

A Survey of EEG-Based Brain-Computer Interfaces for Explicit Interaction

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Abstract

As HCI continues to evolve, the ways in which users can communicate with interactive systems are no longer limited to conventional input devices. EEG-based brain-computer interfaces (BCIs) extend HCI by translating intentionally modulated brain activity into direct control commands for systems. However, fragmented research limits our understanding of how such systems perform and how users experience them in realistic interaction settings. This is particularly relevant for able-bodied users, for whom BCI value depends on their ability to serve as an alternative mode of interaction, rather than to compensate for lost functionality. Therefore, this systematic review investigates the performance, usability and user perception of active EEG-based BCIs in able-bodied users and examines their overall suitability as an HCI modality.

In accordance with the PRISMA 2020 guidelines, we identified studies through systematic searches of Scopus between 27 June and 20 July 2026, including backward and forward citation tracking. Subsequently, this review considered studies that evaluated active EEG-based BCIs in able-bodied participants. Following the screening and eligibility assessment, 37 studies were included in this review and analyzed using an inductive qualitative content analysis.

EEG-based BCIs were applied across diverse HCI contexts and signal paradigms, with P300- and imagery-based systems most commonly examined. Overall, performance outcomes varied among the heterogeneous studies, with most mean accuracy values ranging from 70% to 89%. Further, BCI interaction can place considerable cognitive and physical demands on users, while continued interaction may support users' adaptation. Despite moderate performance, users generally perceived BCIs positively, suggesting that satisfaction and acceptance depend on more than accuracy alone. Thus, active EEG-based BCIs show potential as complementary interaction modalities when their benefits outweigh the required effort.

Überblick

Im Zuge der stetigen Weiterentwicklung von HCI beschränken sich die Möglichkeiten der Nutzer, mit interaktiven Systemen zu kommunizieren, nicht mehr auf konventionelle Eingabegeräte. EEG-basierte Brain-Computer Interfaces (BCIs) erweitern HCI, indem sie bewusst modulierte Gehirnaktivität in direkte Steuerbefehle für Systeme umwandeln. Allerdings schränkt die fragmentierte Forschung unser Verständnis davon ein, wie solche Systeme funktionieren und wie Nutzer sie in realistischen Interaktionssituationen erleben. Dies ist besonders relevant für nicht beeinträchtigte Nutzer, für die der Nutzen von BCIs davon abhängt, ob sie als alternative Interaktionsform dienen können, anstatt verlorene Funktionen zu kompensieren. Daher untersucht diese systematische Übersicht die Leistung, Gebrauchstauglichkeit und Nutzerwahrnehmung aktiver EEG-basierter BCIs bei nicht beeinträchtigten Nutzern und prüft ihre allgemeine Eignung als HCI-Modalität.

Gemäß den PRISMA-2020-Richtlinien identifizierten wir Studien durch systematische Recherchen in Scopus zwischen dem 27. Juni und dem 20. Juli 2026, einschließlich der Rückwärts- und Vorwärtsverfolgungen von Zitaten. Im Anschluss wurden in dieser Übersichtsarbeit Studien berücksichtigt, die aktive EEG-basierte BCIs bei nicht beeinträchtigten Teilnehmern evaluierten. Nach dem Screening und der Eignungsprüfung wurden 37 Studien aufgenommen und mittels induktiven qualitativen Inhaltsanalyse ausgewertet.

EEG-basierte BCIs wurden in diversen HCI-Kontexten und mit unterschiedlichen Signalparadigmen eingesetzt, wobei P300- und Imagery-basierte Systeme am häufigsten untersucht wurden. Insgesamt variierten die Leistungsergebnisse zwischen den heterogenen Studien, wobei die meisten mittleren Genauigkeitswerte zwischen 70% und 89% lagen. Darüber hinaus kann die Interaktion mit einem BCI erhebliche kognitive und körperliche Anforderungen an die Nutzer stellen, während eine fortgesetzte Interaktion die Anpassung der Nutzer fördern kann. Trotz moderater Leistung wurden BCIs im Allgemeinen positiv bewertet, was darauf hindeutet, dass Zufriedenheit und Akzeptanz nicht allein von der Genauigkeit abhängen. Somit bieten aktive EEG-basierte BCIs Potenzial als ergänzende Interaktionsmodalitäten, wenn ihre Vorteile den erforderlichen Aufwand überwiegen.

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Finally, I would like to thank my family and friends for constantly motivating and encouraging me throughout the process of writing this thesis.

Conventions

Throughout this thesis we use the following conventions:

- The thesis is written in American English.
- The first person is written in plural form.
- Unidentified third persons are described in female form.

Short excursuses are set off in colored boxes.

EXCURSUS:

Excursuses are set off in orange boxes.

Where appropriate, paragraphs are summarized by one or two sentences that are positioned at the margin of the page.

This is a summary of a paragraph.

Fill in whatever other text conventions you might have here.

Chapter 1

Introduction

The increasing incorporation of digital technologies into everyday environments has rendered human interaction with interactive systems an indispensable and essential component of daily life. Human-Computer Interaction (HCI) describes a multidisciplinary research area that focuses on how interactive systems are created, assessed and used. Primarily, it examines the ways in which humans interact with computer-based technologies [Rex Hartson, 1998]. However, as computing systems have evolved over the past decades, the ways in which humans can interact with computers have likewise changed significantly. This evolution has led to the development of increasingly diverse and innovative interaction paradigms [Erat et al., 2024].

Continuous evolution of
HCI interaction
paradigms.

1.1 Brain-Computer Interfaces (BCIs)

Among these emerging paradigms, Brain-Computer Interfaces (BCIs), also known as Brain-Machine Interfaces, have gained significant attention, as they enable a communication pathway between users and computers by directly interpreting brain signals [Baek et al., 2019]. BCIs were originally designed as assistive technologies for individuals with disabilities. But their application has since grad-

BCIs evolving beyond
assistive technology.

ually expanded to include able-bodied users and they are now applied in various fields, such as in gaming, spelling, cognitive training and so on [Wu et al., 2022].

This raises the question of what is meant by BCIs and warrants a precise clarification to comprehend their definition. In general, BCIs are understood as follows:

Definition:
Brain-Computer
Interfaces

BRAIN-COMPUTER INTERFACES :

“BCIs allow capturing the brain activity of users by processing and/or classifying their brain signals with the purpose of controlling any system.”

— Kosmyna, N., et al., 2019

This definition highlights that BCIs are not limited to assistive purposes, but constitute a general-purpose interface technology. In general, BCIs can be broadly categorized along multiple dimensions, such as the signal acquisition modality as well as the level of invasiveness :

EEG enables
non-invasive
brain-computer
interfaces.

On the one hand, there are invasive techniques that involve surgically opening or penetrating the skull to place sensors directly into the brain. These sensors then capture electrical signals from a specific, localized region on the brain. On the other hand, electroencephalography (EEG) is one of the most studied non-invasive interfaces. In contrast to invasive methods, EEG records brain activity using electrodes placed on the scalp without surgical intervention. Within different neural signal acquisition methods, EEG remains one of the most widely used due to its non-invasive nature, relatively low cost and suitability in real-world applications [Kosmyna and Lécuyer, 2019].

BCI classification is
based on user
engagement.

Beyond the method of signal acquisition, BCIs are also commonly categorized into three types, namely active, reactive and passive BCIs and they "are based on the user's effort and task to control the BCI" [Zander et al., 2010]. Active BCIs rely on users intentionally and consciously modulating their brain activity to directly control the system. Re-

active BCIs enable the generation of commands through attention to external probe stimuli, whereas passive BCIs do not require any intentional mental task. Instead, they analyse brain activity to infer the user's affective or cognitive state [Zander et al., 2010]. Active BCIs are regarded as a form of explicit interaction, with reactive BCIs frequently considered similarly in the literature. Accordingly, both active and reactive BCIs are considered equivalent for the purposes of this thesis, such that references to active BCIs also include reactive BCIs.

This work concentrates specifically on active EEG-based BCIs, as they represent the most direct form of user-controlled interaction and are particularly relevant in scenarios involving voluntary human-computer interactions [Zander et al., 2010]. Furthermore, the focus is on able-bodied users, referring to individuals who are not physically or cognitively restricted in their ability to use the underlying interactive system or device. This focus allows for investigating BCIs as an alternative interaction modality rather than primarily as an assistive technology.

Focus on active EEG-based BCIs and able-bodied users.

Despite substantial technological progress in signal processing and machine learning methods improving classification accuracy, the practical deployment of EEG-based BCIs in real-world HCI settings remains limited [Zhang et al., 2018]. BCI "is still in its infancy and requires further consideration" [Baek et al., 2019] to have a meaningful impact on human experience in everyday environments.

Limited real-world BCI applicability persists.

A possible reason for this limited real-world impact lies in how current research approaches the evaluation of BCIs. Existing literature often examines performance, usability and user perception in isolation and studies involving able-bodied users are fragmented across different domains. This motivates the need for a comprehensive analysis of active EEG-based BCIs with an emphasis on performance, but also incorporating human-centered factors such as usability and user perception in able-bodied users.

Need for holistic evaluation of EEG-based BCIs.

Following the guidelines outlined in the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [Page et al., 2021], this study examines the current research landscape to identify and address

This thesis conducts a literature review and meta-analysis.

the existing research gaps. To achieve this, a structured literature review combined with a meta-analytical approach is conducted, covering publications across selected leading journals and top-tier conference proceedings. The investigation is further guided by the following research questions:

- RQ1* What levels of performance do active EEG-based BCIs achieve in HCI contexts and which factors influence their performance?
- RQ2* How is the usability of active EEG-based BCIs characterized and what usability challenges are reported in HCI contexts?
- RQ3* How do able-bodied users perceive and evaluate active EEG-based BCIs?
- RQ4* How suitable are active EEG-based BCIs for HCI applications overall?

1.2 Outline

This thesis is organized into five main chapters that are structured sequentially, with each chapter building upon the preceding one to guide the reader through the overall research progression. After this introductory chapter, Chapter 2 on related work provides the theoretical foundation of EEG necessary for understanding the subsequent work. Chapter 3 then outlines the research methodology applied in this study to identify, select and analyze the studies included in the literature review. In addition, it presents the key findings derived from this review. Building on these results from Chapter 3, in Chapter 4 the findings are examined in depth, accompanied by an evaluation and comprehensive discussion. Finally, Chapter 5 concludes the thesis by summarizing its key contributions and outlining potential avenues for further research.

Chapter 2

Related Work

This chapter provides a comprehensive overview of the current state of research on active EEG-based BCIs within the field of HCI. It begins by outlining the brief historical evolution of EEG-based BCIs. Subsequently, it discusses the fundamental principles of EEG signal acquisition and processing. Building on this foundation, it examines various signal paradigms for EEG-based BCIs. This is followed by a concise overview of the key application domains. To support the subsequent meta-analysis and evaluation, this section then introduces essential evaluation dimensions applied in the literature, which are crucial for assessing the practical suitability of BCI systems. Finally, it analyzes existing literature reviews and identifies prevailing limitations, as well as research gaps.

2.1 Brief History of EEG-Based BCIs in HCI

The origins of electroencephalography (EEG)-based brain-computer interfaces (BCIs) can be traced back to early neurophysiological studies conducted in the mid-20th century. EEG, originally developed by Hans Berger in the 1920s, introduced a non-invasive technique for recording the brain's electrical activity via electrodes placed

Early EEG-BCI research focused on medical applications.

Early BCIs enabled
limited communication.

on the scalp. Initial research centered on understanding neural activity patterns in medical contexts, in particular for patients with severe motor impairments. During this period, the concept of directly converting user intentions into control signals for external devices was largely theoretical and confined to medical research frameworks. Consequently, they were not yet regarded as interactive technologies within HCI [Wu et al., 2023].

In the 1970s, [Vidal, 1973] introduced the concept of ‘brain-computer interface’ to refer broadly to computer-based systems that are capable to generate detailed insights into brain activity [Wolpaw et al., 2002]. By the 1980s, research in this field primarily focused on facilitating communication for individuals with significant motor disabilities. A notable contribution by [Farwell and Donchin, 1988] presented a word-spelling system that allowed users to communicate by selecting characters on a visual display through brain activity. This innovation marks a pivotal transition from passive brain observation to active brain-based control, supported in part by advances in signal processing techniques. Despite these developments, their practical use remained constrained, as they can output only a few characters per minute [Wu et al., 2023].

BCI research is
increasingly integrating
with HCI.

In recent years, research expanded beyond clinical populations, with a growing interest in applications involving able-bodied users and interactive settings. Advances in machine learning, particularly deep learning methods for EEG signal decoding, along with the availability of portable EEG technologies, have facilitated BCI research to move into more everyday environments. Modern EEG-based systems seek to dynamically adjust interfaces in response to users’ attention, workload or engagement. As a result, BCI research has become more closely aligned with HCI, with systems now commonly assessed in terms of performance, usability and user perception [Tan and Nijholt, 2010].

