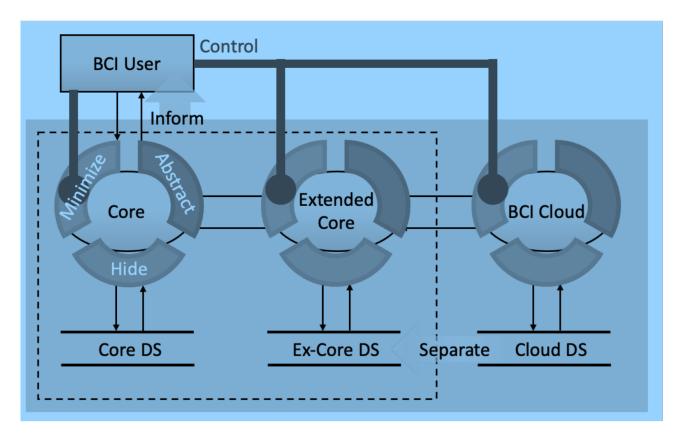
A Framework for Preserving Privacy and Cybersecurity in Brain-Computer Interfacing Applications



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Abstract

Brain-Computer Interfaces (BCIs) comprise a rapidly evolving field of technology with the potential of far-reaching impact in domains ranging from medical over industrial to artistic, gaming, and military. BCIs provide technical interfaces with recording and/or stimulation functionality to connect the brain with computer systems running "decoders" for online analysis of the recorded brain signals. This online analysis in turn can inform various effectors such as robots, vehicles (brain-to-vehicle interfaces), brain stimulation devices, or computer games (neurogaming). Today, these emerging BCI applications are typically still at early technology readiness levels, but because BCIs create novel, technical communication channels for the human brain, they have raised privacy and security concerns. In particular, as brain data contain personal information, adversaries may utilize BCIs to compromise brain privacy. There are first empirical proofs-of-principle that such attacks are indeed possible, possibly foreshadowing a next level of privacy and cybersecurity threats targeting the brain by neurotechnological means. To mitigate such risks, a large body of countermeasures has been proposed in the literature, but a general framework is lacking which would describe how privacy and security of BCI applications can be protected by design, i.e., already as an integral part of the early BCI design process, in a systematic manner, and allowing suitable depth of analysis for different contexts such as commercial BCI product development vs. academic research and lab prototypes.

Here we propose the adoption of recent systems-engineering methodologies for privacy threat modeling, risk assessment, and privacy engineering to the BCI field. These methodologies address privacy and security concerns in a more systematic and holistic way than previous approaches, and provide reusable patterns on how to move from principles to actions. We apply these methodologies to BCI processes and data flows and derive a generic, extensible, and actionable framework for brain-privacy-preserving cybersecurity in BCI applications. This framework is designed for flexible application to the wide range of current and future BCI applications. We also propose a range of novel privacy-by-design features for BCIs, with an emphasis on features promoting BCI transparency as a prerequisite for informational self-determination of BCI users, as well as design features for ensuring BCI user autonomy. We anticipate that our framework will contribute to the development of privacy-respecting, trustworthy BCI technologies.

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Disclaimer

As part of the project "Secure Neural Human-Machine Interaction" of the German Agentur für Innovation in der Cybersicherheit GmbH (Innovation for Cybersecurity), this document outlines a formalism to design neural communication between human and machine in such a way that fundamental personal rights, data security and data integrity are ensured in the acquisition, analysis and interpretation of neural data.

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1 Introduction

Brain-Computer Interfaces (BCIs) are an emerging class of technology enabling direct uni- or bidirectional communication between brains and technical devices [1, 2]. BCIs can measure and convert brain activity to outputs for control of technical effectors, or to perform brain stimulation. BCI applications have been proposed for a wide range of domains from medical and well-being, work and employment, productivity, cognitive enhancement, education, artistic, neurogaming and entertainment including novel interfaces to Virtual Reality (VR), neuromarketing, BCI-informed smart homes and smart cities, to security and military-related BCI applications.

This broad spectrum is the result of a rapid growth of the BCI field: After decades of research confined to a (relatively) small academic group, today a large research community has established itself around BCI-related topics, including the legal, ethical, and societal aspects of BCI technologies. Also the commercialization efforts for medical and consumer BCI systems are intensifying. The global market for BCIs in medical applications has been estimated to grow from \$1.4 billion in 2021 to \$2.4 billion by 2026 and the total global BCI market to \$6.2 billion by 2030 [3, 4]; consumer-neurotechnology research and development includes prominent companies such as Neuralink or Meta. A variety of full BCI systems as well as of wearable EEG-headsets enabling BCI application development are now available on the market – to what extent, however, all of these products truly record and process brain data as their main information source, as could be expected from a true BCI system, is not always entirely clear. Following the model of smartphones, neurotechnology companies provide developer tools such as Software Development Kits (SDKs), Application Programming Interfaces (APIs) for creating BCI-apps – notably, in this way third-parties might gain access to collected brain data. There are companies encouraging and enabling users to share their own brain data recordings, e.g., with the promise to improve the BCIs' functionality [5].

This rise of BCI technology has, over the past decade, also generated attention to new potential cybersecurity and privacy concerns. A fast-growing body of research literature addresses BCI-related privacy and security threats, risks, and their mitigation: As part of the current work we conducted an extensive search of the technical literature and identified 97 original research papers, topical reviews, and non-academic publications in the field of neuroprivacy and -security (see Chapter 4). The topic

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of neuroprivacy and -security has spurred debates in the general public, and, among other initiatives, fueled the worldwide NeuroRights campaign [6]. In general, there is a broad consensus that neuroprivacy and -security are of crucial importance, and it has repeatedly been emphasized that both should be an integral part of the BCI design process ("security and privacy by design and default"). But it is less clear

- how neuroprivacy and -security threats can be identified and the associated risks assessed,
- and how suitable mitigation strategies can be integrated into the BCI design
- using transparent and systematic methodologies that can be reliably applied to the broad and heterogeneous spectrum of current and prospective BCI applications.

To address these points, and to contribute to responsible research and innovation, our aim in the work presented here is to create a framework for neuroprivacy and -security which will be **generic** (suitable for different BCI types/paradigms in general, with necessary adjustments and amendments for specific cases), **use-case independent**, and **extensible**. The latter is important as neurotechnology is a highly dynamic, emerging field of innovation. Our framework and follow-up research aim to ensure and foster the understanding of the security and privacy challenges of current and future BCI usages as well as providing actionable guidelines for detection, evaluation, and mitigation of privacy- and security-related neurorisks.

To this aim we will proceed in the following steps:

- 1. We start out by providing a practical yet holistic working definition of "brain privacy", of the privacy-associated properties, and of the corresponding brain privacy threat categories; and we introduce the ideas of hard vs. soft privacy as well as of "privacy and security by design".
- 2. We then review the state and development of current BCI technology, propose an extended BCI cycle as the basis for our risk analysis, and derive a problem formulation on the background of the current Technology Readiness Level (TRL) and prospective BCI technology.
- 3. In the following *Related Work* section, we present an overview of the related work.
- 4. Next we introduce a basic neuroprivacy and -security architecture, and assess privacy threats using the LINDDUN privacy threat modeling methodology which has been developed to support analysts in systematically eliciting and mitigating privacy threats in software architectures, and estimate the risks associated with the identified threats [7]. As a result we identify critical risks, such as in the categories linkability and content unawareness.

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- 5. Applying generic privacy design patterns, we discuss and propose both general strategies and concrete mitigation techniques for all of the identified critical risks and map these solutions onto a generic privacy- and security-optimized BCI architecture.
- 6. In doing so, we also propose key research questions for the development of next-level privacy and security solutions for BCIs.
- 7. Along the way, we also address a series of more special topics, i.e., regional considerations in the European/German context, regulatory aspects, identification and authentication in the BCI context, how to ensure BCI user autonomy, as well as neurodata governance.

2 Brain Privacy

2.1 Working definition

Privacy in general, and "neuroprivacy" or "brain privacy" in particular, are not easy to define. For example, there have been multiple proposals to define neuroprivacy from a variety of fields such as neuroethics, neurosecurity, neuroscience, or neurolaw [8–16]. General definitions of privacy vary and are contested across cultures, times, and contexts. For example, Tavani distinguishes unitary, derivative, and cluster definitions of privacy, as well as interest-based versus rights-based conceptions which have been adopted by philosophers and legal theorists, and notes that the meaning of privacy has considerably evolved, from relatively narrow concepts of privacy primarily related to property rights to much expanded notions of the right to privacy [17]. It appears unlikely that any single privacy definition will bring the debate about the nature and appropriate definition of privacy to an end; or that this is necessarily desirable given the diversity and ongoing evolution of privacy concepts. Thus, for the current work the aim was to select a practical yet holistic working definition of what is meant by "brain privacy".

We base our working definition on the concept of informational privacy. Informational privacy is centered on access and control of personal information and can be defined as "having control over/limiting access to one's personal information" [17]. Informational privacy is thus different from the notion of physical privacy as non-intrusion with respect to one's physical space, decisional privacy as non-interference with respect to one's choices, and psychological/mental privacy as non-intrusion and/or non-interference with respect to one's thoughts and personal identity. It can be argued that the latter even adds to the problems of constructing a definition of privacy because a general definition of thoughts and mental states would be required in the first place; thus psychological/mental privacy notions may be useful to explain why privacy is valuable, but may be less helpful to define what privacy actually is [18]. Therefore, we base our working definition of brain privacy on the assumption that brain privacy involves a special case of informational privacy, namely, privacy with respect to information derived from brain data – brain data in turn defined as any data obtained directly with respect to the brain, using a technical recording device [15].

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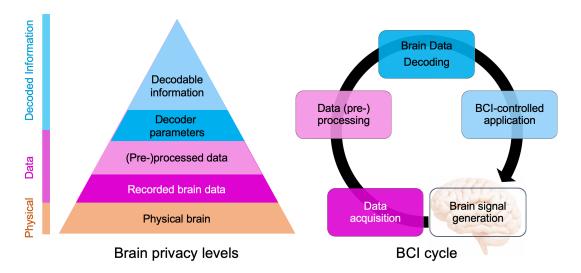


Figure 1: Multi-level approach to brain privacy (left). The different levels of description relevant for a definition of brain privacy are mapped by corresponding colors to the components of the core BCI cycle [20] (right). This mapping will serve as a bridge between the conceptual definition of brain privacy on the one side, and the implementation of a basic safety architecture on the other.

This working definition of brain privacy as brain-data-related informational privacy has not only the advantage that it circumvents definition problems associated with terms as "mental states" etc., but the concept of information appears well suited to connect across different disciplines relevant to the topic of neuroprivacy and -security. For example, our definition is compatible with the original definition of neuroprivacy as "privacy concerns with respect to mental and cerebral functioning as delineated through [information obtained by] brain imaging and other neurodiagnostic techniques" [19]. Information is a central concept in physical, neuro- and computer science. On the legal level, informational privacy is connected to the right to informational self-determination (Recht auf informationelle Selbstbestimmung¹) in German law. Informational privacy has been analyzed to derive sets of privacy properties (Tab. 1), and these in turn correspond to privacy threats. For the analysis of privacy threats, there are systems engineering tools as we will discuss and apply later.

