving cognitive function in healthy elderly individuals.	Randomized controlled trial with an intervention and waitlist-control group. Personalized brain-computer interface training system used to train attention, working memory, and delayed recall.	227 elderly participants (60-80 years) with no neuropsychiatric disorders, randomized into Intervention (INT) and Waitlist-Control (WL) groups.	No significant cognitive performance gains overall, but significant improvements in males' delayed memory and language scores. Women showed no improvement compared to the waitlist group. High adherence and positive feedback for BRAINMEM.
Brain-Computer Interface (BCI) Researcher Perspectives on Neural Data Ownership and Privacy	Stephanie Naufel, Eran Klein	2017	To gather perspectives from BCI researchers on control over neural data, its ownership, and privacy concerns.	Online survey with multiple-choice questions and free-response comments. Survey conducted with BCI researchers.	122 BCI researchers (majority male, aged <45, with varied research backgrounds).	58% of researchers agree participants should have access to raw neural data. Most disagree with participants selling data, citing risks. Concerns about current regulations and data ownership.
Open Multi-Session and Multitask EEG Cognitive Dataset for Passive Brain-Computer Interface Applications	Hinss et al.	2023	To provide an open dataset (COG-BCI) for research on passive Brain-Computer Interfaces (pBCI) to monitor mental states such as workload and vigilance.	EEG data collected over 3 sessions from 29 participants performing 4 tasks (MATB, N-Back, PVT, Flanker) designed to elicit various cognitive states.	29 participants (11 female, 18 male, average age 23.9). All but 4 participants were students.	The dataset was validated using behavioral, subjective, and physiological data. Mental workload estimation pipelines showed promise for pBCI development. Results indicated significant effects of task difficulty, session, and time-on-task on mental workload.
A Cognitive Brain–Computer Interface Monitoring Sustained Attentional Variations During a Continuous Task	Antoine Gaume et al.	2019	To develop and evaluate a cognitive brain-computer interface (BCI) that monitors variations in sustained visual attention during a continuous task.	EEG data recorded during a Continuous Performance Task (CPT) with three levels of task difficulty (easy, medium, hard) analyzed using spectral features.	14 participants (11 male, 3 female, average age 23.7). All had normal or corrected-to-normal vision and no known history of neurological conditions.	EEG classification accuracy reached 75% for 5 s epochs and 85% for 30 s epochs. Sustained attention was best predicted by a combination of prefrontal theta, broad spatial range gamma, fronto-central beta, and alpha power. Results confirmed the potential of BCI for real-time monitoring of cognitive load.

Evaluation of Commercial Brain–Computer Interfaces in Real and Virtual World Environment: A Pilot Study	Athanasios Vourvopoulos, Fotis Liarokapis	2014	To investigate the user adaptation to brain-controlled systems and the ability to control brain-generated events in a closed neuro-feedback loop.	Two prototypes of a robotic system were developed, one using the Neurosky headset and the other using the Emotiv headset.	54 participants for the Neurosky prototype (field study), 31 participants for the Emotiv prototype (lab study)	The results showed that robot navigation was effective and natural in both real and virtual environments. Users adapted to the system quickly, and those with prior gaming experience adjusted faster. Distractions and tiredness were common issues.
Do Publics Share Experts' Concerns about Brain–Computer Interfaces? A Trinational Survey on the Ethics of Neural Technology	Matthew Sample et al.	2020	To explore public attitudes toward brain-computer interfaces (BCIs) and compare these attitudes with expert concerns, focusing on the ethical issues surrounding BCI technology across three countries (Canada, Spain, Germany).	Quantitative survey with 1,403 respondents from three countries (Canada, Spain, Germany) concerns regarding BCI technology, drawing from academic BCI ethics literature.	1,403 respondents from Canada, Germany, and Spain (via a commercial internet panel).	Public concern about BCIs was moderately high, with a focus on "agent-related" and "consequence-related" issues. High concern was reported for issues such as hacking, device failure, and loss of autonomy. Gender, religiosity, and disability status influenced concern levels.
Optimising non-invasive brain-computer interface systems for free communication between naïve human participants	Angela I. Renton, Jason B. Mattingley, David R. Painter	2019	To develop a high-performance, non-invasive BCI speller for free communication in naïve users and evaluate its performance.	Two experiments: 1. Free word association task to assess rapid typing during free communication, 2. BCI-based messaging interface for two-way free conversation.	17 participants in Experiment 1, 2 experienced participants in Experiment 2	BCI speller allowed free communication, but ITRs were slower compared to cued typing tests. In Experiment 1, free communication was slower with ITRs around 80 bpm, while cued typing had ITRs over 100 bpm. Free communication performance varied with classification accuracy (above 80% for high performance).
Natural brain-information interfaces: Recommending information by relevance inferred from human brain signals	Manuel et al.	2016	To introduce a brain-information interface for recommending information based on brain signals related to word relevance.	EEG recorded during reading tasks. The relevance of words was predicted based on brain signals associated with ERPs (e.g., N400, P300, and P600) as the participant read the text.	15 participants (17 recorded, 2 discarded due to technical issues).	Brain signals during reading (specifically N400, P300, and P600) showed clear differences between relevant and irrelevant words. BCI predicted the relevance of words based on EEG signals, achieving better results than random feedback.