2.2 EEG Signal Acquisition and Processing

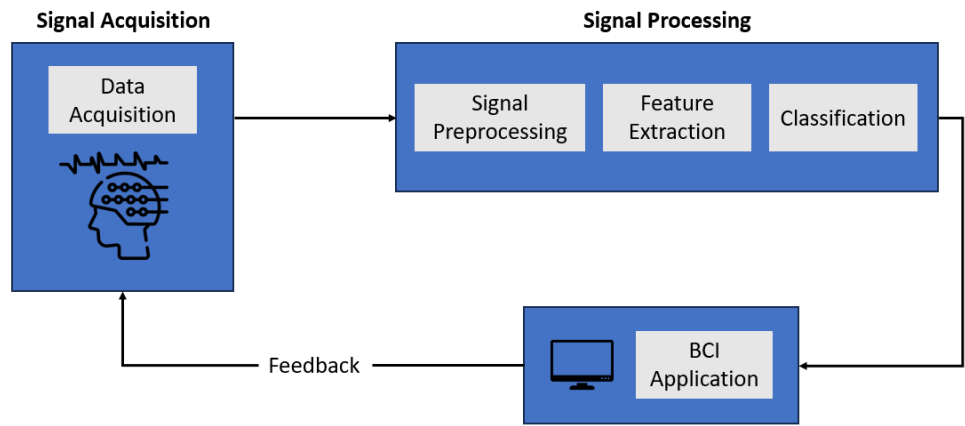


Figure 2.1: Pipeline of an EEG-based BCI, comprising signal acquisition, preprocessing, feature extraction and classification to transform brain activity into control commands. ^a

^a Own illustration incorporating EEG and computer icons from Flaticon, created by Magnific and Talha Dogar.

As shown by [van Gerven et al., 2009], EEG-based BCIs commonly rely on a multi-stage pipeline that transforms raw electrical brain activity into interpretable control signals for human-computer interaction. This pipeline, illustrated in Fig. 2.1, typically consists of signal acquisition and processing, where the latter comprises preprocessing, feature extraction and classification. They constitute the technical foundation of EEG-based BCIs and each of these stages plays a crucial role, directly influencing system performance, usability and user experience in HCI contexts [Kosmyna and Lécuyer, 2019; Tan and Nijholt, 2010].

Core stages of the EEG-BCI pipeline shape evaluation dimensions.

Signal acquisition represents the first stage of the pipeline. It refers to the process of recording or capturing electrical brain signals in different regions of the brain through electrodes placed on the scalp or surrounding the head. As illustrated in Fig. 2.2, the Emotiv EPOC EEG headset exemplifies a cap-like device with electrodes used for scalp

EEG records brain signals via scalp electrodes.



Figure 2.2: Emotiv EPOC EEG headset used for non-invasive EEG signal acquisition in BCI applications [Kaya and Saritas, 2023].

signal acquisition. According to [Ramele et al., 2022], this has been one of the widely used EEG systems in BCI applications [Chaddad et al., 2023].

Transitioning from wet
to dry electrode
systems.

In earlier stages of development, devices predominantly relied on wired configurations and gel was employed to enhance electrical conductivity. Although wet electrodes are often considered to provide more stable recordings, they are associated with increased preparation time due to scalp scrubbing to optimize signal quality. And after few sessions, this may increase skin sensitivity and therefore negatively impact user comfort [Saab et al., 2011]. This limits their suitability for real-world HCI applications. More recently, a notable shift toward the adoption of wireless connectivity and the use of dry electrodes has emerged, reflecting ongoing improvements in usability and user comfort while maintaining effective signal acquisition [Saab et al., 2011; Wu et al., 2022].

EEG preprocessing
reduces noise and
artifacts.

Following acquisition, signal processing is performed, in which the signals obtained during the acquisition step are processed. Raw EEG signals are inherently noisy because external interference may introduce a variety of artifacts that can affect the data, thus degrading the signal quality. This is often caused by experimental conditions, en-

environmental noise or physiological artifacts, such as involuntary eye or muscle movements, blinking and cardiac activity [Sharma and Meena, 2024]. Therefore, EEG signals undergo preprocessing procedures that involve temporal filtering, such as bandpass filtering, to minimize noise and mitigate artifacts, which can affect classification performance and reliability. It also includes spatial filtering, which combines multiple EEG channels to enhance the signal-to-noise ratio [Wu et al., 2022]. Overall, these preprocessing steps are commonly used in EEG-based BCI systems [Chaddad et al., 2023; Erat et al., 2024].

After preprocessing, feature extraction is performed to transform the filtered EEG signals into representative feature spaces. Less relevant features are then removed using feature selection methods. These features are fundamental to categorize user intentions as well as brain states [Yadav and Maini, 2025]. Furthermore, this step plays a crucial role in enhancing prediction accuracy and, consequently, the overall performance of the system. However, the extraction of meaningful features from signal preprocessing remains a highly complex and challenging task. It often depends on the expertise of several specialists with domain-specific knowledge. Recent advances in machine learning, especially in deep neural networks and generative adversarial networks, have enabled the automatic learning and extraction of relevant features directly from EEG data. Thus, this reduces reliance on manual feature engineering [Chaddad et al., 2023].

Feature extraction transforms signals into representative feature representations.

Finally, after feature extraction, classification algorithms are applied to decode user intent and map the extracted features to control commands. These algorithms are typically implemented using machine learning or signal classification models and then the data is trained and interpreted. This may comprise conventional machine learning approaches, such as LDA, SVM, K-Nearest Neighbours (k-NN), as well as more sophisticated deep learning architectures. This step also has a significant effect on system performance, as the classifier determines how accurately user intent is translated into control commands. Misclassifications will lead to incorrect control commands, even if feature extraction was accurate [Yadav and Maini, 2025].

Classifier maps features to control commands.

2.3 Signal Paradigms

Signal paradigms enable neural decoding.

As introduced in Chapter 1, active BCIs require users to intentionally generate or modulate brain activity for interaction. This interaction can be realized through various signal paradigms. The choice of signal acquisition and processing methods is strongly shaped by the underlying BCI signal paradigm, as each paradigm relies on distinct neural signatures [Yadav and Maini, 2025]. These paradigms refer to a set of cognitive tasks or externally applied stimuli that are devised by the system developer. The main aim of such paradigms is to reliably capture neural responses corresponding to a user's intended actions depending on particular neuroimaging methods [Tai et al., 2024]. Typically, EEG-based BCIs are broadly categorized into three major signal paradigms, namely:

- **Motor Imagery (MI)-based systems**
- **Steady-State Visual Evoked Potential (SSVEP) systems**
- **P300-based systems**

Motor imagery activates execution-related brain regions.

These paradigms are the ones frequently used. Each paradigm presents distinct trade-offs.

Motor imagery allows users to control systems by mentally simulating specific movements without explicitly performing any physical execution. Research by [Pfurtscheller and Neuper, 1997] has demonstrated that only the mere imagination of a movement activates brain regions that are also involved in executing the actual movement [Abiri et al., 2019].

SSVEP demands gaze-directed visual attention.

On the other hand, in SSVEP, users are required to actively redirect both their gaze and attentional focus toward rapidly flickering visual stimuli. Therefore, it necessitates a high degree of precise eye control and may cause fatigue when users are required to blink less frequently [Tai et al., 2024]. Because SSVEP needs flickering stimuli, visual attention can also not be disentangled from it [Abiri et al., 2019; Tai et al., 2024].

In addition, P300-based systems are event-related potential-based systems, which means that they rely on brief, quantifiable changes in brain activity. These changes occur in response to a particular stimulus or event and are detectable via EEG signals. The P300 is a brain signal that appears around 300 milliseconds after you notice it. In general, BCI systems utilize mixed target and non-target signals in the form of visual or auditory stimuli. Due to the brain producing a stronger P300 response to the target item you are paying attention to than to non-target items [Kosmyna and Lécuyer, 2019].

P300 reflects attention to target stimuli.

Moreover, there are also hybrid paradigms that combine multiple strategies to enhance overall performance by overcoming the weaknesses inherent in individual paradigms [Yadav and Maini, 2025].

Hybrid paradigms integrate multiple strategies.

A representative example of active BCIs is motor imagery (MI) and they are often regarded as more intuitive for users, as they do not rely on external stimuli. This makes this signal paradigm more convenient, but some limitations also still exist. Namely, users may require dedicated training, which "will waste the users' time and decrease their willingness to use" [Chen et al., 2022]. However, this is often necessary in order to effectively operate an MI-BCI system and achieve dependable performance outcomes [Chen et al., 2022].

MI-BCIs offer intuitive interaction while demanding user training.

In contrast, SSVEP- and P300-based systems generally require considerably less user training. Since both paradigms rely on stimulus-evoked brain responses, they can often be operated immediately after a short calibration period. Furthermore, in SSVEP, for example, the stimuli are presented at multiple distinct frequencies, which allows for the encoding of numerous distinct commands. But because of the mentioned eye control, they are not suitable for people with visual impairments [Abiri et al., 2019].

SSVEP & visual P300 limit users with visual impairments.

For this reason, no single EEG signal paradigm can be regarded as universally superior. Instead, each paradigm exhibits distinct strengths and limitations regarding training requirements, reliability and user acceptance. Consequently, the choice of a signal paradigm represents a funda-

Studies investigate diverse EEG paradigm approaches.

mental design decision. Although these signal paradigms represent the most widely investigated, further variations and approaches have been proposed in the literature. Studies that will be included in this review will employ a variety of paradigms depending on their application domain.

2.4 Applications in HCI

Active EEG BCIs enable diverse applications.	Active EEG-based BCIs are applied across a wide range of application domains, primarily driven by their ability to enable direct communication between the human brain and systems. These applications range from assistive technologies to interactive entertainment systems. As [Tan and Nijholt, 2010] believes, "we have only begun to scratch the surface of the set of applications that brain sensing technologies open". As stated previously, this thesis focuses specifically on able-bodied users. Consequently, assistive use cases are not considered further.
BCI speller as communication interface application.	One of the most prominent application areas is communication interfaces. As previously mentioned, the BCI speller based on P300 signals by [Farwell and Donchin, 1988] is considered one of the earliest documented applications in the field of brain-computer interfaces. It has served as a foundational development, paving the way for several subsequent advancements. Although these systems are commonly linked to assistive technologies, they are also widely employed in research involving able-bodied users to evaluate performance metrics across varying interface designs [Maslova et al., 2023].
BCIs allow attention-based immersive gaming experiences.	In addition, in entertainment and gaming contexts, active BCIs are often used to explore immersive interaction paradigms. By using EEG signals, the user can control interactive games that require players to sustain focused attention. Moreover, BCIs have also been explored in virtual and augmented reality environments where users can navigate virtual spaces or trigger actions without using muscles or traditional controllers. In this setting, interaction is driven by cognitive processes such as attention, intention or mental imagery [Lécuyer et al., 2008]. Furthermore,

BCIs can be integrated into multiplayer environments in which participants compete based on their cognitive performance. Users receive real-time feedback on their brain activity and performance. This introduces an additional dimension to conventional gameplay, where success is determined by the capability to maintain higher levels of focus [Yadav and Maini, 2025].

EEG-based BCIs also hold considerable promise for transforming educational practices by enhancing learning experiences and providing deeper insights into cognitive states of students. In particular, instructional games may support increased engagement and motivation during learning. Further, they can facilitate stress reduction and awareness training [Yadav and Maini, 2025].

EEG-based BCIs enhance learning engagement.

Research has additionally examined smart environment control systems, where BCIs are embedded within Internet-of-Things (IoT) frameworks to enable hands-free interaction with connected devices. Devices such as lights, televisions and doors can also be controlled through neural signals without physical input. It supports environmental interaction for individuals with disabilities and simultaneously ensures usability and comfort for able-bodied users [Maleki et al., 2020].

BCIs integrate IoT for device control.

Overall, these application areas demonstrate the versatility and potential of EEG-based BCIs in HCI, highlighting the need for more evaluations for long-term user acceptance.

2.5 Evaluation Dimensions

Research on EEG-based BCIs in HCI has shown that system evaluation cannot be reduced to a single performance metric, instead effectiveness is generally examined across multiple complementary dimensions. Especially in HCI contexts, evaluation must consider not only technical performance but also human-centered qualities, such as usability and user experience. These dimensions collectively determine whether a BCI system is technically effective and practically viable for end users in real-world applications.

Researchers evaluate EEG-based BCIs multidimensionally.

2.5.1 Performance

Signal-to-noise ratio
governs BCI decoding.

A core dimension is technical performance, which captures how reliably and accurately the system decodes brain activity into control commands. A well-designed and user-friendly device enables users to perform its functions both efficiently and accurately, while simultaneously improving overall productivity [Zaki and Islam, 2021]. In this context, the performance of a BCI fundamentally depends on its signal-to-noise ratio. The objective is to correctly infer and execute the user's intended command from recorded electrophysiological activity, acknowledging that only a subset of the measured signals carries relevant information. The remaining activity constitutes noise. Consequently, the user's role is to maximize this correlation through consistent brain activity patterns. At the same time, the system must accurately capture and extract these features, thereby maximizing the signal-to-noise ratio and leading to higher decoding performance [Wolpaw et al., 2002].

Researchers assess
system performance
using established
metrics.

Several metrics are used to evaluate system performance, but the most commonly reported metrics across devices are classification accuracy, i.e., the proportion of correctly classified commands, and Information Transfer Rate (ITR). [Thompson et al., 2013] notes that although accuracy is commonly used for evaluation, it has several important drawbacks. Such limitations include that it does not incorporate temporal aspects of performance and can be distorted due to chance-level performance effects across systems with varying numbers of output classes. Therefore, many researchers are now designing and using customized evaluation metrics tailored to their specific tasks and evaluation needs [Thompson et al., 2013].