In light of our informational definition of brain privacy, it will also be important to consider what information exactly can be derived (is "decodable") from brain data, such as aspects of thoughts, motor intentions, or brain-health-related information, and how such data are generated in the physical brain. Reasons for this include that brain data may contain information that is not obvious to the BCI user, and attacks may target the level of neural signal generation [21, 22]. We thus propose a multi-level approach, separately considering the Physical level (physical brain); the Data level (raw and processed brain data), in addition to the Decodable Information level as discussed above (including decoder model parameters, as they may also be informative). Fig. 1 shows these different levels of

¹"[...] die Befugnis, grundsätzlich selbst zu entscheiden, wann und innerhalb welcher Grenzen persönliche Lebenssachverhalte offenbart werden" BVerfGE 103, 21 (33). Engl. "[...] the authority to decide for oneself when and within what limits personal life facts are to be disclosed"

2 Brain Privacy

brain privacy map to a BCI cycle as introduced by van Gerven and colleagues [20]. The BCI cycle is a helpful abstraction for analyzing BCI privacy and security issues [23].

2.2 Hard vs. soft privacy and the associated threat models

Privacy can be broadly categorized as hard privacy and soft privacy, respectively [24]. The threat model of hard privacy assumes no trust in third parties. This includes organizational service providers (such as a BCI manufacturer in our case), data holders (e.g., a cloud storage service), as well as the general adversarial environment motivated to breach privacy; in our case for example hackers interested in stealing and selling brain data or secret information.

In the soft privacy case, trust in third parties exists. The threat model is hence softer, including curious insiders, accidental data leaks, but also adversaries external to the trusted third parties. Unlinkability, anonymity & pseudonymity, plausible deniability and non-detectability as in the LINDDUN methodology are hard privacy properties, content awareness and policy/consent compliance soft properties. Importantly, the hard and soft privacy scenarios imply different mitigation strategies.

		Privacy properties	Threats
	Hard privacy	unlinkability	linkability
		anonymity & pseudonymity	identifiability
LINDDUN		plausible deniability	$non-repudiation^2$
		undetectability	detectability
		confidentiality	disclosure of information
	Soft	content awareness	content unawareness
	privacy	policy/consent compliance	non-compliance
		unlinkability	linkability
		pseudonymity /non-identifiability	identifiability
		access control /authorization	uncontrolled access
		integrity	data corruption
GDPR-deriv	bo	confidentiality	disclosure of information
privacy	eu	availability/access	lack of access
properties [2	5]	data minimization	disproportionate data collection
	0]	information/transparency	content unawareness
		storage limitation	disproportionate storage
		purpose limitation	disproportionate processing
		accountability	non-compliance
		encryption	decryption

Table 1: Privacy properties which can be associated with our informational definition of brain privacy, in the LINDDUN privacy threat modeling methodology (top), and derived from the GDPR (bottom), and as well as privacy threats associated with each of the privacy properties. Note that the two sets overlap but are not identical.

 $^{^2\}mathrm{Non-repudiation},$ in contrast to the security context, is considered a threat for privacy.

2.3 Privacy and security by design

The phrases "privacy/security by design" generally refer to making privacy and security part of the design process for new technologies and products, in contrast to "bolting on" privacy and security functionality at a later (and, typically, too late) stage [26]. The historical roots of privacy by design ideas can be traced back to the Fair Information Practice Principles (FIPPs) developed out of a 1973 report from the United States Department of Housing, Education, and Welfare (HEW report) [27]. The term itself was coined later, together with the seven principles of privacy by design, Proactive not Reactive; Privacy as a Default Setting; Privacy Embedded into Design; Full Functionality; End-to-End Security; Visibility and Transparency; and Respect for User Privacy [28]

European General Data Protection Regulation (GDPR), as in effect since 2018, now incorporates in Article 25 entitled "Data Protection by Design and by Default", the concept of "privacy by design" into European data protection law. Given the early stage of BCI technology (see below and Fig. 4), in the current work we will put special focus on "by design" strategies.

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3.1 BCI taxonomy

A BCI has been defined as a system "that measures Central Nervous System (CNS) activity and converts it into artificial output that replaces, restores, enhances, supplements, or improves natural CNS output and thereby changes the ongoing interactions between the CNS and its external or internal environment" [2]. From its beginnings in the 1960s and 70s, BCI technology has now developed into a broad and multifaceted research area and technology class, spanning fields from assistive devices for paralyzed patients to neurogaming, from industry and work-related productivity tools to education, and from military to artistic applications. BCIs may range from high-end research prototypes to low-cost consumer-grade commercially-available products.

The growth of the BCIs domain is reflected in the fact that it can be structured along multiple (though partially related) dimensions:

- 1. Direction of information flow: Recording, stimulating (unidirectional BCIs), or both (bidirectional BCIs).
- 2. Invasiveness: Invasive, minimally / semi-invasive⁴, non-invasive;
- 3. Relatedly, recording techniques: Scalp Electroencephalography (EEG), Magnetoencephalography (MEG), functional Near-Infrared Spectroscopy (fNIRS), functional transcranial Doppler ultrasound, functional Magnetic Resonance Imaging (fMRI), subcutaneous EEG, skull screws, epidural recordings, Electrocorticography (ECoG), micro-ECoG, stereo-EEG, intracortical Local Field Potential (LFP), Single Unit Activity (SUA) or Multi Unit Activity (MUA);
- 4. Type of control: Active, passive, reactive;

⁴The definition of minimally and semi-invasive BCIs is not uncontroversial. Semi-invasive BCIs can, e.g., be defined as those which "involve recording from or stimulating the brain surface or nerves." Rao, R. P. (2013). Brain-computer interfacing: an introduction. Cambridge University Press, p. 101). Others consider, e.g., BCIs based on clinical ECoG grids, as more rather than less invasive compared to intracortical BCIs utilizing small implants like the Blackrock-Array.

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- 5. Timing of information extraction: Synchronous and asynchronous;
- 6. "Non-hybrid/unimodal" vs. "bi-/multimodal/hybrid" BCIs;
- 7. Medical vs. non-medical BCIs with corresponding regulatory consequences;
- Relatedly, the interfacing target: brain to robot, to internet ("Internet of Neurons" [29]), to vehicle [30, 31], silent communication/"Synthetic Telepathy" [32], smart-home control, brainto-spine and brain-to-brain interfaces, both to human and animal [33], etc.;
- BCI paradigm / neurophysiological principle: BCIs based on operant conditioning, based on population decoding, slow-cortical-potential-based, P300 spellers, learned control over oscillatory brain signals; motor-imagery-based, steady-state sensory evoked potentials, e.g., visual: Steady State Visually Evoked Potentials (SSVEPs);
- Type of brain signal processing/decoding: with and without Machine Learning (ML); with ML: linear vs. nonlinear classifiers; traditional (Support Vector Machine (SVM), Regularized Linear Discriminant Analysis (RLDA), random forests etc.) vs. Deep Learning (DL)-based;
- 11. Single-purpose vs. multi/general-purpose BCIs;
- 12. Single user vs. multi-user (collaborative or competitive) BCIs.

For example, the NextMind BCI could be classified as a non-invasive, reactive, synchronous, nonhybrid, consumer single user multi-purpose SSVEP-based BCI using an undisclosed ML algorithm [34].

A special type of BCIs uses brain signals (mostly EEG) as a biometrics for both user identification and authentication. This growing field of research has been extensively reviewed by [35, 36] highlighting that brain signals generally comply well with the general desiderata of biometric signals⁵. As an example, it can be argued that EEG has superior universality compared to retina scanning or fingerprints. Beyond its potential as a general biometric modality, brain-signal-based biometrics such as using the EEG may be used for authentication and identification of users of BCI applications [37]. Such approaches could leverage specific brain responses that are generated during BCI usage anyhow, and thus enable seamless authentication with minimal additional burden on the user. This setup would be a BCI (for biometrics) within a BCI (for another purpose), illustrating the growing complexity of contemporary BCI setups (posing a challenge for coming up with comprehensive BCI taxonomies). Next we consider the hard- and software components used to implement these diverse types of BCIs.

⁵Universality, distinctiveness, collectability, circumvention, permanence, acceptability and performance [36]

3.2 BCI hard- and software

The scope of hard- and software used in BCIs is broad, with important consequences for neurosecurity and -safety. BCIs may be implemented either using off-the-shelf components or custom hardware, such as custom Application-Specific Integrated Circuits (ASICs). Embedded BCIs have been realized, e.g., using the Raspberry Pi and Arduino platforms; future embedded BCI solutions might utilize neuromorphic computing hardware.

Many BCIs (but not all) involve a wireless connection to a local computing device for data processing and storage; and may involve remote/cloud services and components. Such BCIs may also utilize mobile phones and other general-purpose hardware. Presence or absence of wireless communication or trusted hardware may result in very different conditions for the establishment of effective BCI cybersecurity.

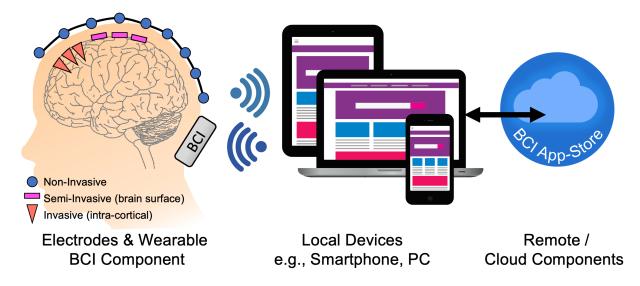


Figure 2: BCI hardware overall structure may involve wearable/embedded components (left), components running on local devices (center), as well as remote/cloud services (right).

In the one extreme, all BCI functions may be on the wearable component (so there is no local or cloud component); in the other extreme, all functions other than recording (and stimulation) may be supported by cloud services. In the typical case, at least as currently prevailing, a substantial part of the BCI functionality is supported by a local device, which may be coupled wirelessly (e.g., Wi-Fi, Bluetooth) or via a wire connection to those components directly connected to the BCI user.

The wide spectrum of BCI hardware is paralleled on the software side. In addition to the diversity of specific ML components used in BCIs as mentioned above, there are different general ML frameworks relevant to BCIs, such as PyTorch and TensorFlow for DL, as well as numerous BCI software frameworks using different programming languages, e.g., Open BCI GUI, Open ViBe, Python MNE (using Java, Python, C++, NodeJS) and Letswave, EEGLab, BCILab (Matlab toolboxes).

3.3 The extended BCI cycle

In light of this conceptual and technological diversity it is crucial to identify generic *functional principles* which are shared by most or even all (currently conceivable) BCIs. One such principle has been formalized as the so-called **BCI cycle**. It was originally described as a closed loop, sequentially involving the measurement of brain activity, classification of the recorded data data, the feedback to the subject as well as the resulting effect back on brain activity of the BCI subject.

In the subsequent literature, several modifications and extensions of the BCI cycle have been put forward. In particular with respect to the BCI cycle as a basis for evaluating cybersecurity, Bernal and colleagues proposed a version of the BCI cycle including stimulation functionality [23]. However, as our focus here is not on bidirectional BCIs with stimulation functions, and as current unidirectional BCIs without stimulation functions have developed far beyond the initial, comparable simple systems, here we propose a different extension of the BCI cycle (Fig. 3). This extended BCI cycle is designed to accommodate the functionality of **current and prospective "three level" BCI setups**:

- 1. The **BCI Core Cycle** corresponds to the classical BCI cycle and interacts with a single user (or a group of users in the case of a collaborative BCI).
- 2. The **Extended Core** may comprise various possible extensions of the core functionality, which may communicate with the core, the global components, or both. There are various such existing or prospective modules extending the core functionality, e.g., modules to implement adaptivity of the core decoder, BCI app store client modules, extension modules for anomaly detection with respect to the core data flow, etc.
- 3. The BCI Global Functionality. The main distinction to the (extended) core is that the global functions concern multiple (other) users, e.g., data pooling across multiple users, training global models on such pooled data, or BCI app store servers.