4.3 Thematic Analysis

Theme 1: Role of Commercial BCIs in Cognitive Data Extraction

Commercial BCIs like Neuralink extract cognitive data such as thoughts, intentions, and mental states and interpret brain signals. Yeo et al. (2018) conducted a randomized controlled trial study to determine whether personalized neurofeedback cognitive training effectively enhances the cognitive performance of ageing individuals [41]. The sample comprised 240 participants aged 60-80 and was divided into an intervention group and a waitlist-control group. Cognitive training was carried out using the BRAINMEM system with the help of the brain-computer interface (BCI). Yeo et al. (2018) findings indicated that males improved significantly in cognitive perception, especially delayed memory and language function, whilst not a single improvement was reflected in females [41]. On the other hand, the study by Naufel and Klein (2017) surveyed the opinion of 122 BCI researchers in an online survey on the ownership, control, and privacy of neural data [21]. The participants ought to know their neural data, but the problems of misinterpretation and the absence of proper regulations were mentioned. Naufel and Klein's

(2017) research limitations were male-dominated, there was bias of self-selection, and few participants were diverse in terms of geographical and occupation [21].

The study by Hinss et al. (2023) emphasised the creation of the COG-BCI database that describes EEG data of 29 participants during three sessions on such mental states as the four tasks, N-Back, MATB, PVT, and Flanker [42]. The study was conducted using subjective data, behavioral, and physiological data to foster open science in the study of passive Brain-Computer Interface (pBCI). The age mean of participants was 23.9 years, their cognitive workload, vigilance and their ability to switch a task was measured. Hinss et al. (2023) results are applicable to the topic of societal implications of BCI pointing out the possibility of the pBCIs usage in real-life practice, in particular, in terms of the mental states monitoring. However, dropout of participants, technical complications in the acquisition of data, and insufficiently diversified set of participants are the limitations of the study [42]. These results correlate with the Role of Commercial BCIs in Cognitive Data Extraction because the paper discusses the possibility of using BCI-based systems to enhance his mental capabilities.

Theme 2: Legal Frameworks for Neuroprivacy Protection

The legal frameworks developed to protect neuroprivacy aim at protecting the neural data of individual to offer confidentiality and free and informed consent to applications of BCI. The study carried out by Vourvopoulos and Liarokapis (2014) discussed the implementation of BCIs in controlling the robots in the real and virtual world regarding the subject of user adaptation [44]. The study relies on two prototype that includes the Neurosky headset that lies basis on the Neurosky headset and the second prototype that consists of the Emotiv Epoc headset. It was composed of 85 participants with 54 during field study and 31 in laboratory environment. Vourvopoulos and Liarokapis (2014) findings highlighted that BCI used to establish reasonable and natural navigation to the robots, and the participants adjusted to this demeanor system very swiftly [44]. However, distractions that were developed by external stimuli and excitement among users were associated with various challenges in the control of the robot.

Comparatively, the research by Antoine Gaume et al. (2019) employed cognitive BCIs as a tool toward monitoring sustained visual attention [43]. The process entailed a Continuous Performance Task (C) to assess the attention based on the EEG signals, whereby 14 individuals were used as the study sample. Antoine Gaume et al. (2019) findings showed that prefrontal theta power, broad gamma power and alpha power were utilitarian to forecast attention load. Limitations were the number of confounders possible such as arousal and stress, which influence the accuracy of classification, and the small number of samples. Antoine Gaume et al. (2019) study raise the issue of surveillance and possible abuse of the data of the state of the brain, which requires strong legal measures of protection of such confidential information [43].