System performance is
categorized as
application-specific and
theoretical.

However, evaluation of system performance can be further distinguished into two complementary dimensions: application-specific performance and theoretical performance. Application-specific performance is generally evaluated in terms of speed and/or accuracy within the framework of a particular task. On the other hand, theoretical performance is typically characterized by the information transfer rate, which seeks to approximate the system's potential capacity independent of any particular application scenario. Many studies focus predominantly on report-

ing application-specific performance, but these metrics are limited in their interpretability because they are strongly dependent on the particular characteristics of the tasks. As a result, comparisons across various studies are often challenging and measures do not necessarily capture the theoretical performance that could be achieved [Wolpaw et al., 2002].

2.5.2 Usability

Usability is also a central dimension in the evaluation of BCIs, especially in HCI contexts where systems are also designed for non-expert users. In contrast to conventional input methods such as touchscreens or keyboards, EEG-based BCIs introduce a fundamentally different interaction paradigm. Due to the fact that, in this paradigm, control signals originate completely from neural activity rather than from physical actions. Usability is one contributing factor to whether a system can be used successfully in real-world applications, where user acceptance and long-term adoption are critical. A well-designed system with high usability allows users to execute the functions with accuracy and ease and ultimately increases overall system productivity [Zaki and Islam, 2021].

Usability, as defined in ISO 9241-11, refers to how effectively, efficiently and satisfactorily users can accomplish specific goals within a particular context of use [iso, 2018]. In practice, it is often ambiguous for practitioners to identify which measures adequately represent these three aspects. Moreover, there is no usability framework that is broadly applicable to BCI evaluation but also systematic. In general, as [O'Brien and Charlton, 2001] argue, usability evaluations are frequently carried out according to the evaluator's preferences and may lead to findings that are of limited relevance and lack structure. As a result, comparing findings across different studies becomes challenging [Choi et al., 2017].

For EEG-based systems in particular, factors such as learnability, cognitive workload and fatigue are frequently included to better capture the disadvantages in the usage of neurophysiological interaction. Learnability describes the

Usability influences user acceptance and impacts long-term system usage.

Usability comprises effectiveness, efficiency and satisfaction, which are not standardized in evaluation.

Users learn systems under cognitive load, which may cause fatigue.

amount of time and effort required for users to acquire proficiency in operating such systems. Typically, users need a certain period of training and practice before they can successfully interact with a BCI system. An indicator of high learnability is if most users are able to learn the system quickly and do not struggle with extensive training. Operating a BCI system requires the user's brain to bear a particular degree of cognitive demand and could lead to fatigue. And this depends on the exact BCI application respectively the intricacy of the task and also how experienced the user already is [Pan et al., 2024].

Researchers often evaluate usability using subjective methods.

Usability is often evaluated subjectively, primarily relying on user involvement. Subjective methods are typically characterized by collecting opinions, such as evaluating a system according to how well it fulfills user requirements through ratings. This is usually done with the help of surveys, questionnaires and interviews. One of the most widely used instruments for measuring perceived workload in HCI studies is the NASA Task Load Index (NASA-TLX). It evaluates subjective workload across six dimensions: mental demand, physical demand, temporal demand, performance, effort and frustration. After completing a task, participants rate each dimension, thereby facilitating researchers in evaluating the cognitive and emotional workload related to interacting with the system [Cao et al., 2009; Choi et al., 2017]. In contrast, the System Usability Scale (SUS) is a widely used questionnaire for the assessment of overall usability. It is a standardized ten-item questionnaire and provides a score ranging from 0 to 100 for each dimension. A higher score reflects a higher level of overall usability of the system [Pan et al., 2024]. In addition to NASA-TLX and SUS, a variety of other instruments are used in HCI research to evaluate usability from different perspectives [Zaki and Islam, 2021].

2.5.3 User Perception

User satisfaction is crucial for BCI acceptance.

User perception is also a critical dimension in the evaluation of the viability of active EEG-based BCIs. Achieving a positive overall user experience is a key objective of user-centered design. This is particularly important, as dis-

satisfaction with a system can significantly impede the acceptance and distribution of BCI applications. As [Kögel et al., 2019] stated, studies therefore examine psychological factors, including affective state, depressive symptoms and motivation. They also consider participants' opinions, judgments and expectations regarding the use of BCIs [Pan et al., 2024].

Novice users often face considerable difficulties during the learning process. Furthermore, reduced engagement and frustration are often the result of prolonged cognitive effort and tend to worsen in the absence of immediate feedback. As cognitive demands increase over time, users may also experience fatigue, which is commonly described as a state of tiredness and reduced alertness and can negatively affect the overall experience. Ideally, BCIs should elicit strong EEG signals for performance, but also require minimal effort to operate to avoid fatigue. For example, SSVEP-based BCIs require users to exert considerable mental effort in order to maintain focus on the visual stimuli. However, the focus on the brightness of the stimulus can lead to fatigue [Cao et al., 2014]. Another important factor is the aesthetic design of BCI systems, which is often overlooked but shapes user perception and acceptance of the technology [Pan et al., 2024]. Moreover, signal quality and concentration are impaired by discomfort and fatigue caused by extended usage [Yadav and Maini, 2025].

User perception refers to the subjective psychological and experiential aspects of interacting with a BCI system and is therefore typically assessed through qualitative feedback and self-report measures. With the help of these, researchers aim to determine whether participants found the system intuitive, how reliable the responses felt and how natural the interaction was. Taken together, these evaluation methods provide insight into users' intentions to continue using a system, indicating whether the system is likely to achieve long-term acceptance or be rejected in practical use due to unfavorable subjective experiences [Zaki and Islam, 2021].

Generally, user perception and usability are closely related concepts and are frequently used interchangeably when evaluating whether user demands are fulfilled. However, there are notable distinctions between these two terms. User perception refers to the overall experience a user has

High mental effort and fatigue reduce engagement.

Subjective evaluation captures EEG-BCI experience.

User perception and usability differ in focus.

when interacting with a system, with particular emphasis on the emotional aspects of that experience. In contrast, usability focuses on the quality of interaction, including learnability, safety and related functional attributes. Both user perception and usability are essential in system development because they ensure that user needs, preferences and expectations are addressed [Zaki and Islam, 2021].

2.6 Limitations of Existing Literature Reviews

Evaluation in EEG-based BCI research is fragmented.

Despite substantial progress in EEG-based BCI research over the past decades, their practical use in real-world HCI scenarios is still very limited. One of the main reasons is not only technical constraints but also how these systems are evaluated. Existing work in the context of HCI and evaluation remains fragmented across different studies. One paper may focus exclusively on the performance aspects, while another may address the user perspective. This raises questions that motivate further investigation.

[Choi et al., 2017] explored hybrid BCIs, but other types are insufficiently addressed.

[Choi et al., 2017] conducted a systematic review of hybrid BCIs with a particular focus on taxonomy and usability evaluation. This review emphasized the need to incorporate user-centered evaluation approaches. However, the study mainly concentrated on hybrid BCIs and included both healthy individuals and participants with disabilities. Consequently, the evaluation of active EEG-based BCIs for able-bodied users remains only partially addressed.

[Kögel et al., 2019] conducts a scoping BCI review.

Furthermore, [Kögel et al., 2019] present a scoping review of empirical studies on BCIs that employ social research methods, with a specific focus on user-related and ethical perspectives. Importantly, the authors highlight a clear imbalance in existing literature: although usability and feasibility have been comprehensively examined, more profound experiential aspects such as self-perception and the subjective experience of using BCIs remain comparatively underexplored. While this review provides a broad

overview of user-centered BCI research, it does not specifically focus only on active EEG-based signal paradigms.

In contrast, [Hamed et al., 2016] provide a comprehensive review of EEG-based motor imagery (MI) brain connectivity analysis, with a particular emphasis on the role of effective and functional connectivity approaches to improve MI-BCI performance. Although this review emphasized connectivity as a promising avenue for enhancing MI-BCI performance, the discussion primarily focuses on signal processing techniques. User-centered factors of individuals using active EEG-based BCIs, particularly within the context of HCI, are not the main focus of this review.

In addition, [Jiang et al., 2026] review deep learning techniques for motor imagery EEG decoding, focusing on model architectures and the applicability of deep learning-based BCI models across both healthy and clinical users. They underscore that, despite considerable enhancements in decoding performance through modern deep learning approaches, their translation into real-world applications is still limited. And this review also primarily addresses algorithmic performance evaluation.

[Vavoulis et al., 2023] analyze online classification performance in MI-based EEG-BCIs within the context of neurorehabilitation, considering both healthy participants and stroke patients while comparing different classification approaches. Their analysis shows that conventional ML methods can achieve comparable performance to more recent deep-learning approaches. However, HCI-related aspects remain outside the scope of their work and it is limited to MI-based paradigms.

Similarly, [Norani et al., 2010] present a review of EEG-based BCI systems with a primary focus on signal processing techniques, including data acquisition, preprocessing, feature extraction and classification approaches. Rather than concentrating on HCI, the paper mainly surveys how various methodological choices affect the general BCI performance and classification accuracy.

[Värbu et al., 2022] present a systematic review of EEG-based BCI applications published between 2009 and 2019, covering both medical and non-medical domains. Addi-

[Hamed et al., 2016],
[Jiang et al., 2026] &
[Vavoulis et al., 2023]
focus mainly on
performance-driven
signal processing of
MI-systems.

[Norani et al., 2010]
reviews EEG-based
BCI signal processing.

[Värbu et al., 2022]
systematically review
EEG-based BCI
applications.

tionally, it discusses current challenges and future research directions. Although it includes active EEG paradigms, its primary focus lies on the broader EEG-based BCI landscape and not on their evaluation.

[Thakur et al., 2025]
survey EEG
communication
paradigms.

[Thakur et al., 2025] review EEG-based BCI communication systems with a focus on assistive applications for Locked-In Syndrome patients. The authors discuss different EEG paradigms, including MI, SSVEP and P300, as well as emerging hybrid approaches that seek to enhance performance through the integration of advanced ML methods. Nevertheless, they mainly concentrate on technical advancements and clinical applications, while not explicitly addressing the role of active EEG-based BCIs in general.

[Tsai et al., 2025]
assesses EEG-BCI
neurofeedback for older
adults.

Further, [Tsai et al., 2025] conduct a systematic review of EEG-based BCI applications for cognitive enhancement in older adults, focusing on neurofeedback paradigms. They emphasize that, while EEG-based BCIs have shown considerable potential, their broader usability and practical applicability are often insufficiently investigated. Also, this paper limits its emphasis to the use of these systems in older populations.

EEG-based vibrotactile
BCIs are systematically
analyzed by [Huang
et al., 2022].

Moreover, [Huang et al., 2022] systematically review EEG-based BCIs that rely on vibrotactile stimulation, encompassing experimental setups, signal processing techniques, evaluation settings and reported outcomes such as classification performance. The authors demonstrate that most studies report above-chance performance, thereby supporting the overall feasibility of vibrotactile BCIs. However, human-centered aspects remain comparatively underexplored and it also does not particularly address active EEG paradigms for healthy users designed for everyday use cases.

[Nijholt, 2015] highlights
multimodal BCI
applications.

[Nijholt, 2015] reviews non-clinical BCI applications, focusing on multimodal and multi-brain interaction in HCI. This paper underlines the shift towards BCI systems for able-bodied users, where EEG signals are integrated with additional input modalities to enable more natural interaction. Although this review provides valuable insights into mul-

timodal BCI applications, it does not consider evaluation aspects.

Unlike these other reviews, [Herbert, 2024] examines psychological human factors and shows that differences in performance are only partly explained by variables such as cognition, motivation or personality. Therefore, the author proposes self-relevance and the user’s self-concept as higher-order constructs that may adequately explain variability. However, this review moves beyond specific active EEG paradigms and instead seeks to establish a more general theoretical framework for user-centered BCI design and interpretation.

[Herbert, 2024]
reframes BCI
performance through
self-relevance.

[Niu et al., 2025] investigate in a recent systematic review how individual factors such as age, cognitive function, attention and mental state influence the effectiveness of EEG-based BCIs. The authors outline the importance of individualized training strategies and adaptive system designs to improve usability and reliability in real-world scenarios. However, this review also indicates that prior studies remain fragmented and lack a unified evaluation framework.

[Niu et al., 2025]
underline that
fragmented literature
lack unified evaluation
framework.

Taken together, existing literature reviews provide valuable insights into EEG-based BCI research from various perspectives. Nevertheless, these perspectives are often considered independently, which results in a fragmented understanding of active EEG-based BCIs as interactive systems. This fragmentation indicates the importance of further identifying existing research gaps within the field.

Fragmentation creates
gaps in BCI research.

2.7 Research Gaps

Although previous literature reviews have substantially advanced the understanding of EEG-based BCIs, several important research gaps remain concerning the evaluation of active EEG-based BCI systems from a HCI perspective.

Various research gaps
still remain.