Many different scenarios are possible of how this functionality may map onto the wearable/embedded, local, and remote/cloud components of a BCI. For example, the core functions may be fully implemented in the embedded/wearable component, and extensions as described above would fit well to a local device such as a PC or smartphone. On the other hand, decoders may also be run locally, on a remote server (such as done in [38]), or even as a cloud service (provided appropriate stability and latency of the remote connection for the given application, such as cloud neurogaming).

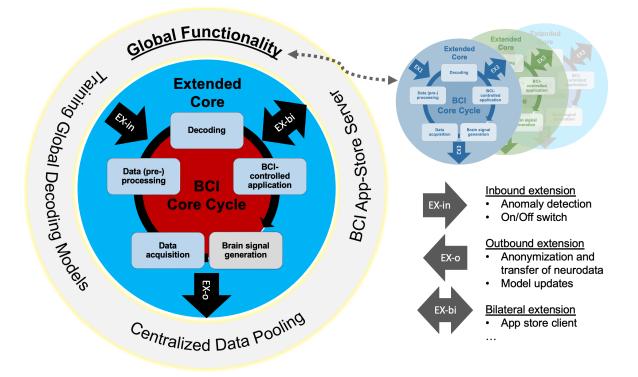


Figure 3: Three-shell, extended BCI cycle. The BCI Core Cycle corresponds to the classical BCI cycle and interacts with a single user (or a group of users in the case of a collaborative BCI). The Extended Core may comprise various possible extensions of the core functionality, which may communicate with the core, the global components, or both. The BCI Global Functionality is defined with respect to multiple cores of other users (symbolized by colored pictograms on the top right), e.g., data pooling across multiple users, training global models on such pooled data. etc. - note that this distinction is based on function, not on hardware implementation; there are numerous different possibilities how this generic functionality can be mapped on hardware (cf. 2). This three-shell BCI cycle will be used to derive a data flow diagram, which in turn is the basis for the subsequent systematic privacy threat modeling.

3.4 Current state and future trajectory of BCI technology

World International Property Organization (WIPO) Technology Trends 2021 report on assistive technology, analyzing patenting and technology trends in assistive technology, using a scale of technology readiness. The report estimates the typical readiness of BCI technology as comparably low, somewhere between "roof of concept" to a "minimal viable product" [39]. Many intriguing BCI application concepts are still in the stage of (academic) lab prototypes. Many of those still are still fraught with fundamental issues which need to be resolved for viable BCI products. One bottleneck, for example, is the limited amount of information which can be derived from recordable brain signals, especially in the non-invasive cases.

This limitation may be overcome by novel recording techniques, such as MEG with Optically Pumped Magnetometers (OPMs). Also progress in the field of ML, especially in the field of DL with Artificial Neural Networks (ANNs), can significantly increase the amount of extractable information from various data types. DL has set a new state of the art in computer vision and natural language processing. Despite promising results, DL has not yet enabled similarly large performance increases in brain signal decoding. One possible reason for this difference lies in the lack of BCI-related "big data". Thus, data pooling such as EEG recordings may be crucial to move the BCI field from lab prototypes to real-world products. In other words, current BCI applications typically do not have a lot (if any) "spare performance" that could be sacrificed for improved security or privacy, in such cases where security- and privacy-preserving methods come at a performance cost (see below).

- Low TRLs
- Low performance
- Data pooling could be crucial to develop realworld products
- PPML for BCIs in infancy, performance costs may be unacceptable

Emerging phase

- Mature TRLs
- High performance
- Data pooling may be replaced by distributed/ federated solutions
 PPML for BCIs mature, acceptable performance cost

Mature phase

Figure 4: Current and anticipated future phases in the maturation of BCI technology. Privacy and security solutions should match the stage of development of BCIs and thus face evolving challenges.

BCI technology today can be seen in an "emerging technology phase", characterized by relatively low TRLs, little or no spare performance (decoding accuracy), by the fact that large-scale data pooling

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could be crucial to develop better ML models and real-world products, and that Privacy-Preserving Machine Learning (PPML) for BCIs is still in a research stage and technological infancy; when PPML incurs a performance cost this may be problematical given the limited amount of decodable information BCIs have to work with anyhow.

We anticipate that after a transition phase, BCI technology will enter a "Mature Technology Phase", characterized by functional TRLs/real-world products, based on solid decoding performance, a situation where data pooling may be replaced by distributed/federated ML solutions.

Considering this technology trajectory is crucial in our context, as it implies three distinct strategic objectives:

- 1. Act: Come up with concrete neurosecurity and -privacy recommendations which are already practical "here and now", during the ongoing emerging technology phase of BCIs.
- 2. **Research**: Identify key neurosecurity and -privacy research questions to be addressed during the transition phase.
- 3. Anticipate: Project how neurosecurity and -privacy issues may be solved in the anticipated mature BCI technology phase.

4 Related Work

We performed a literature search and identified 97 publications on technical aspects of BCI neurosecurity and -privacy (Fig. 5). Around 15% of original studies (11 papers) actually implemented attacks on BCIs and demonstrated successful cyberattacks on BCIs in lab or more real-world settings. Some of the studies were done in laboratory settings, such as Belkacem et al. who implemented Distributed Denial-of-Service (DDoS) and Man in the Middle attacks on P300-based BCI Unicorn speller [40]; Beltran and colleagues successfully implemented misleading stimuli attacks (see below) and different versions of noise-based attacks on P300-based BCIs [41–43]. Interestingly, the majority of the implemented and emulated attacks were performed on Event-Related Potential (ERP)-based reactive BCIs.

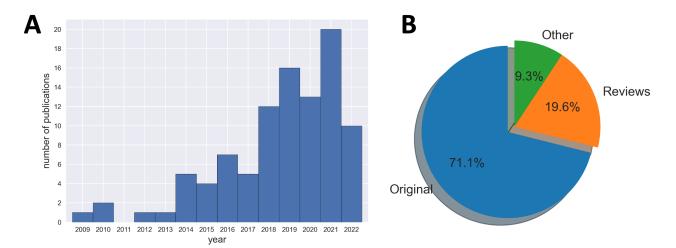


Figure 5: A Publications on technical aspects of neuroprivacy and -security from 2009 until June 2022; B pie chart of paper types; other: editorial, opinion paper, blog post, non-peer-reviewed article, PhD thesis, or book chapter.

One of the first documented successful hacking attempts was Cody's Emokit project, where Cody Brocious cracked encrypted data directly from EMOTIV headset [44]. Later on, Cusack and colleagues used the "*Btlejuice*"⁶ attack: EEG data were hijacked between Emotiv headset and NCD by tethering in Bluetooth wireless network [45]. Similarly, Sundararajan showcased several attacks on Emotiv headset, such as passive eavesdropping, active interception and DDoS (by jamming the connection

⁶Btlejuice https://github.com/DigitalSecurity/btlejuice

4 Related Work

from Emotiv to smartphone) [46]. Xiao and colleagues implemented two sets of Proof-of-Concept (PoC) attacks, consisting of four remote and one proximate attack. Results showed that all 156 BCI apps in the Neurosky app store are vulnerable to the proximate attack and all the 31 free apps are vulnerable to at least one remote attack [47]. Finally, another recent large scale study by Tarkhani et al. used the system security and privacy threats analysis for existing wearable BCI products (Muse, NeuroSky and OpenBCI) from the operating system and adversarial ML perspectives. They designed an information flow control system for attack mitigation and as PoC they implemented a set of attacks across six vectors (AV1: sniffing, spoofing, man in the middle; AV2: inadequate isolation and access control; AV3: privilege escalation; AV4-AV6: adversarial ML) and discovered more than 300 vulnerabilities for real-world BCI devices [48]. For an overview of cybersecurity threats taxonomy for AVs see Bernal et al. [23].

Together, these studies clearly show that cybersecurity issues are an important concern for existing consumer neurotechnology; therefore state-of-the-art cybersecurity defense strategies are of great importance for BCIs. At the same time, these studies also highlight that "hacking the BCI" is a different, yet related, topic area compared to "hacking the brain" violating brain privacy (the latter being the focus of our work described here). It is thus important to distinguish between the following different, but tightly entangled aspects of BCI security: Using "conventional" hacking techniques to get access to a BCI system. Here, the defense is provided by "conventional" cybersecurity measures. Using the BCI to "hack the BCI" - e.g., to steal secret/personal information, or to compromise the autonomy of the BCI user. Here, the defense lies in the design of the BCIs. From our literature review here, however, few papers clearly distinguish between the two concepts of "hacking the BCI" vs "hacking the brain".

A widely explored topic in the literature is misleading stimuli attacks, or so-called "brain malware". The most common ways of using malicious stimuli to extract private information are oddball paradigms, guilty knowledge tests, and priming. For example, Vliet and colleagues showed that the N400 ERP component can be used to determine what a user is primed on [49]. Other studies used consumer grade headset and showed the feasibility of detection of subconscious face recognition from ERPs [50, 51]. Such methods can potentially also be used to infer other subconscious information such as implicit associations, preferences etc. For the excellent review of detection of concealed information from the P300 as well as possible deception strategies, see Rosenfeld [52]. The first study which showed the feasibility of such an attack was already reported in 2012 by Martinovic and colleagues [21]. Utilizing the P300 paradigm and using different types of images, they demonstrated the feasibility to infer PIN codes, bank information, the month of birth, familiar faces, and geographical locations of the user. The results were further reproduced and extended by Lange et al. [53]. Using a "Flappy Whale" BCI game, Bonaci reported the feasibility of probing private information even with subliminal (not consciously

4 Related Work

perceived) stimuli [54], similar to Frank et al., who also reported that by analyzing the responses evoked by short stimuli hidden in video frames it was possible to uncover whether participants were familiar with the subliminally-presented faces [22]. A number of more recent studies, however, tried unsuccessfully to reproduce results with subliminal stimuli [42, 55].

Among the proposed countermeasures for misleading stimuli attacks, the most prominent and frequently mentioned is the "BCI Anonymizer" for which a patent was filed (but later abandoned) in 2014 [56]. To our knowledge, however, it still has not been successfully implemented even in laboratory settings due to lack of neuroscientific understanding of the EEG signal and corresponding difficulties in filtering out task-irrelevant identifying information. Other measures include concentration on nontarget stimuli, adding noise to raw EEG data and API restriction (non-exposing raw EEG data to third parties). However, the effectiveness of the countermeasures (except for API restriction) still requires further research.

Despite the significant number of reviews present in our search, systematic privacy and/or security threat modeling is very scarce. Bonaci [54] used an approach developed by Friedman for "Value Sensitive Design" [57, 58]. She identified the following general threat categories for BCI technologies: 1. Disclosure to Unauthorized Parties, 2. Unauthorized Use of Individual Data, 3. Unauthorized Request (Search) for Individual Data, 4. Unauthorized Use of Aggregated Data, 5. Unauthorized Fusion of BCI data with Unexpected External Data. Another attempt at systematically evaluating privacy in BCIs was done by Wahlstrom and colleagues [59]. This study discusses potential privacy disruptions for BCI typology (active, passive, reactive, hybrid) and for existing, prospective and speculative use-cases. Different privacy theories (control, restricted access, commodification, contextual and ontological) were used for analysis. The result indicates that while all four types of BCIs have potential for disrupting privacy, the major risk is likely to arise from the use of reactive, passive and hybrid BCIs. Pazouki and colleagues attempted to use STRIDE [60] for identifying BCI security risks, but the paper is lacking in detail on this topic [61].