The article by the Sample et al. (2020) discussing the popular concerns of the brain-computer interfaces and contrasting them and the academic approach to ethics [45]. The research involved survey research type, where the researcher collected responses of 1,403 subjects in Canada, Germany and Spain. Sample et al. (2020) findings revealed that the worries over BCIs, especially on issues associated with agents and consequence, were somewhat higher in all the nations [45]. The limitations of the study are self-report research data and the non-random sampling that reduces the field of application. The results of the study are consistent with the theme of legal protection through neuroprivacy since it expresses demand among groups in the society regarding the ethical aspects of the application of BCI technology.

Theme 3: Regulating Commercial Exploitation of Cognitive Data

The ethical issue associated with the commercialization of the cognitive data obtained through BCIs is the protection of individual privacy and autonomy as well as consent. BCIs are engaged with the processing of sensitive neural information, ethical systems should take care of possible misuse of neural information, that neural information should not be used to generate monetary profits without fair protection and regulated controlled conditions. Angela et al. (2019) explains the possibility of the usage of brain-computer interface (BCI) spellers in the scope of free communication and deduces to the optimization of task performance under the circumstances of naive user interaction [46]. The study employed a high performance and non-invasive system BCI speller to assess the free communication skills on the basis of word association games. There were 17 naive users that received a template training procedure and free communication performances. Angela et al. (2019) findings employed that BCI spellers allowed individual to freely communicate, the presence of cognitive load decreased these performances, whereas the classification and information transfer rates appeared to be lower during free communication compared to cued tasks [46]. The major weakness was that of mental load on users and the dependence of users on individualised training at optimal communication rates.

Manuel et al. (2016) examines how brain signals can be used in predicting the relevance feedback of a user on the basis of information retrieval [47]. The research team tried to measure the relevance of terms based on using brain activity signals that were recorded by the EEG during the time the participants were reading documents. It was done in 15 participants shown that brain signal can serve as the use case to gain the relevance of words and also enhanced access ability to relevant document. The weakness of Manuel et al. (2016) study was that it needed explicit categorization according to brain signals hence making it not very scalable to the real world application [47]. The current study is related to the theme of controlling the information about the cognition especially in terms of breaching the privacy of individual neural information used in commercial projects.

5. Discussion

This discussion explores the regulating commercial brain-computer interfaces (BCI), like Neuralink, is emphasized to eliminate the risk of extraction of cognitive data and protecting the rights of neuroprivacy. The objective was to overcome the issues of illegal extraction of the cognitive information, the absence of adequate legal research, and the likes of exploitation in the non-clinical environments. The results of the researches investigating the purpose of the commercial BCIs in the extraction of cognitive data factors indicate the relevant opportunities and issues of such technologies. Yeo et al. (2018) noted the effectiveness of personalized neurofeedback cognitive training with the BRAINMEM system to develop cognitive performance when working with the elderly [41]. However, Hirnstein et al. (2023) discussed that males were experiencing enormous improvements in the delayed memories and language functions and the females were not showing an improvement. Such gender difference in the effectiveness of BCI puts doubt in the generalizability of BCI-based cognitive enhancement in varied demographics.

Conversely, a study by Naufel and Klein (2017) provide insight into how neural data are possessed and controlled and informed consent and coherent regulation and codes of practice are important [21]. It has been found out in the study that majority of BCI researchers think that the participants should be able to access their raw collection of neural data. Although, Yusifova (2020) study highlights the necessity of the legislations enshrining the rights of individual who want their cognitive data to be safeguarded in the emerging discipline of BCI technologies [12]. Besides, Hinss et al. (2023) helped in the development of the COG-BCI database with the purpose of tracking mental states using passive BCIs [42]. Although the results of the study have shown the possible application of pBCIs in the real world, the shortcomings of the research that include the dropout and data collection odds are also mentioned. These findings correspond to the increasing interest toward ethical and social concern of the BCI technologies. Gu et al. (2021) research sustained attention monitoring with the help of EEG signals, supports the fact that the further elaboration of BCIs abilities and risks needs to be done [48]. Due to such progress of these technologies, there is a high level of dependence on resolving the privacy issue with regards to the extraction and utilization of cognitive data in business environments.