Able-bodied users have often not been sufficiently considered as a distinct user group within these studies. While several papers investigate BCI systems as assistive

Able-bodied users
remain insufficiently
investigated in reviews.

technologies for individuals with motor impairments, the expectations, motivation and interaction requirements of healthy users are fundamentally different. In non-clinical HCI contexts, BCIs are not primarily designed to compensate for lost capabilities, but instead serve to provide alternative and novel interaction. Consequently, results from clinical individuals cannot be directly generalized to able-bodied users. Due to this fact, a more specific examination of this user group is required to comprehend healthy individuals' needs in everyday HCI scenarios.

Transferability limits
from different BCI
research domains.

As shown, existing literature reviews often examine EEG-based BCIs within broader application domains, including hybrid BCI architectures, clinical settings, neurorehabilitation or user groups affected by specific medical conditions. In contrast, active EEG-based BCIs in non-clinical HCI environments have received comparatively limited investigation. Consequently, it remains uncertain to what extent insights derived from hybrid or medical BCI research can be transferred to everyday environments involving healthy users. As a result, particular challenges, limitations and potential benefits associated with it remain insufficiently synthesized.

Researchers
underexplore human
factors in BCIs.

Furthermore, prior reviews have often mainly concentrated on technical aspects, such as classification performance, signal decoding techniques and algorithmic optimization. In comparison, user-centered factors such as perceived usability, user experience and satisfaction have been addressed less systematically. However, since BCIs introduce an interaction modality fundamentally different from conventional input methods, it is essential to understand how users experience and interpret this form of interaction for future HCI design.

Users' attitudes
determine BCI
acceptance.

Beyond that, social acceptance in relation to this form of interaction represents a relatively underexamined factor affecting the adoption of EEG-based BCIs. Successful real-world implementation requires a deeper understanding of user attitudes toward wearing EEG devices and their willingness to engage with brain-controlled interaction every day.

Finally, despite the increasing body of research, these gaps emphasize the clear need for a more interdisciplinary and holistic approach that integrates these different evaluation dimensions. This work aims to address these gaps by conducting a systematic review and meta-analysis on how active EEG-based BCIs overall perform and how they are experienced by able-bodied users.

An Interdisciplinary approach is needed for the evaluation.

Chapter 3

Meta-Analysis

The following chapter presents the methodological approach and key findings of the conducted literature review. The review process was carried out in alignment with the PRISMA statement guidelines [Page et al., 2021]. The following sections provide a detailed description of the applied methodology, covering the procedures for data collection as well as the eligibility criteria used for screening and inclusion of studies. The chapter then proceeds to summarize and analyze the results derived from the selected literature.

3.1 Methodology

The literature review followed a systematic approach and was conducted to identify, assess and synthesize existing research on active EEG-based brain-computer interfaces (BCIs) within the field of HCI. As previously outlined, the included studies were examined in relation to key dimensions pertinent to the research question, namely system performance, usability-related factors and user perception among able-bodied participants. The main aim of this review is to present a structured overview of the current research landscape, emphasizing recurring patterns, commonly used performance metrics and approaches to user-

Systematic reviews
enhance transparency
and reproducibility.

centered assessment. As shown by [Higgins et al., 2019], in contrast to narrative reviews, which are often more descriptive and selectively focused, systematic reviews adhere to a predefined and transparent methodological framework designed to minimize bias and ensure the reproducibility of results by other researchers.

Methodological
heterogeneity makes
cross-study
comparability
challenging.

Due to the inherently interdisciplinary nature of BCI research, the studies included in this review span multiple domains such as human–computer interaction, neuroscience and machine learning. Consequently, substantial methodological heterogeneity is to be expected across experimental setups, classification techniques, signal processing pipelines and evaluation metrics. This heterogeneity makes comparison challenging and, as a result, impedes the progress of research [Fernando Nicolas-Alonso and Gomez-Gil, 2012]. Therefore, it requires a well-structured approach to support valid and meaningful cross-study comparisons.

3.1.1 The PRISMA Statement

This systematic review
follows PRISMA
guidelines.

Originally introduced in 2009 and subsequently updated in 2020, the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) by [Page et al., 2021] is a widely adopted reporting guideline and provides a standardized framework. It encourages researchers to explicitly document each step of the review process. This review follows PRISMA, from the initial stages to the final stages of the study selection process. It includes systematic identification of relevant studies, structured screening and eligibility assessment and selection of studies. By adhering to these guidelines, these main phases are conducted appropriately and effectively.

The study selection can be concisely described in a structured manner, typically illustrated as a flow diagram that captures these principal stages of the review process.

PRISMA 2020
standardizes review
and abstract reporting
via checklists.

The PRISMA 2020 statement includes a 27-item checklist for systematic reviews and a separate 12-item checklist for abstracts, which collectively guide authors in reporting essential components of a systematic review and its abstract.

These checklists address key sections such as the title, abstract, introduction, methods, results, discussion and other information for both the full review and the abstract. These checklists can be found in Appendix C, Table C.1 (PRISMA 2020: Checklist) & C.2 (PRISMA 2020: Abstract Checklist).

The PRISMA Statement was originally developed within the field of medical research. Nevertheless, the authors note that this framework may also be applied across various research domains beyond medicine in which systematic reviews or meta-analyses are conducted. The present thesis does not follow all items of the PRISMA checklist, as some recommendations were not relevant or applicable to the specific scope of this work. Certain elements are specifically tailored to medical research, such as protocol registration and were therefore omitted in this study.

Non-relevant PRISMA items were omitted.

3.1.2 Identification of Relevant Literature

In the identification phase, pertinent studies were retrieved from the scientific database *Scopus*¹ (Elsevier Database) by using predefined search strategies. The selection of this database is guided by its coverage of the main research domains regarding BCIs. The database also indexes a substantial proportion of publications from the *Association for Computing Machinery (ACM) Digital Library*² and *Institute of Electrical and Electronics Engineers (IEEE) Xplore Digital Library*³.

We selected the scientific database Scopus.

Given the inherently multidisciplinary character of BCIs, Scopus was selected as a comprehensive database that ensures a more representative and balanced corpus of literature, thereby reducing the risk of database-specific bias. Scopus also enables broader coverage across neuroscience and related fields, ensuring literature retrieval beyond engineering-oriented databases. It thereby supports a more comprehensive dataset for analyzing performance and human-centered evaluation metrics. ACM Digital

Scopus provides broad interdisciplinary coverage, ACM covers HCI and IEEE Xplore focuses on engineering.

¹ <https://www.scopus.com/pages/home#basic>

² <https://dl.acm.org/>

³ <https://ieeexplore.ieee.org/Xplore/home.jsp>

Library provides a strong focus on HCI and offers high-quality publications on usability studies and user-centered evaluation methods, which are crucial when researching user perception and quality of interaction. In contrast, IEEE Xplore is the dominant source for engineering-driven BCI research, including studies that focus on practical implementations and user evaluations of EEG-based interaction paradigms.

Systematic
keyword-based search
strategies enable
reproducible results.

For consistency and reproducibility, we constructed search strategies using various related keywords and Boolean operators. This approach captures variations of EEG-based BCI terminology across different research communities. To identify the keywords needed, we also examined existing systematic reviews.

Using Boolean
operators for different
components.

Figure 3.1 presents this search query applied to identify relevant studies. As previously mentioned, this thesis focuses on several key components. Therefore, the search strategy relies on AND-connected blocks, with each block representing a mandatory dimension of the research question. Using AND ensures that only studies addressing all elements concurrently are retrieved, which significantly enhances relevance for a meta-analysis. Moreover, we included multiple synonyms and abbreviations by utilizing OR to maximize coverage. In addition, keywords were enclosed in quotation marks to enforce exact phrase matching. This prevents the database search engines from implicitly inserting OR between individual terms and thus minimizing the occurrence of noisy or irrelevant results.

SEARCH QUERY:

("brain-computer interface" OR "brain-computer interfaces" OR BCI* OR "brain-machine interface" OR "brain-machine interfaces")

AND

(EEG OR electroencephalogra*)

AND

(healthy OR able-bodied OR non-disabled OR non-clinical OR non-patient OR non-impaired)

AND

(evaluation OR survey* OR interview* OR questionnaire* OR "user study" OR "user experiment" OR "empirical study" OR usability OR effective* OR efficient* OR satisfact* OR learnability OR "user perception" OR "cognitive load" OR workload OR "mental effort" OR fatigue OR accept* OR reject* OR "System Usability Scale" OR SUS OR "NASA Task Load Index" OR NASA-TLX OR "human-computer interaction" OR HCI OR "human-machine interaction" OR HMI OR "user interface" OR UI OR "user experience" OR UX)

Figure 3.1: The search query applied in Scopus (1192 results) to identify relevant literature. This query consists of four keyword blocks connected by AND operators, covering BCI terminology, EEG-based systems, able-bodied users and evaluation-related aspects.

The first keyword block focuses on the terminology associated with brain-computer interfaces. Because different research communities use varying terms, commonly used terms and their plural forms were included, as well as the abbreviation BCI. However, the abbreviation BMI for “brain-machine interface” was not included in the search strategy. This decision was made because BMI also stands for “body mass index” and is more widely used for that, which would lead to irrelevant search results. Moreover, this keyword group ensures the fundamental requirement that every retrieved study must concern BCI-based systems rather than unrelated EEG applications.

1. Keyword block: BCI

2. Keyword block: EEG Further, the second block restricts the search to EEG-based systems and, to be more precise, ensures that EEG is explicitly addressed in the included papers. This is essential because BCIs can rely on various signal acquisition methods and it restricts the review specifically to non-invasive BCIs.
3. Keyword block: Participants In the penultimate block, the target population of this review is addressed and multiple synonyms and abbreviations were incorporated involving able-bodied users. This restriction is important because BCI research is often conducted with clinical populations, such as individuals with neurological disorders or motor impairments.
4. Keyword block: Evaluation The last keyword group targets evaluation-oriented research related to performance, usability and user perception. It is important for aligning the review with HCI research outcomes. As depicted, these different terms ensure that papers are identified addressing either performance evaluation and/or user-centered aspects in the form of user studies.
- Keyword exclusions to preserve review focus. Moreover, the term “active” was not included as a separate keyword or in the form of a separate block. Although this thesis focuses specifically on active EEG-based BCIs, the term is not consistently used in publications or is often not mentioned directly. Instead, the differentiation between active and other BCI paradigms was made during the screening process.
- It should be noted that direct terms such as “performance” or “accuracy” were also not included as search terms. Although these words are widely reported in EEG-based BCI research, they are frequently examined from a technical perspective with a primary focus on machine learning optimization and classifier development. Further, including these terms would substantially increase the number of studies, resulting in a broader search scope and reducing the focus on the user-centered aspects that are central to this review.

The literature search with these keywords was carried out between 27 June and 20 July 2026 and this process yielded 1192 results from Scopus. The retrieved records were subsequently imported into *Zotero*⁴, a reference management software used to organize and manage scientific publica-

⁴ <https://www.zotero.org/>

tions. Zotero was used to support the screening process for the identification of relevant studies.

3.1.3 Screening & Eligibility Assessment

The screening process followed a two-stage approach. Prior to screening, duplicate records were removed to reduce redundancy, so that each study is counted only once during the following screening phase. Subsequently, the titles and abstracts were initially screened carefully for relevance. This phase primarily aims to exclude publications that are evidently irrelevant. Therefore, they were independently reviewed against predefined inclusion and exclusion criteria for the scope of this review.

We removed duplicates and screened title/abstract.

Inclusion criteria:

- Studies involving active EEG-based BCIs
- Reporting at least one of the following outcomes: performance (e.g. accuracy, ITR), usability (e.g. learnability, ease of use) or user perception (e.g. satisfaction, frustration)
- Studies were included only if there is a user study conducted with able-bodied (non-clinical) participants
- Only studies written in English

These inclusion criteria are directly reflected in the keywords used in the search strategy. Although the search strategy described above was used, literature that nevertheless emerged and focused exclusively on non-EEG modalities or did not evaluate EEG-based BCIs was not included. But also when there were only clinical populations regarding user studies or passive BCI paradigms were investigated without an active control component and so on. But another major exclusion criterion is when the focus is only on machine-learning-based optimization or classification performance without a corresponding user-centered

Studies clearly not meeting inclusion criteria were excluded.

We excluded purely algorithmic & ML studies.

evaluation. Research primarily aimed at enhancing classification algorithms, feature extraction methods or signal processing frameworks was excluded when it lacked empirical assessments related to HCI. Although classification performance is an essential technical aspect of EEG-based BCI development, such studies were considered beyond the scope of this review. This review focuses on HCI-related performance, i.e., how effectively users can interact with the system and how system performance is experienced within a user-centered perspective. However, such user-centered evaluations do not appear to be frequently reported in the existing literature, as many studies primarily focus on technical system performance.

At this stage, we excluded studies that clearly did not meet the inclusion criteria. Non-English publications are also excluded in general to maintain consistency and quality of the dataset. Further, this review included only original empirical research published in peer-reviewed journals and conference proceedings. If there was any uncertainty about the relevance of a study, it was included for full-text screening so as not to prematurely exclude it.

Full-text eligibility
assessed for final
inclusion.

In the second stage, the eligibility of full texts of the 712 remaining studies was retrieved and assessed in greater detail to confirm relevance. This step ensured that only studies providing adequate contribution were included in the final analysis. In other words, from this stage onward, all studies that did not meet these thematic requirements were completely excluded.