Literature survey conclusions:

- There are relatively few publications addressing BCI security and privacy by design, and few publications clearly distinguishing between "hacking the BCI" and "hacking the brain", and, to our knowledge, no publications applying a combination of systematic threat modeling, risk assessment, and privacy or security engineering tools to the field of BCI technology.
- Safety and privacy by BCI design to prevent "hacking the brain" in BCIs is the central topic of the proposed framework.

5 Basic Neuroprivacy and -security Architecture

5.1 Methodology overview

To establish a basic neuroprivacy and -security architecture in a systematic manner, here we leverage systems engineering methodologies. **Privacy engineering** addresses privacy issues in a systematic and holistic way and provides patterns on how to move from principles to actions. Privacy engineering has been defined as "a specialty discipline of systems engineering focused on achieving freedom from conditions that can create problems for individuals with unacceptable consequences that arise from the system" as it processes personal information [62].

In the first step, we derived a Data Flow Diagram (DFD) based on our functional model (extended BCI cycle, Fig. 3) and overall hardware structure (Fig. 2). The following steps then involve privacy threat modeling, risk assessment, and privacy engineering based on a set of basic privacy design patterns (Fig. 6).

5.2 Privacy threat modeling

To establish a basic neuroprivacy and -security architecture, we start with a systematic approach to modeling of brain privacy threats. As shown by our literature review above, such a systematic evaluation is so far lacking. We selected LINDDUN as our threat modeling tool. Similar to Microsoft's threat modeling framework STRIDE, LINDDUN leverages an information-flow-oriented system model to systematically guide the threat analysis and to provide a broad coverage of different threat classes. In contrast to STRIDE, LINDDUN is oriented towards privacy threats and thus appeared especially well suited, given the pivotal role of brain privacy in our context⁷. Furthermore, LINDDUN can be

⁷However, we are well aware that these threat modeling methodologies were not designed for the very specific cases of brain privacy and interfacing; thus we considered it as a question to be answered whether or not this approach would turn out to be useful in the BCI context.

5 Basic Neuroprivacy and -security Architecture



Figure 6: Flowchart of analysis steps and related methodologies.

used not only for single systems but also for broader analyses; for example Iwaya et al. recently used LINDDUN to analyze a large group of top-ranked mental health apps from Google Play Store [63].

Three **threat sources** are distinguished in LINDDUN: *organizational*, which may refer to the organization as a whole or an employee, in our case first of all the BCI service provider; *external*, which refers to a misactor external to the organization, in our case for example a malicious adversary with a motivation to steal brain data or sensitive information derived from it; and *(future) receiving parties*: e.g., a cloud storage service, Amazon Web Services (AWS), PayPal, etc., receiving data from the organization.

Threat modeling according to LINDDUN proceeds in three steps:

- 1. Modeling the system using a DFD
- 2. Eliciting threats using the LINDDUN threat catalog and mapping the identified threats to hotspots in the DFD
- 3. Identifying mitigation strategies.

Thus, as the first step, we derived a DFD from the extended BCI cycle schematic as introduced and discussed in the previous sections. The resulting DFD is shown in Fig. 7.

Next, we systematically evaluated the 34 threats in the 7 threat classes: linkability, identifiability, non-repudiation, detectability, disclosure of information, content unawareness, and noncompliance, as provided by the LIND(D)UN GO⁸ system [64]. In addition to the standard evaluation, we also asked whether each of the threats may be considered BCI-specific. The LINDDUN framework (as also STRIDE) supports threat but not risk assessment and is compatible with the standard risk assessment techniques. We chose the widely used Open Web Application Security Project (OWASP)'s Risk Rating Methodology to estimate the risk associated with each identified BCI-specific threat. This means, to keep the document concise, here we focused on the clearly BCI-specific threats, as opposed

⁸Note that the second "D" in LINDDUN stands for "Disclosure of information" which is a security category. It is not included in LINDDUN GO as it focuses on privacy. The LINDDUN authors however advise combining their approach with security threat modeling as privacy highly depends on security. For the same reason, in our framework we will also consider the relevant security aspects, such as with respect to disclosure of information and confidentiality.

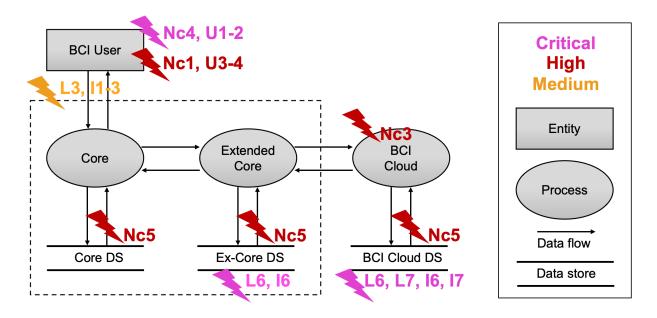


Figure 7: BCI data flow diagram (DFD) and BCI-specific privacy threats mapped to their potential hotspots (here we assume global functions to run in the cloud). Legend of risk levels and DFD elements on the right. Dashed line indicates one possible trust boundary. Threat categories; L: Linkability; I: Identifiability; U: Unawareness; Nc: Noncompliance. Detailed threat acronyms: See main text.

to the less- or non-BCI-specific threats (however, it would be straightforward to extend the same kind of analysis also to the latter). OWASP overall risk severity ranges from "note", "low", "medium" and "high" to "critical" (critical risk level for threats with high associated impact and likelihood) [65].

The aims when applying these methodologies here (i.e., to a generic model representing the architectures across the wide, emerging field of BCI technologies) obviously must be different from the aims when applying these methodologies to an existing and concrete system. Existing and prospective BCIs, e.g., range from low-cost systems with a few, low-quality EEG sensors to high-end BCIs with potentially thousands of implanted electrodes. Accordingly, the amount of personal information that can be inferred from the recorded brain data acquired with different kinds of BCIs (low- vs. high-end, non-invasive vs. invasive) can be expected to vary enormously. As a consequence, identical privacy threats can have very different impacts and, consequently, lead to very different privacy-related risks.

Therefore, our aim is an assessment of the landscape of potential BCI-specific privacy threats and risks. Thanks to the systematicity of the system engineering tools applied, it is also the aim to lay out a general and extensible framework that can be flexibly adapted and applied to concrete and specific BCI application examples. It was not our aim to provide ready-made/out-of-the-box risk assessments and mitigation recipes which can be just copied and put onto arbitrary BCI application scenarios.

LINKABILITY threats:

- L1 Linkability of credentials (Organizational)
- L2 Linkable user actions (Organizational)
- L3 Linkability of inbound data (Organizational)
- L4 Linkability of context (Organizational/External)
- L5 Linkability of shared data (Receiving party)
- L6 Linkability of stored data (Organizational)
- L7 Linkability of retrieved data (Organizational, [Future] receiving party)

The first threat category in the LINDDUN catalog comprises **LINKABILITY threats**, threat L1 being LINKABILITY OF CREDENTIALS: Actions and data can be linked by re-using credentials (for multiple system interactions). We considered this risk as non-BCI specific and therefore did not include it in our further analysis. The first BCI-specific threat which we identified was L3 LINKABILITY OF INBOUND DATA (The data sent to the system are linked to already collected data of the same or other data subjects, from the same or other source). We considered this threat as BCI-specific because correlating different brain signal recordings of the same subject in a data-driven manner is a highly specific task due to the special signal properties of such data, e.g., EEG recordings. However, we also argue that the main risk from such data linkage arises in the stage of stored data (especially for remote/cloud storage of neuro-data), thus we assigned only a medium risk to item L3, but critical risk level to L6 LINKABILITY OF STORED DATA. Stored data are not only the raw or processed brain signals, but also the context, such as visual and auditory stimuli presented (and possibly also other modalities such as electrooculo- or cardiogram). Without knowing the context of "what happened" with precise synchronization, the information that can be extracted from brain signals is reduced. For example, the whole class of misleading stimuli attacks via BCIs requires exact knowledge of when the misleading stimuli appear in the data stream. Thus, we classify linkability of stored BCI-acquired data as a critical risk. The same reasoning also applies to L7 LINKABILITY OF RETRIEVED DATA, provided the scenario that data would be passed on to third, receiving parties.

IDENTIFIABILITY threats:

- I1 Identifying credentials (Organizational)
- I2 Actions identify users (Organizational)
- I3 Identifying inbound data (Organizational)
- I4 Identifying context (Organizational/External)
- I5 Identifying shared data (Receiving party)
- I6 Identifying stored data (Organizational)
- I7 Identifying retrieved data (Organizational, [Future] receiving party)

Closely related, as a special case of linkability, are **IDENTIFIABILITY threats** including another risk that we consider critical, I6 IDENTIFYING STORED DATA. BCI-acquired data being stored may be identified (linked to the user) because they are insufficiently minimized/anonymized before storage; analogously I7 IDENTIFYING RETRIEVED DATA applies to data passed on to third parties. These threats were considered critical as they represent the basic risk of data leakage and theft, i.e., that brain-signal-derived personal information can be linked back to an individual. I1 IDENTIFYING CREDENTIALS, I2 ACTIONS IDENTIFY USER, and I3 IDENTIFYING INBOUND DATA we considered as medium risk threats.

REPUDIATION threats:

- Nr1 Credentials non-repudiation (External)
- Nr2 Non-repudiation of sending (Organizational)
- Nr3 Non-repudiation of receipt (Organizational)
- Nr4 Non-reputable storage (Organizational)
- Nr5 Non-repudiation of retrieved data ([Future] receiving party)

The next category, **NON-REPUDIATION threats**, is especially interesting in the BCI context. As mentioned above, in contrast to the security context, non-repudiation is considered a threat for privacy. From a privacy perspective, non-repudiation ensures that one can, for example, plausibly deny having logged into a questionable website. However, as stated in the GDPR: "The right to the protection of personal data is not an absolute right; it must be considered in relation to its function in society

and be balanced against other fundamental rights, in accordance with the principle of proportionality" (Recital 4 GDPR). From a security perspective, non-repudiation ensures that users cannot arbitrarily shift the blame for their actions to a BCI - "I did not do that - this was my BCI misinterpreting my intentions!"). Weighing the privacy and security considerations, we are convinced that here security prevails, thus, we have not assigned any risks in this threat category (see also Ensuring user autonomy section).

DETECTABILITY threats:

- D1 Detectable credentials (External)
- D2 Detectable communication (External)
- D3 Detectable outliers (External)
- D4 Detectable at storage (External [with access to the system])
- D5 Detectable at retrieval ([Future] receiving party)

The next category are **DETECTABILITY threats**, which refer to the ability to detect whether an item of interest exists or not, without having access to the data. An example given in LINDDUN-Go: "By detecting that a celebrity has a health record in a rehab facility, one can infer the celebrity has an addiction, even without having access to the actual record." In our view, this threat category is neither specific nor critical for current BCI applications and we have not assigned any substantial risk to the five threats in this category.