The results of the studies that concentrate on the legal frameworks of neuroprivacy protection indicate that the issues of the protection of the neural information and the rights of the individuals in the sphere of BCI. Vourvopoulos and Liarokapis (2014) reviewed the application of the BCIs to control the robots in real and virtual worlds and proved that the users became quite familiar with the BCI systems [44]. This is the pivotal issue when it comes to the BCI technology, as outside factors can potentially impact the privacy and integrity of processes that occur in the nervous system. A study by Antoine Gaume et al. (2019) analysed the ethical aspect of the BCI technology by measuring focus it is maintained attention with the help of the BCI equipment [43]. Hassan et al. (2021) indicated that brainwave pattern such as prefrontal theta- and gamma power were able to predict cognitive load [3]. However, Bublitz et al. (2019) expressed doubt concerning the likelihood of stalking and abuse of mental information, including the possibility of unwarranted access to the mind of person intentions [49].

The research by Sample et al. (2020) also outlined the increasing number of issues regarding the BCI technology which concern, in particular, the ethical and legal consequences of its widespread use [45]. According to Sample et al. (2020) study, citizens of some countries including Canada, Germany, and Spain were concerned with the Havens of BCIs issues in terms of privacy and control revealed that these issues were significant as it concerns the citizens. However, Nami et al. (2022) study imply the urgent necessity of legal frameworks that can comprehensively guide use of BCI technology including the ownership of data, the consent to use such data, and the moral use of mental data [25]. This would make sure that the neuro-rights of individual is secured but at the same time the further development and use of BCI technology would remain open [7].

Commercial use of cognitive information obtained by BCI is a serious ethical issue of privacy, autonomy and consent of persons. Yang and Jiang (2025) elaborated that BCIs work with sensitive neural material, the potential danger of abuse would increase, considering that the data would be privately exploited, not properly secured and also out of control [33]. Among the prominent problems, there is a possibility of using cognitive data to market a particular commodity or surveillance without the consent of the person. Angela et al. (2019) discussed the possibility of using BCI spellers to freely communicate by noting that such systems can help the end-user freely give neural communication [46]. However, they also found that there are issues to do with mental load because the more the cognitive load, the poorer the performance.

Proper training procedures should also be stressed as additional studies have shown that help maximize the rate of communication and user fatigue [50]. Besides, Manuel et al. (2016) explored whether brain signals might suggest how relevant the information is in reading and proved that BCI could improve the process of information search [47]. But there have been a scalability problem in their research because it involved distinct classification of brain signals and this is a limiting factor as far as its use in the real world is concerned. However, Fontanillo Lopez et al. (2020) highlight the relevance of ethical aspects of using BCIs in the commercial using process, in terms of the secrecy of neural data [51]. Cassinadri AND Ienca (2024) highlighted definite regulation that can help curb use of cognitive data in a non-desirable manner such as in the case of protecting the neuro-right of individual as BCIs continue to evolve [52]. Although BCIs have a strong promise to enhance the communication and information search, their commercial application should be well regulated to avoid unethical application and ensure that individual keep their cognitive information under control.

6. Conclusion

This research examines the ethical, legal, and privacy issues of commercializing BCIs, particularly near privacy. The findings demonstrate the dangers of cognitive data mining since BCIs, including Neuralink, can retrieve personal data and parameters of the brain, like thoughts, feelings, and intentions that can be used maliciously to make a profit. The study has found primary shortages in current privacy legislation, especially in controlling non-clinical areas of BCI usage where cognitive data are retrieved outside a healthcare facility. The research points out the necessity of sound regulatory systems to ensure and ensure neuro privacy, such as informed consent, cognitive data security and unauthorized surveillance and manipulation. It emphasizes that ethical aspects are to be considered, including but not limited to avoiding abuses of neural information so that it can be used in marketing or other commercial purposes. The results promote the idea of developing a legal framework that protect individuals' neuro-rights and allow managing their cognitive information with BCI technologies.

6.1 Recommendations

Understanding the right to neuro privacy in the BCI, following recommendations can ensure the preservation of cognitive data and the development of BCI technology. It is also essential to set legal frameworks that safeguard cognitive liberty, whose examples include setting laws to acknowledge neural data as consumer protection law to ensure that neural activity data cannot be disclosed without permission [19]. Moreover, it is necessary to implement privacy-by-design frameworks of BCI technologies, in which privacy and cybersecurity factors are embedded into the design development to avoid data breaches and abuse by the users [53]. Effective informed consent practices should be adopted to allow users to understand precisely how their neural data are collected, stored, and used and make decisions based on freely available and clear information. The research promotes the development of international governance standards under neurotechnology, which would regulate brain data acquisition and processing and support the ethical usage of BCIs without violating human rights [33]. This set of recommendations offers an equitable way of promoting innovation and protecting the neuro-privacy of individuals where regulation and innovation could coexist safely within the framework of BCI.