3.1.4 Identification of Additional Studies

Following the initial screening and eligibility assessment of the records identified through Scopus, only 24 studies met the predefined inclusion criteria. But to further expand the identified body of literature, additional search strategies were subsequently employed to identify other potentially relevant studies.

Supplementary Search Through Existing Literature

Prior to conducting the Scopus search, we examined an existing systematic review by [Kögel et al., 2019] as a supplementary source to ensure that a sufficient body of literature was available to conduct this review. The studies reported in this review were compared with the other studies already retrieved through the preceding search. Studies not previously captured were then assessed against the predefined eligibility criteria. Overall, this supplementary search identified 10 additional relevant studies, although the preceding database search had already captured a substantial number of relevant studies.

We verified literature coverage using an existing review.

Backward and Forward Citation Searching

Although systematic keyword-based searches provide a reproducible approach for literature identification, the predefined selection of keywords inherently restricts the search space. Consequently, other relevant publications may remain unidentified due to differences in terminology and indexing limitations.

Therefore, in addition to database-based literature search, we also applied citation-based search techniques (also referred to as citation-based snowballing) to further identify relevant studies. This comprises backward and forward citation tracking.

Keyword choices may limit the identification of additional relevant literature.

Backward snowballing was conducted by examining the reference lists of the included studies at the end. In other words, through this approach, papers that are cited by the included studies are retrieved. This approach allowed the identification of foundational studies. In contrast, forward snowballing was performed by examining studies that cite the included publications. This was conducted using citation information provided by Scopus, thereby allowing the detection of more recent research building upon previous findings.

Citation-based methods support literature coverage.

Overall, this method resulted in the identification of 3 additional relevant studies, which were included after applying the predefined eligibility criteria described.

In total, 37 studies were identified through the database search and supplementary search strategies, including citation-based snowballing and examination of an existing literature, and fully met the predefined inclusion criteria. This final set of included studies forms the basis for the subsequent meta-analysis and evaluation of active EEG-based BCIs in HCI contexts. A detailed overview of all included studies is provided in Appendix A, Table A.1.

Flow chart illustrates study selection process.

Fig. 3.2 presents the flow chart which summarizes the literature selection process and illustrates the sequential stages of it. Here, *Identification of new studies via databases* and *Identification of new studies via other methods* denote the predefined sources of literature retrieval employed in the search process. The former refers to the systematic retrieval of publications from scientific literature databases. And the latter encompasses additional sources beyond database searches, namely the examination of an existing scoping review as well as backward and forward citation tracking.

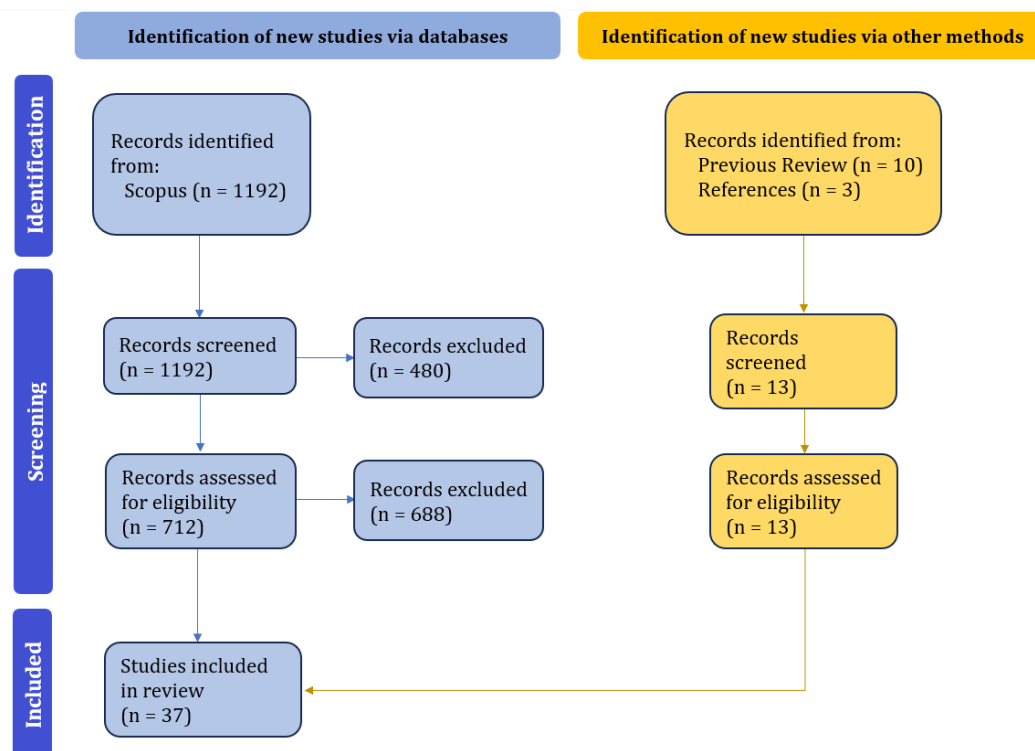


Figure 3.2: This flow diagram, based on the PRISMA Statement [Page et al., 2021], visually represents the number of records identified through database searches, the records screened, excluded and ultimately included in the final analysis. Additionally, it includes records identified through supplementary search strategies, such as the examination of an existing scoping review and citation tracking.

3.1.5 Analysing the Corpus

The following sections describe the methodology applied to analyse the collected body of research on active EEG-based BCIs. This process consists of conducting an inductive qualitative content analysis and developing a codebook through an iterative coding process. Following the identification and refinement of relevant codes, the resulting categories and components included within the codebook are discussed in greater detail.

Inductive Qualitative Content Analysis & Codebook Development

The analysis identified and synthesized relevant study characteristics.

Given that only a limited number of existing frameworks specifically address the scope of this review, no directly applicable codebook could be identified. Therefore, an inductive qualitative content analysis was conducted, guided by established methodological literature on qualitative content analysis and qualitative research, particularly [Hsieh and Shannon, 2005] and [Clarke and Braun, 2013]. This approach enables the systematic identification, examination and synthesis of relevant characteristics reported across the included studies. Initially, the research objectives and research questions presented in the Introduction guided the identification of relevant aspects to be analyzed.

Studies were assigned codes, which were refined into a final codebook.

Each included study was thoroughly reviewed and important information was extracted and assigned to an initial set of codes. During the initial stage of coding, recurring patterns and concepts emerging across the studies were identified. Related codes were then grouped into broader categories for the analysis to establish a structured analytical framework. Furthermore, these categories underwent continuous evaluation and refinement to maintain consistency and to accurately represent the features of the reviewed studies. Based on the refined categories and codes, the final codebook was established and an overview and detailed description of it is presented in Appendix B. The individual categories and their associated codes are discussed in the subsequent sections.

By addressing the research questions and examining each included study, we derived and labeled 6 categories:

- **Application Domains:** The intended area of application in which the specific EEG-based BCI system is implemented.
- **Signal Paradigms:** The type of EEG signal paradigm used to enable interaction and control BCI systems.
- **Sample Size (Able-Bodied Participants):** The number of able-bodied participants involved in the study evaluation.
- **Mean Accuracy Ranges:** The range of mean accuracy achieved by the EEG-based BCI system.
- **Usability Dimensions:** The aspects used to assess the usability of the EEG-based BCI system during user interaction.
- **User Perception Dimensions:** The aspects used to capture users' subjective perceptions and experiences of the EEG-based BCI system.

The defined categories correspond to the research questions and were developed to also support the answering of these questions. While some categories mainly address a single research question, others provide contextual information that contributes to the interpretation of findings across multiple research questions. Further, evaluation methods were not included as a separate category because the included studies predominantly relied on questionnaires to assess usability and user perception.

RQ1 (performance) was investigated by analyzing the mean accuracy values reported across the included studies and examining their distribution. Furthermore, *RQ2* (usability) was examined through the analysis of usability dimensions, which capture the specific aspects of usability investigated in the included studies. For *RQ3* (user perception), the analysis focused on the dimensions used to characterize users' subjective experiences and perceptions of the investigated BCI systems. *RQ4* (overall suitability) is addressed through the combined analysis of all six categories.

Categories structured around the research questions.

Application Domains

Describes the practical contexts and application areas of active EEG-based BCIs.

The category *Application Domains* represents the various fields and interaction contexts in which active EEG-based BCIs are applied to enable direct communication between users and computer systems. Analyzing application domains is essential within the context of HCI, as the intended use case directly affects system requirements, the interaction and therefore the user experience. Furthermore, the application context plays an important role in determining how users interact actively with BCI systems and how these technologies can be incorporated into practical scenarios.

- **Entertainment:** Active EEG-based BCIs are applied in entertainment-oriented contexts in which brain activity is used for engaging or immersive interactions. This category includes applications such as BCI-based games, virtual environments, brain painting, music composition and other interactive experiences mainly intended for enjoyment or creative expression.
- **Speller:** EEG-based speller systems are among the most established applications of active BCIs. They are mainly designed to enable communication by selecting letters, words or symbols through direct brain activity. The selection mechanism depends on the underlying BCI paradigm, but is often visual attention to flickering stimuli. They are an alternative for communication and allow composing messages without relying on conventional input devices.
- **Machines:** Another application area involves the control of physical machines and mobile systems, including robots, vehicles, drones and so on. Here, EEG-based BCIs enable users to control movement, navigation or other system functions of these machines through brain activity.
- **Medical:** Medical applications refer to clinical and medically relevant contexts, including cognitive training, neurorehabilitation and BCI-supported interaction during medical procedures such as neuro-

surgery. These applications demonstrate how BCI-based interaction can support people in improving their cognitive abilities, where conventional input methods may be unsuitable.

- **Smart Home:** In addition, active EEG-based BCIs have also been investigated for controlling smart homes to operate household devices and environmental functions. For example, with BCIs, activating lights, televisions, coffee machines and other household appliances would generally be possible. From an HCI perspective, smart home BCIs represent a shift from conventional interaction modalities towards environment-aware interaction.
- **Cursor Control:** Another application domain focuses on controlling a computer cursor through brain activity. Such systems enable users to navigate graphical user interfaces, select targets and interact with digital content without relying on conventional input devices such as a mouse.
- **Authentication:** Furthermore, they are used for user authentication by recognizing individual patterns of brain activity. In this context, neural signals serve as biometric characteristics for verifying a user's identity and providing access to protected systems or services.
- **Multifunctional:** Multiple interaction functions can be integrated into a single BCI system, which allows users to perform various tasks and control several applications through brain signals. It can support multiple application domains, including communication, entertainment and web access.

Signal Paradigms

Further, the category *Signal Paradigms*, as described, refers to the type of neural activity needed and the EEG-based control mechanism to generate user commands. As active BCIs rely on users intentionally generating specific brain

Describes the neural mechanisms underlying BCI control.

signals to interact with a system, identifying the underlying signal paradigm is essential to differentiate between approaches. Because different paradigms require varying levels of interaction strategy, cognitive effort and user training, which can directly affect usability and users' perceived experience.

- **Imagery:** Users intentionally generate mental representations of movements, actions or concepts without physically performing or interacting with them. These imagined activities elicit characteristic patterns of neural activity and can be detected and used as a control signal.
- **Visual Evoked Potentials (VEP):** Rely on users focusing their attention on visual stimuli presented that evoke characteristic responses in the EEG signal. The corresponding response can be detected in the EEG signal and then used as an intentional control command.
- **Event-Related Potentials (ERP):** ERP-based BCIs use event-related brain responses elicited by specific stimuli or events. P300-based BCIs, for example, utilize an event-related potential that occurs approximately 300 milliseconds by directing attention toward specific targets. The attended stimulus elicits a stronger P300 response than non-target stimuli. This enables the system to determine the user's intended selection through the EEG signal.
- **Neurofeedback-Based:** Active BCI research in HCI has extended traditional command-based paradigms by exploring cognitive and affective states as interaction modalities. These approaches allow users to intentionally modulate neural activity related to attention, emotional states or relaxation and use the resulting EEG signals as input for interactive systems. Users learn to influence their own brain activity rather than directly selecting commands.
- **Hybrid:** Hybrid BCIs combine two or more neural signal paradigms to generate control commands.

By combining complementary paradigms, hybrid approaches can exploit the strengths of different signal types and enable additional control dimensions.

Sample Size (Able-Bodied Participants)

The category *Sample Size (Able-Bodied Participants)* describes the number of able-bodied participants involved in the evaluation of EEG-based BCI systems. Since this review focuses on healthy users, only sample sizes of individuals without motor or neurological impairments are considered in included studies. Reporting the sample size is essential for evaluating the robustness and reliability of user studies, as findings based on a small number of participants may have limited generalizability.

Indicates the number of healthy participants included in each study.

- Very Small ($N = 1-5$): Studies including between 1 and 5 able-bodied participants.
- Small ($N = 6-10$): Studies including between 6 and 10 able-bodied participants.
- Medium ($N = 11-20$): Studies including between 11 and 20 able-bodied participants.
- Large ($N \geq 21$): Studies including 21 or more able-bodied participants.

Mean Accuracy Ranges

Mean Accuracy Ranges captures the ranges of mean accuracy achieved by the EEG-based BCI systems across the included studies. This categorization offers an overview of the performance levels achieved during system evaluation and illustrates the variation in accuracy across the studies. However, differences in accuracy should not be interpreted as directly comparable, because performance may be influenced by factors such as the application domain and signal paradigm.