UNAWARENESS threats:

- U1 No transparency (Organizational)
- U2 No user-friendly privacy control (Organizational)
- U3 No access or portability (Organizational)
- U4 No erasure or rectification (Organizational)
- U5 Insufficient consent support (Organizational)

This is in contrast to **UNAWARENESS threats**, namely U1 NO TRANSPARENCY, U2 NO USER-FRIENDLY PRIVACY CONTROL (and related also Nc4 AUTOMATED DECISION MAK-ING, see below). We argue that unawareness may be the most dangerous source of risks in the present stage of BCI technology; in our view it is fundamentally impossible to exert the right to informational

5 Basic Neuroprivacy and -security Architecture

self-determination in a meaningful way if brain data of unknown information content are processed by opaque algorithms implemented in closed-source proprietary software - a black box within a black box within a black box. We advocate to **"Avoid security through obscurity"**, relying on transparent and interpretable solutions (cf. Tesla's open-source patent philosophy for autonomous car security software [66]). U3 NO ACCESS OR PORTABILITY and U4 NO ERASURE OR RECTIFICATION we consider as additional high risk unawareness-related threats.

NON-COMPLIANCE threats:

- Nc1 Disproportionate collection (Organizational)
- Nc2 Unlawful processing (Organizational)
- Nc3 Disproportionate processing (Organizational)
- Nc4 Automated decision making (Organizational)
- Nc5 Disproportionate storage (Organizational)

The final threat category addressed by the LINDDUN framework is **NON-COMPLIANCE threats** which arise if the system does not comply with data protection principles. The GDPR, for example, establishes 6 data protection principles including purpose limitation, data minimization, integrity and confidentiality (as well as accountability as an overarching seventh principle related to the other six). In the LINDDUN framework, this category has been developed mainly in the context of the EU's GDPR, but the underlying principles may be considered independent of a specific geographic or legal domain. On the other hand, threat manifestation in this category appears highly context-dependent, for example, contingent on differences in legal and political factors. Assessments of non-compliancerelated threats in BCI applications, due to their highly context-dependent nature, can only be preliminary and in our view indicate a threat potential rather than an actual threat. Specific threats Nc1-5 are DISPROPORTIONATE COLLECTION, UNLAWFUL PROCESSING, DISPROPORTIONATE PROCESSING, AUTOMATED DECISION MAKING, and DISPROPORTIONATE STORAGE. Except for Nc2 (unlawful processing) we consider all non-compliance threats as BCI-specific (due to the specific nature of the collected and processed data) and have assigned a high risk level (in the sense of a general risk potential rather than an actual risk, see above). Nc2 Unlawful processing we consider as non-BCI-specific as long there are no specific "BCI laws" in place (but cf. the introduction of "NeuroRights" in Chile [67]).

In addition, we also consider **DISCLOSURE OF INFORMATION threats** which imply risks to brain data confidentiality, as (brain) privacy highly depends on this core aspect of security. Associated

risks may exist across the whole BCI data flow, including all stages of data at rest and data in transit. Measures to ensure brain data confidentiality will be discussed in the Hide Strategy Section.

Fig. 7 shows a summary of the BCI-specific privacy threats as discussed above mapped to their hotspots in the BCI flow diagram, including **several BCI-specific**, **critical risk-level threats**.

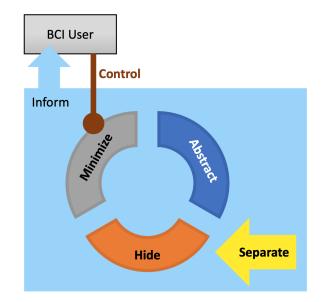


Figure 8: Privacy design patterns after Hoepman [68], in our color-coding (also used in the following figure). Note that the circular arrangement here was chosen to symbolize that these strategies "protect" the processing nodes (see Fig. 9).

In the next step, to develop suitable mitigation strategies addressing this threat landscape, we need strategies that can be used modularly for flexible application scenarios, and which lead to actionable tactics, including descriptions, requirements, and implementation aspects regarding the different levels to be considered, such as suitable Privacy Enhancing Technologies (PETs).

5.3 Threat mitigation by privacy engineering

We selected the privacy engineering approach by Hoepman [69]. This methodology has the advantage that it covers the whole range of GDPR privacy requirements: In the review by (Huth & Matthes 2019 [25]), the Hoepman privacy engineering approach was the only one with "GDPR completeness". In contrast to the also recent PRIPARE methodology by Notario et al. [70], Hoepman also offers explicit links to specific techniques for implementation.

The Hoepman methodology is based on 8 privacy design strategies which are derived from the Organisation for Economic Co-operation and Development (OECD) privacy guidelines, the draft of the GDPR, as well as the ISO 29100 privacy framework (Fig. 8). Specifically, the design strategies comprise 4 more technical, **data processing-oriented** strategies: Minimize, Hide, Separate, and Abstract; as well as 4 **process-oriented** strategies: Inform, Control, Enforce, and Demonstrate, which deal with the organizational and regulatory aspects of privacy engineering. Crucially, each strategy comes with a set of **tactics** guiding the concrete implementation of the various strategies. Fig. 9 shows a mapping of these strategies onto our BCI flow diagram (note that the strategies Demonstrate and Enforce, which are directed to the data controller, will be discussed in the context of legal and regulatory aspects).

The abstract flow diagram combined with the mapped engineering strategies provides **general architecture for BCIs to protect brain privacy**. This architecture can be applied to concrete BCI examples in a flexible way, can be extended for future use cases, and offers a systematic link to concrete implementation tactics, as we discuss in the following for the individual design strategies.

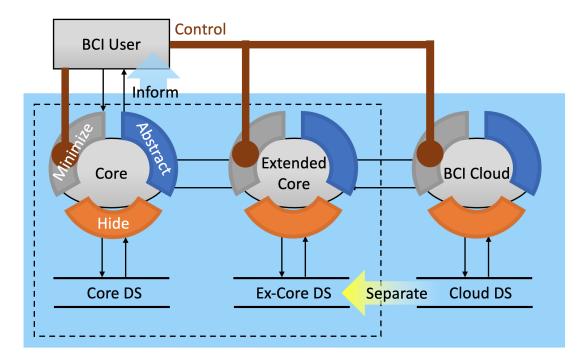


Figure 9: Basic neuroprivacy and -security architecture mapping the Hoepman privacy engineering strategies onto the BCI data flow. Minimize, abstract, and hide strategies may apply to processing in core, extended core, and cloud components. The Inform strategy plays a fundamental role in our architecture and pervades all levels and components of the BCI system, corresponding to the critical risk of unawareness threats. The main role of the Separate strategy lies in the transition of centralized to decentralized solutions (see main text for further details).

6 Privacy Design Strategies for BCIs

In this chapter, we will discuss how the 8 privacy design strategies as introduced above can be applied to BCI applications. We will highlight both actionable design features as well as research questions:

Actionable design features: After the discussion of the strategies we include boxes with concrete privacy-by-design BCI components which do not require extensive further research to be already useful for BCI privacy-preservation.

Research questions: We also highlight selected research questions related to privacypreserving BCI techniques and methods which may be helpful or required for the transformation of today's emerging BCI technologies to a mature and productive technology stage (c.f., Fig. 4).

6.1 Minimize

The Minimize strategy requires limiting as much as possible the collection and the processing of personal data: "The most obvious strategy to protect privacy is to minimise the collection of personal data. Nothing can go wrong with data you do not collect." [68]. The Minimize strategy has the implementation tactics Select, Exclude, Strip and Destroy.

For BCI applications, the most basic and straightforward implementation of the Minimize strategy would be to discard the recorded neurodata after they have been passed through the decoder - during intended use, the neurodata do not leave the core BCI cycle. It has been argued that under such conditions, a BCI used for cursor control would raise few, if any, privacy issues as it would not reveal any more personal information than occurs when controlling a cursor with an ordinary computer $mouse^9$ [72].

However, such minimal data storage may have disadvantages for the development and operation of safe and performant BCI applications. It would prohibit large-scale data pooling, which however may

⁹However, even in this case privacy issues may arise, e.g., through unsecure wireless data transmission [71]

6 Privacy Design Strategies for BCIs

be required to develop improved decoding models at least in the current stage of BCI technology, for example in the context of exploratory algorithm development, research on robust subject-independent models or on meta-decoders. Also certain variants of important techniques such as adaptive decoding [73, 74] and data-driven anomaly detection may require storage of data, although not necessarily permanent, but at least over shorter time horizons. Thus, another concept for implementing the *Select* tactics is storing the data, but applying a **feature limitation** approach to the stored data (also following the EU data minimization principle). In this approach, only a limited set of features of the neurodata is stored, or certain features are removed from the data before storing.

Although this seems an attractive idea, the feature limitation in the context of EEG data and BCIs is not necessarily straightforward and may require further research. Questions here would for example be "Is it possible to do reliable feature limitations (and if yes, to what extent) for brain signals?", "Which information is relevant and irrelevant for the task?". As an example, one can think of limitations on the sensor level (recording only a subset of electrodes relevant to the task). For example, the NextMind BCI is based on visually-evoked potentials and fitting to this signal source, all electrodes are positioned above the occipital area containing the primary and secondary visual cortex. However, EEG electrodes positioned in such a way, e.g., above the visual or motor areas, may also pick up signals from brain areas involved in cognitive processes, e.g., speech processing.

Therefore, a next logical step is to take the feature limitation approach from sensor space to the signal space, and to strip signal components, such as by filtering out certain frequency ranges, etc. Feature selection is the process of selecting an optimized subset of features for ML model training and a broad spectrum of different algorithms has been developed for this purpose [75]. As a BCI example, filter banks are an important component of many classical pipelines and can also be integrated, e.g., with deep networks for EEG [76].

The concept of the so-called BCI Anonymizer¹⁰ [54, 56] is based on such a feature limitation approach. This tool has been proposed as a way to remove private information from EEG data before they are stored or transmitted. The hypothesis here is that recorded brain signals can be decomposed into a collection of characteristic components in real-time. From these components, one wishes to extract exactly the information needed for the BCI application while filtering private information out. Several issues with the BCI Anonymizer idea have been identified, including resource constraints in BCI devices, lack of access to proprietary algorithms, lack of a clear method for separating private information from intentions and a general lack of any implementation details. Despite the attractiveness of the BCI-anonymizer idea, appropriate methods for selectively removing all sensitive information from EEG data are not yet available, and it appears unlikely that this can be achieved by simple

¹⁰Note that the concept of the BCI anonymizer refers to online BCI usage, in contrast to EEG anonymization for offline analysis, see Section 9.

removal of (additive) components, reflected by the abandoned status of the BCI Anonymizer patent application [56].

In contrast, a promising yet methodologically more complex approach to feature limitation leverages generative ML methods. Yao and colleagues have adopted domain adversarial DL techniques for feature removal from EEG. Generative ML methods such as Generative Adversarial Networks (GANs) can solve a wide range of tasks. For example, they can generate photorealistic images from high-dimensional noise [77], generate segmentation masks for medical imaging data [78], translate photographs into an image with a learned artistic style [79], or generate arbitrary images from verbal instructions [80]. Similarly, generative methods can be set up to translate a signal into a corresponding one of the same dimensions, but enforcing that information such as age or gender cannot be inferred from the generated one. For example, Yao et al. report that using a model structure with multiple generators and discriminators it was possible to simultaneously achieve state-of-the-art accuracy on a public EEG data set, while removing privacy-related features [81].