Declarations

Availability of data and material: Not applicable. This study is a narrative literature review and does not involve new empirical data.

Acknowledgements: The authors wish to express gratitude to the Journal for enabling open access dissemination of this research. We also acknowledge with appreciation the anonymous reviewers whose expert evaluation and valuable insights will strengthen the final manuscript through the publication process.

Funding: This research received no specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Competing interests: The authors declare no competing financial or non-financial interests.

ORCID

Abayomi Ogayemi: https://orcid.org/0000-0003-3576-6869
Odunayo Oyasiji: odunayoolumayowa@gmail.com
Adeola Okesiji: https://orcid.org/0009-0006-8706-9466
Ayotunde Omosule: https://orcid.org/0009-0004-8244-8913
Oluwabiyi Olafimihan: https://orcid.org/0000-0002-5477-7355

Authors' Contributions

AO (Abayomi Ogayemi): Conceptualized the study, designed the research framework, conducted the systematic literature review, performed thematic analysis, drafted the manuscript, and led revisions.

OO (Odunayo Oyasiji): Contributed to legal analysis of regulatory frameworks, synthesized ethical implications, co-drafted the methodology and results sections, and revised the manuscript.

AK (Adeola Okesiji): Analyzed data privacy dimensions, evaluated compliance gaps in existing regulations (GDPR/HIPAA), and co-authored the discussion and recommendations.

AOM (Ayotunde Omosule): Investigated commercialization risks, assessed neuro-rights legislation, and critically revised the manuscript for intellectual content.

OOL (Oluwabiyi Olafimihan): Supported literature screening, validated quality assessments (AMSTAR 2), coordinated reference management and co-authored the discussion and recommendations.

All authors read, edited, and approved the final manuscript.

References

[1] ALMofleh, A., et al., *Brain computer interfaces: The future of communication between the brain and the external world.* Science, Engineering and Technology, 2023. 3(2): p. 106-118.
[2] Kawala-Sterniuk, A., et al., *Summary of over fifty years with brain-computer interfaces—a review.* Brain sciences, 2021. 11(1): p. 43.
[3] Hassan, M.M., et al., *A predictive intelligence approach to classify brain–computer interface based eye state for smart living.* Applied Soft Computing, 2021. 108: p. 107453.
[4] Maiseli, B., et al., *Brain–computer interface: trend, challenges, and threats.* Brain informatics, 2023. 10(1): p. 20.
[5] Gallagher, H., *Regulating the Sixth Sense: The Growing Need for Forward-Looking Data Privacy and Device Security Policy as Illustrated by Brain-Computer Interfaces.* Wash. UJL & Pol'y, 2021. 66: p. 157.
[6] Parikh, P.M. and A. Venniyoor, *Neuralink and Brain–Computer Interface—Exciting Times for Artificial Intelligence.* South Asian Journal of Cancer, 2024. 13(01): p. 063-065.
[7] Adeoye, S. and R. Adams, *Neuralink's Brain-Machine Interfaces: A New Frontier in Healthcare Transformation.* 2025.
[8] Blank, R.H., *United States Policy on BCIs: Funding Research, Regulating Therapies, and Commercializing Consumer Technology*, in *Policy, Identity, and Neurotechnology: The Neuroethics of Brain-Computer Interfaces*. 2023, Springer. p. 189-206.
[9] Vidal-Rosas, E.E., et al., *Wearable, high-density fNIRS and diffuse optical tomography technologies: a perspective.* Neurophotonics, 2023. 10(2): p. 023513-023513.
[10] Reuters. *Musk's Neuralink raises $650 million in latest funding as clinical trials begin*. 2025; Available from: https://www.reuters.com/business/healthcare-pharmaceuticals/musks-neuralink-raises-650-million-latest-funding-round-2025-06-02/.
[11] Straits. *Brain Computer Interfaces Market Size is Projected to Reach USD 8.73 Billion by 2033*. 2025; Available from: https://www.globenewswire.com/news-release/2025/02/19/3028582/0/en/Brain-Computer-Interfaces-Market-Size-is-Projected-to-Reach-USD-8-73-Billion-by-2033-Growing-at-a-CAGR-of-15-13-Straits-Research.html.