Categorizes studies according to mean accuracy ranges.

- Low ($< 60\%$) : Studies reporting a mean accuracy of below 60%.
- Moderate (60–69%) : Studies reporting a mean accuracy between 60% and 69%.
- Good (70–79%) : Studies reporting a mean accuracy between 70% and 79%.
- High (80–89%) : Studies reporting a mean accuracy between 80% and 89%.
- Very High ($\geq 90\%$) : Studies reporting a mean accuracy of 90% or above.

Usability Dimensions

Identifies usability dimensions assessed across the included studies.

Furthermore, we have the category *Usability Dimensions*, which represents the aspects of system usability considered when evaluating the interaction. Rather than treating usability as a single construct, this category provides a more differentiated view of how usability was assessed. As a result, studies may address multiple dimensions depending on the objectives of their evaluation. Accordingly, studies were multicoded when covering more than one usability dimension. Identifying the dimensions allows for the comparison of these usability factors examined in the included studies.

- **Ease of Use:** Describes the extent to which users perceive the EEG-based BCI system as easy and straightforward to use. It means how uncomplicated the system is to operate, rather than the cognitive or mental effort required during interaction.
- **Workload:** Refers to the mental and cognitive effort required from users while interacting with an EEG-based BCI. It describes the level of mental effort, concentration and attention involved in performing the intended BCI task. Workload is particularly relevant in active BCIs, as users must intentionally generate and maintain specific brain activity or mental states to control the system.

- **Learnability:** Describes the ability to acquire the knowledge and skills needed to effectively operate and interact with an EEG-based BCI system over time. It is distinct from *Ease of Use*, which refers to how simple the system is perceived to operate once the interaction is understood.
- **Comfort:** Reflects whether users are physically comfortable during EEG-based BCI use. It includes aspects such as the comfort of wearing the EEG equipment, as well as discomfort resulting from visual stimuli or other sensory aspects of the interaction. Discomfort can negatively affect the overall usability of the system.
- **Fatigue:** Addresses the physical or mental exhaustion that users feel as a result of using EEG-based BCI. High levels of fatigue may negatively affect the willingness to continue using the system. Fatigue is especially relevant when assessing the sustainability of BCI interaction over extended periods of use.

User Perception Dimensions

The category *User Perception Dimensions* describes assessed aspects reflecting users' subjective perceptions and experiences of the EEG-based BCI system. While usability focuses on the quality and ease of interaction in achieving intended goals, user perception refers to users' impressions and their overall experience with the system. As studies may assess several aspects of user perception, a study here can also be assigned multiple codes within this category. Examining these dimensions provides insight into factors that may influence users' acceptance and engagement.

Captures aspects of subjective user impressions and overall system experience.

- **Sense of Control:** Captures users' perceived capability to intentionally control the system through their own actions or mental states. A higher sense of control reflects that users perceive a stronger correspondence between their intentions and the actual resulting system responses.

- **Satisfaction:** Refers to the overall satisfaction and enjoyment of users with their experience of interacting with the EEG-based BCI system. It describes the extent to which users perceive the interaction as satisfying and whether the system meets their expectations.
- **Frustration:** Represents users' negative emotional responses, such as annoyance and irritation, arising from failures or difficulties encountered while interacting with the EEG-based BCI system. It may arise when the system does not respond as expected or the assigned tasks cannot be successfully completed.
- **Motivation:** Means the drive to actively engage with the EEG-based BCI system and to maintain interaction with it. It captures users' level of interest and determination to perform the assigned tasks consistently.
- **Acceptance:** Encompasses users' overall readiness to accept an EEG-based BCI as an interaction technology and to consider using it beyond the experiments. It includes users' openness towards BCI-based interaction, willingness to use the system and whether they would recommend it. Also, whether they prefer it over alternative interaction methods or consider it generally suitable for future use.

3.2 Results

In the following sections, the results are presented according to the categories defined during the qualitative coding process. To provide a structured overview of the identified characteristics across the included studies, the frequency distributions of the coded categories were analyzed. *Microsoft Excel*⁵ was used to organize and summarize the extracted data.

⁵ <https://www.microsoft.com/de-de/microsoft-365/excel>

Distribution of Application Domains

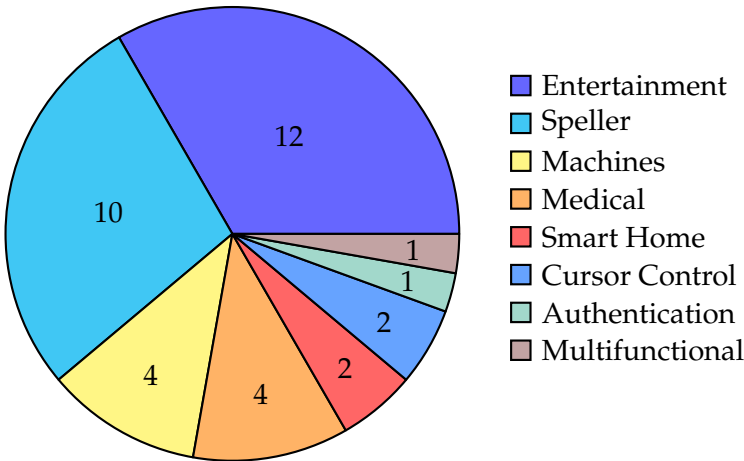


Figure 3.3: This pie chart depicts the distribution of 36 of the 37 studies across the different application domains.

Across the included studies, active EEG-based BCIs were explored in a broad range of application domains, highlighting the diversity of contexts in which brain-based interaction has been investigated. However, as shown in Figure 3.3, the distribution is not uniform across these domains. Also, one included study could not be assigned to any application domain, as it did not involve a specific application context. Among the 36 categorized applications, Entertainment represents the most extensively investigated domain, comprising 12 studies (33.3%), followed by Speller applications with 10 studies (27.7%). These two domains combined represent more than half of the applications examined in the included studies, suggesting a strong research focus on interactive entertainment and BCI-based communication.

The remaining studies cover a range of different application areas. The application domains Machines and Medical were each represented by four studies (each 11.1%). Smart Home applications were investigated in two studies (5.6%), as was Cursor Control (5.6%). Whereas Authentication and Multifunctional applications are each examined in only one study (each 2.8%). As mentioned above, the latter category refers to a single

Entertainment and speller applications account for over half.

Less frequently investigated applications span several domains.

system that integrates several interaction functions and therefore spans multiple application areas.

Application domains
involve different
interaction
requirements.

The observed distribution indicates that BCI systems in certain application domains are more frequently represented and evaluated in the current literature than in others. These application domains differ in their intended purposes and the ways in which users interact with the systems. For instance, entertainment-oriented BCIs may primarily aim to enhance immersion and engagement, whereas a speller may tend to emphasize accurate and efficient communication. Accordingly, differences in the requirements and objectives across application contexts could influence how these systems are evaluated. This should therefore be taken into account when interpreting the general findings across the reviewed literature.

Distribution of Signal Paradigms

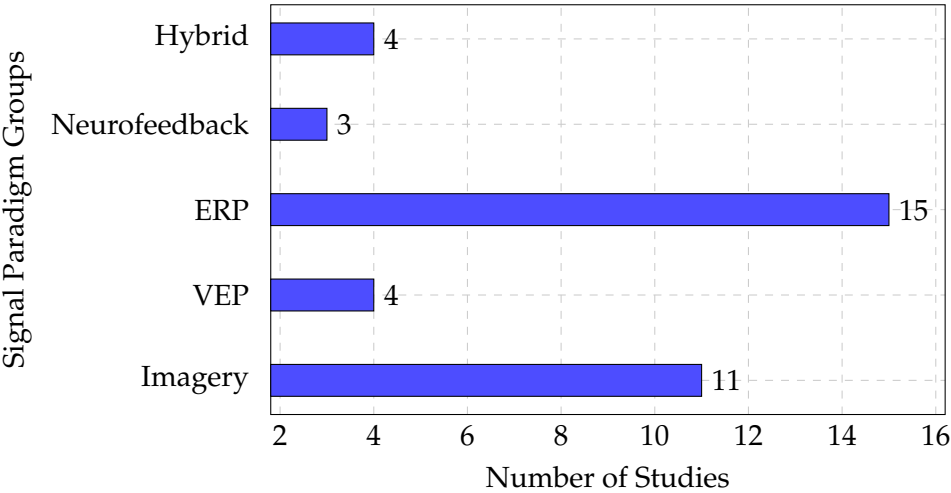


Figure 3.4: This bar chart depicts the distribution of the 37 studies across the five signal paradigm categories.

ERP and imagery are
the predominant
paradigms.

In Figure 3.4, the distribution of signal paradigms across the included studies is presented. The results indicate that Event-Related Potential (ERP)-based approaches were the most frequently represented paradigm, account-

ing for 15 of the included studies (40.5%). This is followed by Imagery-based approaches, encompassing motor, visual and conceptual imagery, which constitute the second largest category, with 11 studies (29.7%). Taken together, these two categories account for more than two-thirds of the included studies (70.2%). This shows that they are the clearly predominant paradigms employed in studies evaluating active EEG-based BCIs within the reviewed literature.

In contrast, Visual Evoked Potentials (VEP)-based and Hybrid approaches were each used in four studies (each 10.8%). Thus, both paradigms were substantially less common than ERP and Imagery. Furthermore, Neurofeedback-based approaches were identified in three studies (8.2%).

Remaining paradigms were substantially less represented.

All in all, the distribution demonstrates that research on the evaluation of active EEG-based BCIs in HCI is mainly centered around ERP and Imagery-based control. At the same time, the diversity of signal paradigms underscores the heterogeneity of the included BCI systems in this review. These paradigms are characterized by differences in their underlying interaction mechanisms, training requirements and cognitive demands. Therefore, this influences how performance, usability and user perception are evaluated and experienced. Furthermore, the uneven distribution of paradigms across the included studies limits the extent to which conclusions can be drawn regarding the role of the signal paradigm across these evaluation dimensions.

Different paradigms involve distinct interaction mechanisms and demands.

Distribution of Sample Size (Able-Bodied Participants)

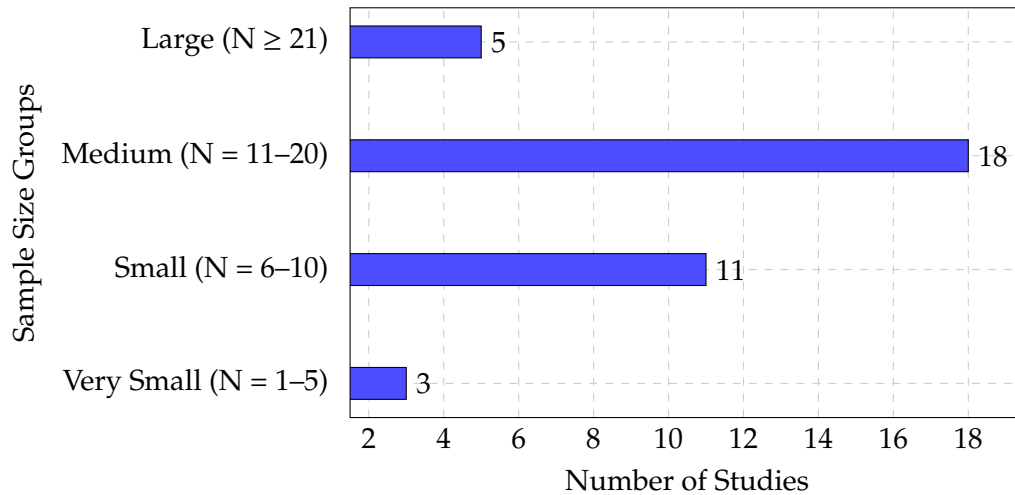


Figure 3.5: This bar chart depicts the distribution of the 37 studies across the four sample size categories based on the number of able-bodied participants.

Sample sizes were
predominantly small to
medium.

Figure 3.5 illustrates the distribution of sample sizes across the included studies, considering only able-bodied participants. Of the 37 studies analyzed, the majority employed Medium-sized samples, with 18 studies (48.6%) including between 11 and 20 able-bodied participants. Followed by 11 studies (29.7%) using Small samples of 6 to 10 participants. In comparison, only five studies (13.5%) recruited 21 or more healthy participants and were categorized as Large. Very small samples of 1–5 participants were also comparatively rare, occurring in only three studies (8.2%).

Sample size influences
the generalizability of
findings.

Overall, the distribution demonstrates that the investigation of active EEG-based BCIs in HCI mainly relies on Small to Medium-sized user studies, as defined in this review. In general, this distribution is important for interpreting the generalizability of the reported findings. Because studies that involve only a few participants may offer limited support for drawing broader conclusions. Nevertheless, these studies can also contribute valuable insights into the assessment of active EEG-based BCIs. The considerable variation in sample sizes across the included

studies further reflects differences in the scope and experimental designs of the individual evaluations. While smaller studies often focused on exploratory evaluations, larger studies appeared to provide more robust findings.