In summary, the Minimize strategy offers a wide range of tactics ranging from simple and immediately applicable to highly complex, and should always be evaluated for a BCI application, as early as in the current "Emerging Technology Phase". Feature limitation techniques based on generative ML are a highly promising research priority for the coming transition phase to more mature BCI solutions.

BCI-Limiter: Integrating channel pre-selection and feature selection, such as using optimized filter banks, for feature limitation.

How can generative ML be used, likely combined with multi-objective optimization (to balance extent of feature reduction with computation and performance costs), to achieve finegrained feature limitation with minimal performance and computation costs and intuitive control not only by domain experts, but also BCI users?

6.2 Abstract

The Abstract strategy aims at limiting as much as possible the detail in which personal data are processed. "The less detailed a personal data item is, the more we 'zoom out', the lower the privacy risk is." [68]. The Abstract strategy includes the tactics Summarise, Group, and Perturb, for processing personal data in a more coarse-grained or aggregate manner. Examples are replacing the exact birth date by an age category, e.g., rounded to years, or a full address by the city of residence.

6 Privacy Design Strategies for BCIs

Application of the **Abstract strategies to the meta-data** acquired and stored alongside the brain data is straightforward and natural, and may provide substantial privacy advantages. These steps are directly applicable when meta-data are stored alongside the brain signals. For example, if handedness is determined with a handedness questionnaire such as the widely-used modified Oldfield questionnaire [82], just the resulting handedness index might be stored, not the answers to all questions. Another example would be subject age, where exact dates of birth could be replaced by age categories, for example in applications involving age as a covariate or aiming at "brain age" decoding [83].

Applications of the Abstract strategies to the brain data themselves appear less straightforward, as there is a conceptual closeness to other strategies such as feature limitation which is considered part of the minimization strategy (see above). The Abstract strategy might seem naturally implemented in feature-based brain signal decoding pipelines. For example, Riemannian-Geometry-based decoders (among the currently most successful class of decoders for EEG BCIs) use the covariance matrix of the input signals as their input, thus the input is not a time series anymore, "abstracting" the detailed temporal structure in the covariance structure of the data. However, the same approach could also be seen as an example of feature limitation (all features except the covariance are omitted). Another example is the so-called Low frequency component (LFC) which, in particular combined with an RLDA decoder for intracranial EEG data, can be highly informative, e.g., about hand movement kinematics [84]. Again, the LFC could be seen as an abstraction in the sense of "zooming out" (reducing detail due to the low-pass filtering of the data), or as a feature limitation (omitting the high-frequency features of the brain signals). For brain signals, Abstract strategies might be best seen as a special case of limitation, namely coarse-graining feature limitation.

Closer to the concept of a privacy-preserving abstraction, and an interesting topic for research in the domain of brain signals, could be learned privacy-preserving **low-dimensional embeddings** of the input data; for example Bezzam and colleagues [85] demonstrated for lensless cameras the privacy-preserving potential of joint optimization of an image classifier together with rich (allowing accurate classification) but lower-resolution optical embeddings learned already at the sensor level of the camera. On the other hand, such techniques - adapted to the brain signal domain - could also be included in the Hide strategy category together with other kinds of PPML (see following section).

In summary, privacy engineering using the Abstract strategy is straightforward and important with respect to the meta-data acquired and stored alongside the brain data; at least current brain data processing techniques which possess an abstraction aspect seem to more naturally fit into related categories (Minimize, Hide). BCI-MetaAbstract: Use suitable abstractions for BCI metadata when possible.

Closely related to the research question on limitation methods - How can ML approaches, combined with advanced optimization, be used for performance- and computation-efficient abstraction not only on meta- and behavioral data, but also for **abstraction on the brain or multimodal signal level**? It may not be optimal to implement limitation and abstraction methods separately, but rather jointly, allowing joint optimization.

6.3 Hide

This important strategy comprises a broad spectrum of privacy-enhancing tactics and techniques employed to ensure the **confidentiality**, **unlinkability**, and **unobservability** of personal data. Its logical place is downstream to the Minimize and Abstract strategies as discussed above: After it has been decided that personal data need to be recorded, and at which level of abstraction, the aim of the Hide strategy is to make sure that these data do not become public or known.

Importantly, this strategy also addresses confidentiality, which can be seen as a security rather than a privacy topic (see footnote[8] Section 5.2), but due to its pivotal role for privacy we consider it crucial to include this aspect in a brain-privacy-centered framework as well. Tactics within the Hide strategy are to *Restrict, Obfuscate, Dissociate*, and to *Mix*. From the implementation side, access control policies, encryption, anonymization (removing directly-identifying data), and a large part of the rapidly-growing PPML field all fall into this broad category. In the following we discuss key aspects for the adoption of the Hide strategy to BCI applications, focusing on (i) brain data anonymization and its relation to EEG biometrics, (ii) PPML for BCIs, and (iii) the crucial role of unlinking brain data and contextual data.

6.3.1 Brain data: Anonymization and re-identification

Can brain data be anonymized, and if yes, how? This is a topic of paramount importance, as Recital 26 EU GDPR states that the principles of data protection should apply only to information concerning an identified or identifiable natural person (personal data), and not to anonymous information (non-personal data). If brain data can be anonymized, this could greatly facilitate large-scale data pooling,

for example. To determine whether a natural person is identifiable, GDPR refers to the **risk of identification**, considering all means which are *"reasonably likely"* given factors such as costs, time, current and prospective technology. What does this mean and what are the consequences for brain data recorded by BCI systems?

Finck and Pallas [86] have recently examined the concept of personal vs. non-personal data under the GDPR from both a legal and computer science perspective. They point out that there is a basic contradiction between the GDPR on the one hand, which implies an acceptable residual risk of identification compatible with the anonymous status of data, with interpretations by national supervisory authorities as well as the European Data Protection Board on the other, which consider that no remaining risk of identification is acceptable for data to qualify as anonymous. Purtova has provided a similar analysis of the uncertainties surrounding the concept of identification and identifiability as critical boundary concepts of data protection law [87]. Another open thread of legal discussion concerns the question whether the scope of personal data protection should be extended to ML models, such as DL networks trained on personal data [88].

On the technical side, what can we say about the feasibility and risk of (re-)identification of brain data, EEG data in particular? Here, the literature on EEG for biometrics is helpful, as this literature provides insights into the feasibility of re-identification of an otherwise anonymous EEG recording against a database of known EEGs¹¹. The EEG data used for biometrics may be spontaneous ongoing activity, or may also contain different kinds of event-related responses, such as to "passthoughts". As a large number of studies have reported high biometric accuracies, the feasibility of EEG re-identification is sometimes taken as a fact. However, how well established is it that EEG recordings can be re-identified on a large scale of individuals, across large time scales, and with high accuracies?

According to the survey by Bigdoly and colleagues, only 13% of the included studies used EEG from as many as 100 to 150 participants, while arguably an EEG biometric system would have to be functional in a population several orders of magnitude larger in size. 27% of the reviewed studies used 10 subjects or even fewer [89]. As also stated by Bigdoly and colleagues, it has been argued that the accuracy of EEG biometrics may decrease as a function of an increasing number of participants (c.f. also [90]). Also the number of studies investigating the long-term stability of EEG biometrics is relatively small. One notable exception is for example the study by Ruiz-Blondet et al., who re-tested their "Cognitive Event RElated Biometric REcognition" (CEREBRE) protocol in 20 subjects after 48 to 516 days, reporting 100% recognition accuracy [91]. Other factors which may challenge the real-world performance of EEG biometrics are changes in affective, vigilance, and hormonal state, medication, sobriety, occurrence (or disappearance) of neurological disorders, all of which can change the recorded EEG patterns. Thus, it

¹¹However, see Bigdoly et al. [89], for an EEG-based authentication approach based on a privacy-preserving EEG fingerprint function.

may be argued that despite the impressive reports in the EEG biometrics literature and encouraging results, at present it is unclear what accuracy re-identification/biometrics of EEG will be able to achieve on large scales (10s of thousands of users or more, over years). It will be crucial to find out whether these accuracies at scale will be high enough to enable reliable EEG-based identification and authentication, or, on the other hand, low enough to dispel privacy concerns due to the risk of EEG re-identification.

Furthermore, even if the raw EEG recordings can be re-identified, feature limitation approaches may be employed to reduce or remove personally-identifying EEG features. As discussed above, the concept of the so-called BCI Anonymizer was based on a simple feature limitation approach. Generative ML (as also discussed above with respect to feature limitation in general), however, may help to better remove personally-identifying EEG components. **Large scale studies** with substantially more subjects will be needed for the development and evaluation of advanced EEG anonymization algorithms, assessment of the risk of identification, and, in parallel with advances on the legal side, clarifying the personal vs. non-personal status of data processes with different anonymization approaches.

6.3.2 Privacy-Preserving Machine Learning (PPML) for BCI applications

PPML is a class of ML specifically designed to mitigate data privacy concerns¹² [92]. This field for example includes research on methods for DL on encrypted data (e.g., CryptoNets [93]). Recently, studies have started to explore the potential of PPML for EEG data analytics. For example, Popescu et al. have used **homomorphic encryption**, designed for model inference on encrypted data and giving encrypted predictions decipherable only by the data owner, for privacy-preserving classification of EEG data. They report comparable prediction performance of the models operating on the encrypted and plaintext data, but increased computational time for training in the homomorphic encryption case [94].

Agarwal et al. proposed cryptographic protocols based on Secure Multiparty Computation (SMC) for EEG [95]. SMC is a specialty of cryptography that studies methods to allow a party of participants joint computation of a public function while keeping their respective inputs private. In the cited work, Agarwal et al. utilized SMC for estimating drowsiness of drivers using linear regression

¹²Many of the strategies adopted in PPML fit to the Hoepman "Hide strategy", therefore we discuss PPML for EEG and BCI applications as a whole in this section. However, PPML is a wide field comprising many different techniques across the whole ML pipeline and life cycle. Addition of noise is systematically exploited by differential privacy PPML, which would fit to the perturb tactics in the Hoepman Abstract Strategy. Hoepman also discusses homomorphic encryption in the Abstract Strategy section, and SMC in the Separate Strategy section, respectively [68]. We would argue that the assignment of methods to strategies can be ambiguous and should not be overcomplicated; what we want to encourage is that the full range of advantages and solutions offered by state-of-the-art PPML be evaluated and included in a systematic BCI privacy engineering strategy.

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over EEG signals from multiple users in a fully privacy-preserving manner and report a manageable computational cost.

A series of recent works has studied the feasibility and performance of **federated learning** for EEG [96–99], such as for online seizure detection in epilepsy [100]. Federated learning addresses similar privacy scenarios as SMC, but instead of cryptography relies on ML techniques to train ML models, such as deep neural networks, on distributed data, by training local models on the local, private data, and providing methods to combine the local models into a global model without the need to disclose the local data.

Others have recently started to explore PPML for brain data using **synthetic data generation**. For example, GANs are a novel, powerful generative ML model class that can be used to generate synthetic yet realistic EEG data [101]. Debie and Mustafa have proposed a GAN trained under a differential privacy model for generating privacy-preserving synthetic EEG data [102]. Similarly, Pascual and colleagues proposed a GAN model to generate synthetic seizure-like EEG signals used to train seizure detection algorithms, reporting that their GAN model was both successfully privacy-preserving and without performance degradation during seizure monitoring [103].