[12] Yusifova, L., *Ethical and Legal Aspects of Using Brain-Computer Interface in Medicine: Protection of Patient's Neuro Privacy.* 2020.

[13] Wierzgała, P., et al., *Most popular signal processing methods in motor-imagery BCI: a review and meta-analysis.* Frontiers in neuroinformatics, 2018. 12: p. 78.

[14] Botes, M.W.M. *Brain Computer Interfaces and Human Rights: Brave new rights for a brave new world*. in *Proceedings of the 2022 ACM Conference on Fairness, Accountability, and Transparency*. 2022.

[15] Mandal, A. and N. Saxena. *SoK: Your mind tells a lot about you: On the privacy leakage via brainwave devices*. in *Proceedings of the 15th ACM Conference on Security and Privacy in Wireless and Mobile Networks*. 2022.

[16] George, A.S., *Protecting Brain Privacy in the Age of Neurotechnology: Policy Responses and Remaining Challenges.* Partners Universal Innovative Research Publication, 2024. 2(5): p. 18-33.

[17] Houssein, E.H., A. Hammad, and A.A. Ali, *Human emotion recognition from EEG-based brain–computer interface using machine learning: a comprehensive review.* Neural Computing and Applications, 2022. 34(15): p. 12527-12557.

[18] Cinel, C., D. Valeriani, and R. Poli, *Neurotechnologies for human cognitive augmentation: current state of the art and future prospects.* Frontiers in human neuroscience, 2019. 13: p. 13.

[19] George, A.S., *Safeguarding Neural Privacy: The Need for Expanded Legal Protections of Brain Data.* Partners Universal Multidisciplinary Research Journal, 2024. 1(1): p. 56-82.

[20] Kellmeyer, P., *Big brain data: On the responsible use of brain data from clinical and consumer-directed neurotechnological devices.* Neuroethics, 2021. 14(1): p. 83-98.

[21] Naufel, S. and E. Klein, *Brain–computer interface (BCI) researcher perspectives on neural data ownership and privacy.* Journal of Neural Engineering, 2020. 17(1): p. 016039.

[22] Wegemer, C., *Brain-computer interfaces and education: the state of technology and imperatives for the future.* International Journal of Learning Technology, 2019. 14(2): p. 141-161.

[23] Karami, M.M., *Neuroscience and Brain-Computer-Interface: Bridging Medicine and Technology for Advancing Patients Care.* Pharmacophore, 2024. 15(1-2024): p. 6-13.

[24] Pisarchik, A.N., V.A. Maksimenko, and A.E. Hramov, *From novel technology to novel applications: Comment on "An integrated brain-machine interface platform with thousands of channels" by Elon Musk and Neuralink.* Journal of medical Internet research, 2019. 21(10): p. e16356.

[25] Nami, M., et al., *A proposed brain-, spine-, and mental-health screening methodology (NEUROSCREEN) for healthcare systems: Position of the society for brain mapping and therapeutics.* Journal of Alzheimer's Disease, 2022. 86(1): p. 21-42.

[26] Osman, N.M., et al., *A literature review of bcis for assisting scis with disabilities from a developmental point of view and potential future trends.* Journal of Al-Azhar University Engineering Sector, 2024: p. 53-83.

[27] Värbu, K., N. Muhammad, and Y. Muhammad, *Past, present, and future of EEG-based BCI applications.* Sensors, 2022. 22(9): p. 3331.

[28] Martini, M.L., et al., *Sensor modalities for brain-computer interface technology: a comprehensive literature review.* Neurosurgery, 2020. 86(2): p. E108-E117.

[29] Lavazza, A., et al., *Neuralink's brain-computer interfaces: medical innovations and ethical challenges.* Frontiers in Human Dynamics, 2025. 7: p. 1553905.

[30] Karikari, E. and K.A. Koshechkin, *Review on brain-computer interface technologies in healthcare.* Biophysical reviews, 2023. 15(5): p. 1351-1358.

[31] Xia, K., et al., *Privacy-preserving brain–computer interfaces: A systematic review.* IEEE Transactions on Computational Social Systems, 2022. 10(5): p. 2312-2324.

[32] Quiles Pérez, M., et al., *Breaching Subjects' Thoughts Privacy: A Study with Visual Stimuli and Brain-Computer Interfaces.* Journal of Healthcare Engineering, 2021. 2021(1): p. 5517637.