Distribution of Mean Accuracy Ranges

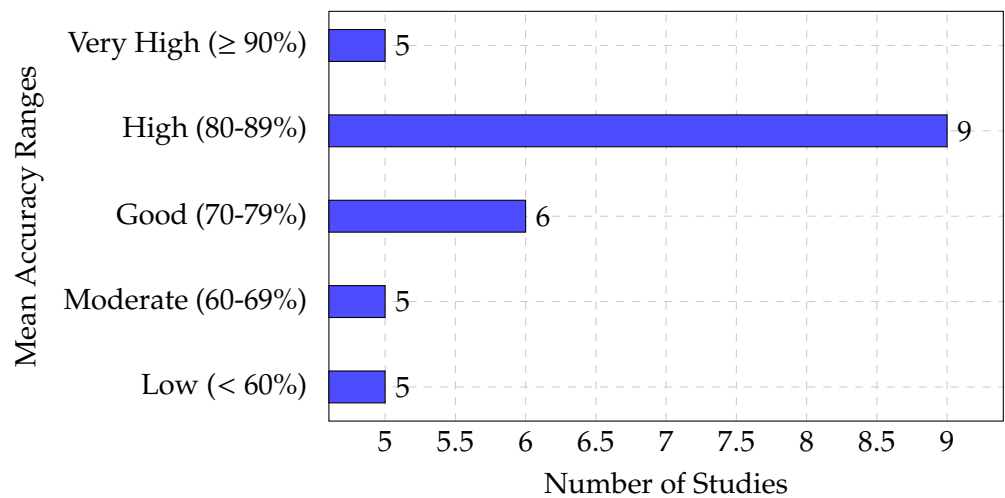


Figure 3.6: The bar chart illustrates the distribution of mean accuracy ranges reported across 30 of 37 studies.

In Figure 3.6, the distribution of the included studies across the predefined mean accuracy ranges is depicted. In total, 30 mean accuracy values were reported. The largest number of mean accuracy values falls within the High range (80–89%), comprising 9 studies (30,0%). This was followed by the Good range (70–79%), which has 6 studies (20,0%). The remaining ranges, Low, Moderate and Very High, all consist of 5 studies (each 16,7%).

Most reported mean accuracies fall within higher ranges.

The distribution shows that the mean accuracy varied across the included studies. However, it was predominantly centered within the 70–89% range, which accounted for 15 of the 30 reported mean accuracy values (50%). This general variation reflects the differences between the included studies, because mean accuracy can be affected by multiple methodological and experimental factors, as

The findings illustrate performance variation across studies.

previously mentioned. For example, the signal paradigm, application domain, characteristics of the participants and so on have a huge impact. Thus, the reported accuracy values are used to illustrate the range of performance observed across the selected studies, rather than enabling a direct comparison of system effectiveness.

Distribution of Usability Dimensions

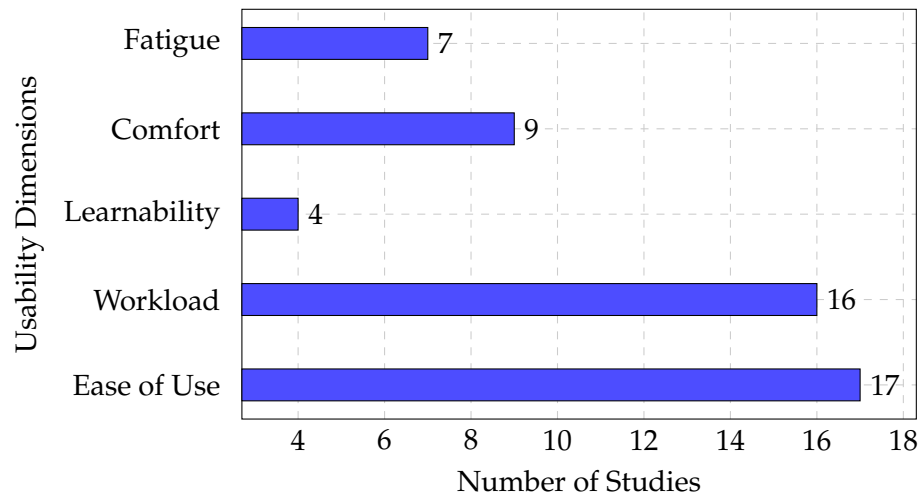


Figure 3.7: This bar chart depicts the distribution of the identified usability dimensions across 33 of 37 studies.

Usability dimensions
were assessed using
multicoding.

As illustrated in Figure 3.7, the included studies evaluated a range of usability dimensions, underlining that usability was assessed from several perspectives across the investigated EEG-based BCI systems. However, four included studies were not assigned any codes within this category because they did not research any of the predefined dimensions. Further, the distribution was multicoded and also not uniform. Consequently, the reported percentages reflect the share of the 33 studies covering each dimension and are therefore not intended to constitute a distribution that sums up to 100%.

The most often analyzed dimension is Ease of Use, being investigated in 17 of the 33 studies assessing usability (51.5%), closely followed by Workload, which was assessed in 16 studies (48.5%). Therefore, in almost half of the usability-focused studies, the simplicity respectively straightforwardness and mental demands of the interaction with the EEG-based BCI system were evaluated. In contrast, Comfort was investigated in 9 studies (27.3%), making it the third most frequently examined dimension. Moreover, Fatigue was assessed in 7 studies (21.2%), while Learnability was examined in only 4 studies (12.1%), making it the least commonly assessed usability dimension. The comparatively infrequent evaluation of these dimensions demonstrates that physical and longer-term factors of the interaction received less attention than more immediate aspects of system interaction.

Taken together, this distribution indicates that usability was evaluated across a range of dimensions. However, the distribution also suggests that some aspects of usability received substantially more attention than others. Up to this point, it appears that the emphasis was more on evaluating short-term interaction characteristics than on usability over extended periods of use. Furthermore, the general diversity in the dimensions assessed reflects that there is not only a single consistent approach to evaluate usability.

Usability assessment focused primarily on ease and workload.

Physical and long-term factors were comparatively underexamined.

Most studies emphasized short-term aspects, but did not follow a consistent approach.

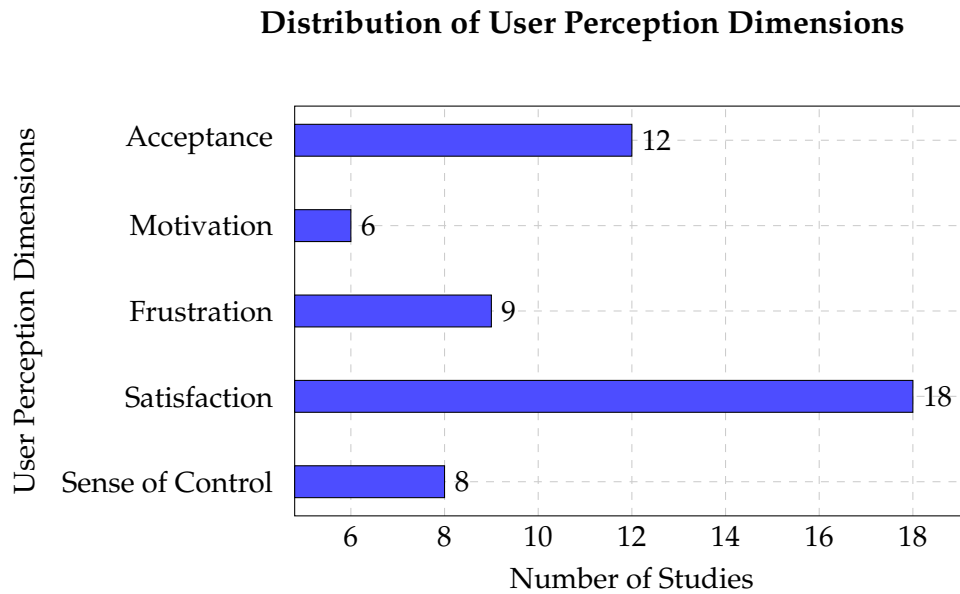


Figure 3.8: This bar chart depicts the distribution of the identified user perception dimensions across 32 of 37 studies.

User perception dimensions were assessed using multicoding.

Satisfaction and acceptance dominated user perception assessment.

The distribution of the identified user perception dimensions is illustrated in Figure 3.8. Since individual studies could address several user perception dimensions, the included studies were here also not assigned to mutually exclusive categories. Therefore, the reported percentages again do not sum to 100%. Additionally, 32 of the 37 included studies contributed to this distribution, while five studies did not evaluate any of these dimensions.

Among these five dimensions, Satisfaction was the most often assessed, occurring in 18 studies (56.3%). Notably, almost half of the included studies investigated subjective evaluations of users' overall experience with the EEG-based BCI. In addition, Acceptance was assessed in 12 studies (37.5%) and was the second most frequently examined dimension, reflecting an interest in the willingness of users to accept and continue the interaction with BCI-based systems. Frustration was evaluated in 9 studies (28.1%), followed by Sense of Control which was assessed in 8 studies (25.0%). Compared with the other dimensions, Motivation was analyzed in 6 studies and received the least attention (18.8%).

The distribution of the examined dimensions reveals a special focus on general evaluations of users' experiences, particularly through measures of Satisfaction and Acceptance. Whereas more specific aspects of the users' subjective experience, such as Frustration, Sense of Control and Motivation, were examined to a lesser extent across the reviewed literature. This demonstrates that users' general assessments of BCI interaction were prioritized over more specific psychological aspects.

Research emphasized overall experience over specific psychological dimensions.

Chapter 4

Evaluation

In this chapter, the final findings are discussed with respect to the four research questions introduced in Chapter 1. Finally, we conclude by outlining the limitations of this study.

4.1 Discussion

The following sections discuss the results from the meta-analysis based on the 37 studies we reviewed as part of this systematic literature review. The discussion is structured according to the four research questions defined in Chapter 1, focusing on the evaluation of performance in HCI contexts (RQ1), usability aspects and challenges (RQ2), users' perceptions and experiences (RQ3) and the overall suitability of active EEG-based BCIs (RQ4).

Based on the findings of the included studies, this chapter presents the current state of active EEG-based BCIs in HCI and highlights remaining challenges.

Taken together, the four research questions examine complementary aspects of BCI evaluation, ranging from what these systems can achieve to how usable they are and how they are perceived by users, as well as the broader potential of active EEG-based BCIs within HCI. Together, these per-

Evaluation of active BCIs through four research questions.

The four research questions establish a holistic framework for BCI evaluation.

spectives provide a holistic assessment of their suitability for HCI applications.

4.1.1 RQ1: Performance in HCI Contexts

Studies primarily
assessed performance
using accuracy.

Performance represents a fundamental criterion for assessing the practical effectiveness of active EEG-based BCIs in HCI. Within the scope of this review, performance mainly refers to the extent to which a BCI enables users to accurately, successfully and reliably accomplish the intended interaction tasks through the BCI. Although accuracy was the most frequently reported quantitative measure, some studies also reported interaction performance using other measures, such as information transfer rate (ITR), selection time and task completion. But, due to their inconsistent reporting, these measures could only be treated mainly as contextual information, rather than the basis for comparisons.

Performance varies
considerably across
systems and contexts.

As illustrated in Figure 3.6, 30 reported mean accuracy values are suitable for the present descriptive analysis. Overall, 15 of the 30 reported values (50%) were located between 70% and 89%, as previously stated. At the same time, the remaining studies were evenly distributed across the other accuracy ranges. Thus, the findings show that active EEG-based BCIs can achieve relatively high levels of mean accuracy in HCI contexts, while it appears to vary considerably depending on the specific system and experimental conditions.

Performance extended from relatively low values, such as 36.7% in visual-imagery-based drone swarm control by [Jeong et al., 2020], to very high values of 96.6% for the P300-based virtual world tour application by [Woo et al., 2021]. This considerable range indicates that performance is not determined solely by the EEG-based BCI technology itself, but is also shaped by factors such as the particular signal paradigm and interaction task.

P300 systems generally
achieved relatively high
accuracy.

Multiple P300-based applications achieved relatively high accuracies. This includes 94% with gel-based electrodes compared with 87% with dry electrodes in the multi-functional home system by [Käthner et al., 2017], also

94% for the 3D P300 speller compared with 89.1% for the conventional 2D interface by [Qu et al., 2018] and 88–90% in telepresence control by [Escolano et al., 2012]. However, high accuracy was not universal within the P300 studies. For instance, the auditory P300 speller, evaluated by [Käthner et al., 2013], achieved a considerably lower mean accuracy of approximately 66%.

On the other hand, SSVEP-based systems could likewise demonstrate high performance. For example, the SSVEP-based authentication system achieved high classification accuracy across all configurations (95–99%) [Kiser et al., 2026]. Moreover, the c-VEP-based multiplayer game achieved a mean accuracy of 93.74% [Moreno-Calderón et al., 2023]. Nevertheless, accuracy alone does not fully capture the practical efficiency of such systems. Because selecting each command in the same study took approximately 5.25 seconds, underlining that even if the mean accuracy is high, it can have temporal constraints on interaction. The influence of stimulation frequency was also evident, with higher-frequency stimulation resulting in more stable classification performance, as shown by [Won et al., 2015]. But here, even then, the accuracy was at most 68.9%.