In summary, there are first encouraging steps highlighting the potential of PPML in the brain signal domain. The application of PPML in this context is a very recent development – all of the works summarized above were published not earlier than 2019. It is important to underscore the fact that PPML for brain signals is still a research-level technology in a very early stage. There still seems to be a long way to go to implement these approaches in commercial products. PPML in itself is also a highly dynamic field of research with new, promising solutions being generated which have not yet been investigated in the BCI domain. For example, Mo et al. have recently proposed privacy-preserving federated learning with Trusted Execution Environments (TEEs), showing the feasibility of running deep networks in TEEs on the client side for local training, and on the server side for secure aggregation, thus strongly hiding model updates from adversaries [104].

Given the convergence of two dynamic technologies, neurotechnology/BCI and PPML, in our view, at the present stage of development it would be by far premature to prescribe any concrete PPML technique as a general solution to BCI privacy concerns. Rather, we think that **research on a broad spectrum of PPML solutions for BCI applications will be a key component in the transformation of the BCI** field from its current, early phase to a more mature level in the future (Fig. 4). Such research will enable informed choices which PPML techniques are practicable applicable for online BCIs considering their potential computation and performance costs, and relatedly, which PPML techniques may or may not be necessary and/or useful for specific BCI applications.

6.3.3 Unlinking brain data and contextual data

Unlinkability is one of the main concepts within the Hide Strategy. In this last section within the Hide Strategy chapter, we want to draw attention to the important role of unlinkability in the BCI/brain privacy context. This is due to the fact that in most cases, decoding information from brain signals also requires synchronized information about the sensory or behavioral context. For example, trying to decode the emotional reaction to different faces requires knowledge about which face the subject was looking at when. Trying to steal PIN codes by presenting numbers also requires knowledge about time and identity of the numbers presented. Brain data without context contain much less decodable personal information (still decodable may be information about (approximate) age, gender, or neurological disorders). Thus unlinking brain and contextual data provides a powerful means to substantially reduce the risk of information leakage.

In contrast to the complex and methodologically demanding techniques discussed above, such unlinking could be implemented with much simpler means and already "here and now", for example by systematically storing brain data and context data in separate files, without mutual identifiers, and keeping the linking information encrypted. We believe that this approach is so simple and powerful that it should be widely applied, and we refer to this principle as:

BCI-AntiLink: In the different data streams (brain signals, behavioral data, stimuli, multimodal signals), any plaintext mutual identifiers should be removed before storage. This includes subject identifiers or common time stamps, which would allow linking corresponding files.

6.4 Separate

Another important privacy-by-design strategy is to logically or physically Separate the processing of personal data. This strategy has two associated tactics, *Isolate* and *Distribute*. *Isolate* refers to logical and physical separation even though databases or applications are still run on centralized hardware. In contrast, *Distribute* refers to distributed processing over separate physical locations. As laid out by Hoepman, this latter tactic involves relying on the local equipment (in our scenario the local BCI hardware) of the data subject as much as possible, and centralized components (in our scenario the remote BCI components) as little as possible. Therefore, the Separate strategy is closely linked to PPML techniques including SMC and federated learning which allow moving from centralized to decentralized solutions as discussed above (cf. Fig. 9 where we indicate this transition by the yellow arrow).

6.5 Inform

The aim of the Inform Strategy is to ensure transparency about personal data processing. This includes transparency about what data are processed how and to what purpose, and the three tactics *Supply, Explain*, and *Notify*. In our view, at the present developmental stage of BCI technology, this strategy is arguably the most important component of a BCI privacy strategy at all. On the level of the individual, transparency is a necessary precondition for exerting the right of informational self-determination and for users to make informed decisions. On the societal level, transparency is a precondition for verifying the legal and regulatory compliance of organizations (as put by Hoepman: *"Sunlight is said to be the best of disinfectants."*).

Transparency in the context of brain data and BCIs is especially challenging, as we do not have a natural intuition about the information contents of brain signal recordings and the related privacy issues, in contrast to, e.g., e-mails or photographs, where we have a much better understanding about the private information they contain about us. Therefore we argue that measures to implement an elaborate Inform Strategy is to ensure "BCI transparency" and should be woven into the fabric of the whole BCI setup - as indicated by the blue box (Fig. 9) encompassing all of the BCI components.

We propose transparency as a key element of a privacy-preserving strategy for BCIs, addressing (at least) the following two different levels of transparency:

- What is decoded in an online BCI?
- Which information can be derived from the stored data?

6.5.1 What is decoded in an online BCI?

To address the first level (*What is decoded in an online BCI*?) we propose a transparency- oriented mode of operation for online BCIs. This will be a useful mechanism also to ensure that a BCI is only used for the stated and legitimized purpose.



Figure 10: Design sketch for BCI TransparentMode based on a BCI-controlled VR neurogame (currently developed by the authors and coworkers), where subjects use imagined right (R) and left (L) hand movements to interact with virtual robots. On the top left, the TransparentMode display components show decoded classes over time, bars scaled by model confidence of classification. Maps below would visualize an EEG map of the features important for the classification decisions. Subjects are hence able to verify that the decoded information makes sense given their behavior in the game and to report suspicious events.

TransparentMode for online BCIs:^{ab}

- Most BCIs today are based on decoders which are trained in a supervised manner, e.g., to infer right vs. left imagined hand movement from EEG.
- For this supervised training, in most of the cases there is a human-interpretable, semantically meaningful class or regressor label (such as which hand was moved, which letter was selected, the level of tiredness).
- BCIs should have a **transparent mode**, which can be arbitrarily switched on and off by the user, in which all decoded labels are displayed to the user online.
- The key advantage of such a transparent mode is that it allows the user to make sanity checks online. In the hand-movement decoding case, for example, the user can match the decoded labels to the imagined hand movement. For example, if the decoded labels do not match at all to the associated behavior, either the decoder is not working properly, or the decoder is in fact inferring something different than pretended. Thus, a transparent mode could not only contribute to uncover attempts to steal information online, or to uncover "fake BCIs" which otherwise may hide behavior a magic black box marketing.
- In addition, all decoded labels should by default be stored in a plaintext log file which is also accessible for the user.

6.5.2 Which information can be derived from the stored data?

In the previous paragraph we addressed the issue of transparency of the online processing of data during BCI usage. Equally, or maybe even more important is transparency with respect to the offline

^aNote that the Inform Strategy addresses Unawareness Threats falling into the soft privacy category (Tab.1). Thus, transparency-oriented measures as described above are only helpful if the BCI provider (who would also be responsible for implementing, e.g. the transparency mode as described above) is trusted. ^bSuch a transparent mode might distract users in critical applications, therefore as stated, it would be important that it can always be switched off.

How can **interpretable/explainable ML** be used to provide **online feedback** helping to understand the decisions of the ML model including uncertainties / model confidence, visualizing which signal components are used, etc., not only by domain experts, but also BCI users?

processing of data collected during BCI usage.

As a BCI-specific step towards more transparency with respect to offline processing of BCI-related brain data, we propose **BCI quality benchmarking (BCIQ-bench)**, a standardized benchmarking for addressing the fundamental issue that BCI users so far have no means to gain even a most basic insight into the informativeness of the brain signals recorded and stored in the context of the BCI usage. It has been stated that "(*EEG*), even with low number of sensors, is an extremely rich signal" [105] - but can we a priori be sure of this? And what does extremely rich mean exactly? BCIQ-bench (or other similar benchmarking approaches) could be implemented "here and now" to address these questions without the need for complex methods development, and yet could substantially help promote informed user decisions.

BCI.Q-Bench: Age and gender are two widely available labels which can be decoded from brain data, in particular there are good baselines about the performance one can expect from EEG data [83, 106], and there are efforts to promote standardized and reusable benchmarks for example for age decoding from EEG [83]. Requiring BCI providers to publish age and gender decoding accuracies for the data recorded with their BCI systems would provide users with at least basic information. BCI benchmarking, prospectively, could be extended to other standardizable, privacy-related tasks, to provide users with a solid overview about how informative (or not) the recorded brain signals are.

How can the **amount of personal information decodable from brain signals** with a given set of ML methods be reliably assessed? Public benchmarks as above are an important first step, but over time such benchmarks tend to be overfitted and if all labels are public, are open to cheating. In the best case, they reveal only the "tip of the iceberg", as many aspects of personal information will not be covered by such benchmarks. Also, performance on offline benchmarks cannot substitute for evaluation in online applications. Competition (similar to the Cybathlon^a) could offer a way ahead.

^ahttps://cybathlon.ethz.ch/de

6.6 Control

The Control Strategy fulfills the fundamental role to ensure that users have control over the processing of their personal data. The control tactics are *Consent*, *Choose*, *Update*, and *Retract*. Logically the Control strategy builds on the Inform aspects as discussed above, as it impedes the meaningful control of a system if one has no understanding of it. Therefore we argue that a major focus at the current development level of BCI technology should aim at increased transparency and promote better understanding, including BCI competence of the users, explainability of the used ML methods, etc., and that appropriate control strategies can be built on the basis of such transparency and improved understanding.

This being said, there also is a range of **basic control functions** which can already be implemented in the "here and now" of the current stage of development, without needing to wait for the development of a better BCI transparency fundament. For example, to ensure user control over the data, BCI providers should have strong data governance (see 6.7.1) and provide detailed information to users about how and where the data are stored, and delete the data upon request. Informed consent should be systematically obtained from the BCI users, with possibility of withdrawal.

6.6.1 No "Always-On BCIs"

One very simple yet apparently not entirely self-evident example of an effective BCI control is that BCIs should have an **On/Off switch**, as called for by [72, 107]. This switch may, if necessary, be incorporated both in software and hardware BCI design, to ensure fine-grained temporal control of the device by the user. This is important, as there are known privacy and security threats with "always on" devices [108]; studies highlighted the feasibility of decoding private information from long-term BCI usage (all -day recordings), especially in scenarios when the main activity for which BCI is intended (e.g. gaming) is briefly stopped and a user is, for example, using an online banking system while still wearing the continuously recording BCI [109, 110]. Privacy risks may also arise when combining brain data from an always-on BCI with other types of user activity, such as keystroke dynamics [110]. Also, similar to webcams, BCIs should clearly indicate to the user whether they are in recording mode or not.

Not-AlwaysOn-BCI: On principle, unless there are medical or safety reasons which would require continuous operation, BCIs should not be designed as always-on devices, have an On/Off switch, and clear indicators whether they are in recording mode or not.

6.6.2 Ensuring user autonomy

Beyond brain privacy, it is also crucial to ensure that users maintain control over actions mediated via active BCI devices. We envisage this functionality as a final "safety net" to catch as early as possible all BCI actions which are against the user's intent before they unfold (BCI errors due to misclassification or malicious activities). Equally, user autonomy is related to the notion of liability, therefore we also aim here to prevent "cheating" and ensure that BCI outcomes are genuine and reflect true user intent. Thus the BCI device cannot be blamed if the adversary is the user him/herself (non-repudiation). Note that in the case of closed-loop BCI /stimulation the notion of user autonomy gets another level of complexity and requires separate considerations.