[33] Yang, H. and L. Jiang, *Regulating neural data processing in the age of BCIs: Ethical concerns and legal approaches.* Digital Health, 2025. 11: p. 20552076251326123.

[34] King, B.J., G.J. Read, and P.M. Salmon, *The risks associated with the use of brain-computer interfaces: a systematic review.* International Journal of Human–Computer Interaction, 2024. 40(2): p. 131-148.

[35] Gordon, E.C. and A.K. Seth, *Ethical considerations for the use of brain–computer interfaces for cognitive enhancement.* PLoS biology, 2024. 22(10): p. e3002899.

[36] Gusenbauer, M. and N.R. Haddaway, *Which academic search systems are suitable for systematic reviews or meta-analyses? Evaluating retrieval qualities of Google Scholar, PubMed, and 26 other resources.* Research synthesis methods, 2020. 11(2): p. 181-217.

[37] Bramer, W.M., et al., *A systematic approach to searching: an efficient and complete method to develop literature searches.* Journal of the Medical Library Association: JMLA, 2018. 106(4): p. 531.

[38] Lu, C., et al., *Use of AMSTAR-2 in the methodological assessment of systematic reviews: protocol for a methodological study.* Annals of translational medicine, 2020. 8(10): p. 652.

[39] Lorenz, R.C., et al., *A psychometric study found AMSTAR 2 to be a valid and moderately reliable appraisal tool.* Journal of Clinical Epidemiology, 2019. 114: p. 133-140.
[40] Humble, N. and P. Mozelius. *Content analysis or thematic analysis: Similarities, differences and applications in qualitative research*. in *European conference on research methodology for business and management studies*. 2022.
[41] Yeo, S.N., et al., *Effectiveness of a personalized brain-computer interface system for cognitive training in healthy elderly: A randomized controlled trial.* Journal of Alzheimer's Disease, 2018. 66(1): p. 127-138.
[42] Hinss, M.F., et al., *Open multi-session and multi-task EEG cognitive Dataset for passive brain-computer Interface Applications.* Scientific Data, 2023. 10(1): p. 85.
[43] Gaume, A., G. Dreyfus, and F.-B. Vialatte, *A cognitive brain–computer interface monitoring sustained attentional variations during a continuous task.* Cognitive neurodynamics, 2019. 13: p. 257-269.
[44] Vourvopoulos, A. and F. Liarokapis, *Evaluation of commercial brain–computer interfaces in real and virtual world environment: A pilot study.* Computers & Electrical Engineering, 2014. 40(2): p. 714-729.
[45] Sample, M., et al., *Do publics share experts' concerns about brain–computer interfaces? A trinational survey on the ethics of neural technology.* Science, Technology, & Human Values, 2020. 45(6): p. 1242-1270.
[46] Renton, A.I., J.B. Mattingley, and D.R. Painter, *Optimising non-invasive brain-computer interface systems for free communication between naïve human participants.* Scientific reports, 2019. 9(1): p. 18705.
[47] Eugster, M.J., et al., *Natural brain-information interfaces: Recommending information by relevance inferred from human brain signals.* Scientific reports, 2016. 6(1): p. 38580.
[48] Gu, X., et al., *EEG-based brain-computer interfaces (BCIs): A survey of recent studies on signal sensing technologies and computational intelligence approaches and their applications.* IEEE/ACM transactions on computational biology and bioinformatics, 2021. 18(5): p. 1645-1666.
[49] Bublitz, C., et al., *Legal liabilities of BCI-users: Responsibility gaps at the intersection of mind and machine?* International journal of law and psychiatry, 2019. 65: p. 101399.
[50] Roc, A., et al., *A review of user training methods in brain computer interfaces based on mental tasks.* Journal of Neural Engineering, 2021. 18(1): p. 011002.
[51] Fontanillo Lopez, C.A., G. Li, and D. Zhang, *Beyond technologies of electroencephalography-based brain-computer interfaces: A systematic review from commercial and ethical aspects.* Frontiers in Neuroscience, 2020. 14: p. 611130.
[52] Cassinadri, G. and M. Ienca, *Non-voluntary BCI explantation: assessing possible neurorights violations in light of contrasting mental ontologies.* Journal of medical ethics, 2024.
[53] Kapitonova, M., et al., *A framework for preserving privacy and cybersecurity in brain-computer interfacing applications.* arXiv preprint arXiv:2209.09653, 2022.