Furthermore, we propose two classes of functions for ensuring user autonomy: The first class comprises explicit *alert* and *emergency functions* or intervention options, e.g., the BCI analog to an **emergency stop function**. For example, in one of our previous online BCIs for robot control [38], users could stop the BCI-controlled robot actions any time by an imagined command. Alert functions will notify users in case of detection of suspicious activities within the BCI system. Emergency functions are intended to also notify trusted parties (for example, caregivers) about device malfunctioning and halt the device if possible. The mandatory On/Off switch as mentioned above would also give users more granular temporal control of the device.

The second class of functions to detect BCI behavior violating the user's intent is based on *brain* responses caused by unintended actions. Decoding such implicit error-related brain responses, like the Error-Related Negativity (ERN), online provides an elegant approach to ensuring that users maintain control over the BCI [111, 112]. Notably, explicit and implicit methods could also be combined within one and the same BCI application. Further, data-driven anomaly detection may help to identify outliers in the BCI-controlled behavior and ask for additional confirmation ("Do you really want olives on your pizza, you never eat them otherwise?"). Thus for specific BCI use cases, it will be important to consider such approaches and how they can be optimally engaged/combined to ensure user autonomy over their BCI.

BCI-AutonomyGuard 1.0: Including an emergency stop function to ensure the possibility of a user veto over their active BCI.

BCI-AutonomyGuard 2.0: How can we use an optimized combination of explicit (emergency stop function), intrinsic (error-related brain responses), and data-driven (anomaly detection) methods to ensure user autonomy over their active BCI at all times?

6.7 Enforce and Demonstrate

Finally, the Enforce and Demonstrate strategies address how to anchor privacy policies as part of the organizational culture, how they can be propagated by management, as well as how to demonstrate compliance to privacy regulations towards the data protection authorities. These strategies are thus less concerned with the design of secure and privacy-preserving BCIs, which is the main topic of our framework, but these strategies clearly need to be embedded on on the legal and regulatory level. Thus, in the following, we will review some legal and regulatory aspects related to BCI privacy and security considerations.

6.7.1 Regulatory and legal aspects of BCIs

Since the Charter of Fundamental Rights of the European Union became binding in 2009, data protection has acquired the status of a fundamental right (Article 8) throughout the EU. The implementation of the GDPR (Datenschutzgrundverordnung (DSGVO) in Germany) has subsequently positioned the EU as a global leader in data protection regulation. Furthermore, data protection is of particular relevance in Germany - not only against the rapid development of information technology, but also because of historical experiences with political regimes that collect information to suppress citizens. For a recent analysis of this German perspective, see [113]. Another study reported Germans stood out as the only nationality placing more value on the privacy of health data than credit card information [114].

In Germany, a number of different legal texts address the security of patient data for medical facilities or data protection in general. In addition to the DSGVO and the Bundesdatenschutzgesetz (BDSG), there are also regional state data protection laws (e.g., the Datenschutzgesetz Nordrhein-Westfalen).

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Application of general principles to brain data may require special considerations, such as the Principle of data avoidance and data economy of the BDSG. Data anonymization and limitation is a special challenge in the context of BCI devices, as discussed above. The detailed legal situation with respect to BCI technology in Germany has been recently reviewed by Martini and Kemper [115]. The authors conclude that on the one hand, our current legal system already formulates individual requirements for the cybersecurity of BCIs, but that it lacks a complete regulatory concept that adequately guarantees the security of the applications. Medical device law in Germany regulates security with respect to patient safety, the situation for non-medical BCIs is however substantially different and is characterized by various open regulatory gaps. Martini and Kemper argue that the new EU directives on digital products may at least close these gaps to some extent, as companies are obliged to provide software updates in order to maintain contractual compliance of digital products, which would at least encompass the BCI software components.

The EU Commission's draft regulation on Artificial Intelligence (AI) also provides for strict requirements for safety of AI systems. On the European level, in Article 52 of the EU AI act, the proposed EU AI law regulates "Transparency obligations for certain AI systems". This article states that users of "an emotion recognition system or a biometric categorisation system shall inform of the operation of the system the natural persons exposed thereto." This article could thus be applied at least to some BCI systems using AI technology in the context of emotion recognition. Given the pivotal role of transparency obligations for AI-BCI systems also beyond the narrow topics of emotion recognition and biometric categorization could be fruitful.

6.7.2 Do we need a special governance framework for BCI data?

On a general governance level, we have recently proposed a **Governance Framework for Brain Data** [15]. In this framework, we have identified distinctive ethical and legal implications of brain data acquisition and processing, and have outlined a multi-level governance framework for brain data. The rationale of this framework is aimed at maximizing the benefits of brain data collection and further processing for science and medicine whilst minimizing risks and preventing harmful use. The framework consists of four levels of regulatory intervention: binding regulation, ethics and soft law, responsible innovation, and human rights. This framework considers brain data in general, including brain data obtained through BCIs. Due to its comprehensive nature, we are confident that this Governance Framework for Brain Data also adequately covers the BCI data case, and that on this generic level, at least for the time being, no additional BCI-specific considerations and specifications are obviously necessary.

7 Application to Specific BCI Use Cases and Contexts

Up to here, we have described a general Framework for Brain-Privacy-Preserving Cybersecurity in BCI Applications. How can this framework be applied to specific use cases? Such use cases may include a wide range of application scenarios, and imply different security and regulatory requirements, broad BCI categories include:

- Clinical vs. non-clinical,
- Invasive vs. non-invasive,
- Commercial BCI product development vs. academic research and lab prototypes.

Importantly, different contexts will require a **different depth of analysis and considerations**. Commercial BCI products may require a fine-grained, full-fledged analysis. For academic research and lab prototypes, our work may offer a more high-level, systematic, conceptual framework even in cases where a detailed, step-by-step analysis is not feasible or useful.

Basically, application of our framework to specific use cases will proceed in the same steps as described above, namely threat modeling, risk assessment, and privacy engineering. Starting with a DFD, it is important to emphasize that not all BCI use cases will necessarily have all the components we have mapped out in our extended BCI cycle and the corresponding DFD. For example, a research-grade implantable BCI system for communication in a locked-in patient may not have remote components; BCI model training in this case may proceed purely within-subject but longitudinally over a long time period. On the other hand, it is also imaginable that for example a neurogaming BCI might run all functionality except for the core BCI cycle in the cloud, thus omitting the extended core according to our terminology. Future BCIs may also include additional components not envisaged in our schematic, or more fine-grained DFDs may be called for.

In the next step, threat modeling and risk assessment is performed. In contrast to our general framework, however, not only general risk potential but also specific risks for a concrete use case can be

7 Application to Specific BCI Use Cases and Contexts

assessed, because the specifics of the BCI system, such as the information content of the recorded brain data, are known (or else should be determined). For example, a risk assessment of a low-cost BCI with a few channels of non-invasively recorded signals will result in much lower risk assessments compared to a high-end system potentially providing hundreds or even thousands of much more informative recording channels.

Such differences in the estimated risk which have profound consequences for the threat mitigation will be implemented in the following step, moving through the 8 privacy strategies as described in detail above. For example, in our general architecture (Fig. 9), we have assigned the *Minimize*, *Abstract* and *Hide* strategies to all three processing nodes of our general BCI data flow schematic. However, in a low-privacy-risk BCI application, it might be deemed sufficient to implement the Minimize strategy for the BCI core, and the Hide strategy on the remote level. Implementation of sophisticated PPML techniques may be waived considering an overall low risk. In contrast, in a high-risk and safetycritical BCI application, the full range of technically possible defenses across all BCI components may be required.

Finally it is important to emphasize that we have made specific choices concerning the tools we selected for each of these steps; we have discussed the motivation of these choices above, such as for example the aim of achieving GDPR compliance. However, the development of systems engineering methodologies is a dynamic field, and more suitable tools may exist in the foreseeable future, or already now in other legal contexts, e.g. the US data privacy framework Health Insurance Portability and Accountability Act (HIPAA). Thus the choice of specific tools for threat modeling, risk assessment, and privacy engineering should be reviewed and if necessary they should be adapted to the specific legal and regulatory context. For example the LINDDUN framework, and similarly also STRIDE, is designed to be independent of the specific risk assessment technique that is used, providing the analyst freedom of choice, if needed, thus contributing to the flexibility and extensibility of the systematic approach to BCI privacy and security as advocated here.

8 Conclusions and Outlook

8.1 Conclusions

Here, we have presented a framework for preserving privacy and cybersecurity in BCI applications. We started out with a working definition of brain privacy based on concepts of informational privacy and self-determination. Then, we delineated the functional, hardware, and software scope of current and prospective BCI applications. We introduce a novel, extended model of BCI functionality, consisting of the core BCI cycle, an extended core, and global functionality. We discuss the different ways in which this functionality can be implemented in concrete BCI applications with embedded, local computing, and cloud components. Based on these considerations we derive a BCI DFD as the key abstraction underlying the following steps of analysis.

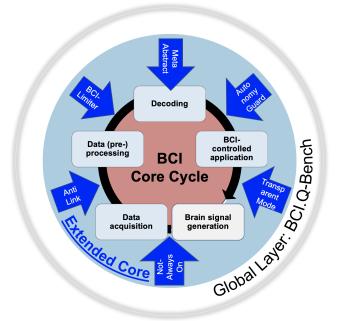


Figure 11: Privacy-preserving BCI design features overview. Most of the features proposed within our framework could be implemented as part of the extended BCI core. We envision that such an extended BCI core might serve as a "BCI privacy shield" integrating multiple privacy-preserving mechanisms

8 Conclusions and Outlook

We performed a systematic privacy threat modeling and risk assessment using the LINDDUN and OWASP methodologies, respectively, and systematically evaluated design patterns addressing these risks along the Hoepman privacy design strategies. Thus, we delineate both a landscape of BCI-related privacy threats and risks as well as of mitigation strategies and tactics. Because our framework is entirely based on systematic methodologies, it can be also adapted to concrete BCI use cases.

Our results here provide both a blueprint for brain privacy-preserving BCI architectures, and concrete, actionable design features. In Fig 11, we have mapped these features to our functional BCI overview. Most of the proposed features are naturally fitting to an implementation within the extended BCI core, namely the BCI-Limiter, BCI-AntiLink, TransparentMode, Not-Always-On-BCI, BCI-AutonomyGuard, and BCI-Meta-Abstract (BCI.Q-Bench as a benchmarking tool for data from multiple users also involves global functionality) – highlighting the usefulness of distinguishing the extended core as a separate important functional BCI layer. We envision that such an extended BCI core might serve as a "BCI privacy shield" integrating multiple privacy-preserving mechanisms.

8.2 Outlook: Privacy and security across the BCI life cycle

Ensuring privacy and security across the BCI life cycle brings additional challenges. Brain signals display nonstationarities on timescales from milliseconds to years. Dealing with these changes in the measurement streams of neuronal activity is a fundamental challenge in brain signal analytics and a topic of ongoing research. Thus consistent safety of BCI applications must be ensured under the presence of such nonstationarities in the brain signals. Specifically, robust and adaptive decoders should be designed to deal with this challenge. For example, in our previous work we implemented and successfully tested a first online BCI using adaptive DL [38], finding that the adaptivity of the networks was critical to high BCI performance. Adaptive algorithms, however, come with their own risks and challenges, for example, an adaptive decoder may become unstable or adapt to a suboptimal EEG feature. On the other hand, neuronal variability may impede, e.g., side-channel attacks on BCI systems [53]; thus variability may even help to make BCIs safer. Extending our current framework to encompass the entire BCI life cycle would therefore be a perspective for future work.

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