In contrast to many ERP and VEP-systems, imagery-based BCIs comparatively tend to have lower mean accuracy and show an even broader range of performance across the included studies. However, mean performance remained at a moderate level throughout and did not reach particularly high levels at all. [Friedrich et al., 2013] reported in a long-term evaluation of a four-class imagery-based BCI that eight of the fourteen participants achieved mean accuracies ranging from 61% to 72%. Despite performance remaining stable over many weeks, the authors concluded that the overall performance was still insufficient for effective everyday control. Moreover, the conceptual-imagery-based smart home application by [Kosmyna et al., 2016] had a mean accuracy of 77%. In contrast, as already mentioned, the visual-imagery-based drone swarm control by [Jeong et al., 2020] had a much lower mean accuracy, namely 36.7%. While the result was above the 25% chance level, its relatively small improvement over chance suggests that achieving reliable control remained difficult. These findings underscore a key challenge of imagery-based

SSVEP performance depended strongly on stimulation conditions.

Imagery-based BCIs demonstrated moderate yet variable performance.

Hybridization did not necessarily guarantee superior performance.

BCIs, as effective control is highly dependent on the user's ability to generate reliable and sufficiently distinguishable mental patterns.

The included studies also analyzed the performance of some hybrid BCIs, which combine different paradigms with the intention to exploit their complementary strengths. For example, the hybrid SSVEP/P300 painting system by [Tang et al., 2022] achieved higher tool-selection performance (approximately 89%) and ITR than the conventional P300 condition. However, hybridization was not consistently associated with improved performance across the different applications. Both [Allison et al., 2012] and [Rekrut et al., 2022] employed combinations of MI- or motor-execution-based control and SSVEP, but their reported performance did not indicate a clear advantage of hybridization. In the study by [Allison et al., 2012] simultaneous two-dimensional cursor control is enabled and mean performance was only around 60% and varied considerably between participants. A similar pattern was reported by [Rekrut et al., 2022], whose hybrid BCI integrated SSVEP-based positioning with motor-execution-based control of other microscope functions. Although the SSVEP component achieved an average task success rate of 51%, the motor-execution component failed to exceed chance-level performance during the actual interaction task. This demonstrates that hybrid BCIs do not automatically result in higher or more reliable overall performance.

Individual user states and concentration directly influence interaction performance.

BCI performance is also affected by factors that extend beyond the underlying technical implementation. In particular, the current user's state can have a direct impact on interaction performance. [Myrden and Chau, 2015] demonstrate that moderate levels of frustration were linked to above-average performance, while low fatigue was associated with reduced performance. Moreover, [da Silva-Sauer et al., 2016] also found a significant effect of concentration on performance in the standard P300 speller, showing that lower levels of concentration were related to reduced performance. Specifically, they demonstrated that less dynamic interfaces require greater levels of user concentration. This indicates that performance should not directly be seen as a fixed property of a BCI system. Instead, it may

also vary depending on the specific context in which the system is utilized and the individual user.

Training also emerged as another relevant factor for some studies, although its influence was not consistent across studies. For instance, [Simon et al., 2015] observed an increase in auditory P300 accuracy from 76.7% on the first day to 90.2% on the second day of training. Similarly, [Vu-jic et al., 2023] reported significant performance improvements across training sessions in Joie, an affective BCI. Namely, participants who received mental strategy instructions and real-time neurofeedback progressively improved to generate the desired left frontal activity across five training sessions over a two-week period. In contrast, [Allison et al., 2012] found no significant training-related improvement in objective performance across six online sessions. These contrasting findings suggest that, while repeated practice may improve users' capability to generate or modulate the neural activity, training is context-dependent rather than universally beneficial.

Training can improve performance, but its effects vary across contexts.

Taken together, the relatively limited number of included studies shows that active EEG-based BCIs can achieve varying levels of accuracy. However, notably, half of the reported mean accuracy values ranged from 70% to 89%. The strong performance of especially some P300-, SSVEP- and c-VEP-based systems demonstrates that reliable real-time interaction is technically feasible. In contrast, the more variable results of imagery-based systems underscore the ongoing challenge of robust control across users. In general, the examples show that performance should be understood not only as a technical property of the underlying BCI paradigm itself but also as an outcome of the exact interaction design and application context. Moreover, performance may be influenced by user state and training, as some studies reported advancements through training while others did not.

BCI performance depends on the paradigm, user factors, context and importantly, the specific system.

4.1.2 RQ2: Usability Considerations

The findings prioritize more immediate user effort.	Active EEG-based BCIs should not be evaluated solely according to their technical performance, as effective HCI also depends on how demanding, comfortable and accessible it is for the user. Within the reviewed literature, usability was addressed through a range of dimensions, with Ease of Use and Workload emerging as the most frequently investigated dimensions, as illustrated in Figure 3.7. This indicates that the effort required from users during interaction received considerably more attention than longer-term usability dimensions.
BCI interaction can be more demanding than conventional input.	Operating an EEG-based BCI may impose considerable attention and cognitive effort, especially when concentration is needed for prolonged interaction. This is reflected in several studies comparing BCI-based interaction with conventional input methods. Higher levels of mental demand and frustration were reported during motor-imagery-based control [Felton et al., 2012], as well as during auditory paradigms compared with visual interaction [Kleih et al., 2015; Käthner et al., 2013]. Similarly, the use of a BCI in gaming resulted in longer selection and game completion times and greater mental workload than automatic speech recognition [Gürkök et al., 2011]. Furthermore, moderate to high workload was reported even in applications that were otherwise perceived positively [Pinegger et al., 2017; Simon et al., 2015]. This highlights that successful usability does not necessarily imply low user effort.
Users reported physical discomfort across different BCI setups.	Physical comfort was also identified as a relevant usability consideration, although it was investigated less often than ease of use and workload. The choice of electrodes can also influence usability. For example, dry electrodes in a multifunctional home-use BCI resulted in greater workload and lower comfort than gel-based electrodes, whereas users also reported pressure over time and the conspicuous appearance of the equipment as practical concerns [Käthner et al., 2017]. Physical discomfort was also observed in virtual-reality BCI interaction, as multiple participants reported discomfort when wearing the EEG equipment alongside a head-mounted display [McClinton et al., 2019].

Moreover, stimulation parameters also play a major role regarding usability. Higher-frequency SSVEP stimulation reduced visual fatigue and supported more stable interaction over time [Won et al., 2015], although visually demanding stimulation could still challenge usability by requiring sustained visual attention and imposing time pressure [Moreno-Calderón et al., 2023]. Users may therefore also prefer stimulation modalities that place lower demands on attention and cognitive processing [Severens et al., 2014]. In addition, fatigue may interact dynamically with users' mental states during BCI operation. [Myrden and Chau, 2015] observed an association between moderate fatigue levels and higher BCI performance, indicating that a certain degree of fatigue may occur alongside focused BCI engagement.

Moderate fatigue may coexist with focused and effective BCI control.

The included studies further indicate that usability can change with continued interaction. Familiarity through repeated interaction can make users more confident and experienced and they can better adapt to the required mental strategies [Escolano et al., 2012]. Likewise, long-term evaluations of an imagery-based BCI showed improvements in task ease and imagery quality over extended use [Friedrich et al., 2013]. However, training does not appear to guarantee improved usability across all systems. For instance, [Allison et al., 2012] found no significant training-related advancements for their hybrid BCI, highlighting that practice may not be sufficient to compensate for the demands imposed by the interaction itself. These findings show that usability may evolve over the course of interaction. Therefore, it is better understood as a dynamic property rather than a stable system characteristic from only one session.

Usability can evolve through continued user interaction.

Overall, the usability findings highlight the challenge of ensuring that an active EEG-based BCI balances low cognitive effort, ease of interaction and physical comfort rather than addressing only a single usability factor. Although ease of use and workload are the most frequently examined aspects, the comparatively limited examination of comfort, fatigue and learnability leaves important factors of long-term usability less well understood. But these findings suggest that active EEG-based BCIs may be suitable for specific interaction contexts. Extending their use to a wider range

Broader use requires reduced burden without sacrificing benefits.

of contexts, however, depends on reducing the effort and practical burden without compromising the intended benefits of the system.

4.1.3 RQ3: User Perceptions and Experiences

Researchers primarily examined overall user appraisal and engagement.

Beyond usability-related aspects, the findings also highlight users' subjective perceptions and experiences when interacting with active EEG-based BCIs. Across the reviewed literature, Satisfaction and Acceptance received the greatest attention, as illustrated in Figure 3.8, while Frustration, Sense of Control and Motivation were addressed less frequently. Therefore, it appears that researchers tended to evaluate whether users perceive BCI-based interaction as desirable and worth continuing, rather than on more specific psychological aspects.

Users often reported positive experiences despite only moderate objective performance.

One notable pattern was that positive user perceptions did not consistently correspond to higher objective BCI performance. Users reported enjoyment and positive affect across multiple systems and application contexts, even when classification accuracy remained moderate. In the conceptual-imagery smart-home system by [Kosmyna et al., 2016], users rated the interaction positively despite a mean task accuracy of 77%, reporting high perceived usefulness, satisfaction and acceptance. Furthermore, the hybrid ERD/SSVEP system of [Allison et al., 2012] achieved only around 60% average accuracy, yet participants generally did not perceive the interaction as particularly difficult or annoying. In the VR study conducted by [Friedman et al., 2010], participants described the BCI interaction as enjoyable, with some users even perceiving it as easier and more intuitive than traditional monitor-based BCI despite reduced performance in the free-choice condition. Similarly, [McClinton et al., 2019] reported favorable user experiences in their VR brain-painting study, although self-reported task accuracy frequently fell below 60%. In contrast, [Woo et al., 2021] found that their virtual world tour achieved a high accuracy of 96.6%, but enjoyment and perceived completeness were rated only moder-

ately. These findings indicate that users' perceived quality of EEG-based interaction extends beyond objective classification performance.

Nevertheless, positive user experience did not consistently imply willingness to adopt the system in particular contexts. In the study of BCI-based control for automated vehicles by [Astudillo et al., 2017], users generally expressed positive attitudes towards BCI technology, yet 61.1% of participants were unwilling to use such a system for autonomous driving. This was mainly attributed to concerns about safety and loss of control. Acceptance appears to be shaped not only by the interaction experience itself, but also by users' perceptions of the system's safety and trustworthiness within its intended context. Acceptance also varied across application contexts, with participants in the cognitive-training study by [Lee et al., 2013] and [Lee et al., 2015] reporting highly positive acceptance of the EEG-based BCI. The system was perceived as useful for supporting cognitive training and therefore the users showed a high willingness to recommend it to others. Acceptance may ultimately depend on whether users see a meaningful purpose for incorporating the BCI into the intended activity.

Acceptance varies with perceived usefulness across different contexts.

Another recurring observation is related to users' sense of control during the interaction. A positive interaction experience was often associated with users feeling that their mental intentions could reliably influence the system [Pinegger et al., 2017; Woo et al., 2021]. In contrast, users' perceptions could be undermined when the system failed to consistently translate their intentions into the corresponding commands, leading to a reduced sense of control. [Kosmyna et al., 2016] investigated a smart-home BCI and found out that participants appreciated the possibility of controlling household devices through their thoughts. However, the occurrence of incorrect classifications could make the interaction feel less controllable and could diminish users' confidence to influence the system as intended. Perceived control appears to connect users' experience of system responsiveness with their overall evaluation of the interaction.

Perceived control links system responsiveness and overall evaluation.

Occasional frustration
may coexist with
sustained positive user
engagement.

The findings on frustration and motivation further show that user experience was dynamic rather than uniformly positive. Users sometimes experienced frustration during challenging or inconsistent interactions, without this necessarily resulting in rejection of the technology. The study by [Myrden and Chau, 2015] shows even a potential motivating role of frustration, while increased attention may help compensate for rising frustration. Enjoyable application contexts appeared to mitigate the negative effects of occasional frustration, enabling continued engagement with the BCI interaction [Friedrich et al., 2013; Gürkök et al., 2011]. Moreover, the Joie study provides an especially interesting example, as it is explicitly designed around positive emotional engagement, while negative feedback could undermine this positive experience and induce frustration [Vujic et al., 2023]. Nevertheless, the overall perception of the BCI remained largely positive, with most participants describing the experience as interesting or exciting. Thus, occasional frustration did not necessarily translate into a negative overall perception and can coexist with a generally positive perception of the BCI. This was particularly the case when users remained motivated by the interaction or perceived value in the application context.

Positive evaluations
extend beyond
successful system
operation.

Finally, the reviewed literature indicates that active EEG-based BCIs are generally capable of generating positive user experiences. However, satisfaction and acceptance are influenced by factors beyond technical performance alone, with engaging or meaningful interaction contexts potentially contributing to more positive evaluations. Users' evaluations also seem to be shaped by broader interaction experience, such as the application context, perceived control and emotional responses.

4.1.4 RQ4: Overall Suitability of Active EEG-Based BCIs

Active BCIs show
system-dependent
potential in HCI.

The findings of the reviewed studies regarding performance, usability and user perception of active EEG-based BCIs support promising opportunities for HCI. However, their suitability depends strongly on the particular system

and application context and cannot be regarded as universal. This is reflected in the diverse range of HCI contexts in which active BCIs have been applied, including spelling, entertainment, smart-home control and so on.

Across different application contexts, P300- and VEP-based systems tended generally to achieve better real-time performance, while motor imagery-based systems showed greater variation in their results. However, this does not imply that any particular paradigm is universally preferable. For instance, auditory P300 was associated with higher workload than visual interaction [Käthner et al., 2013], while visual stimulation could introduce fatigue, annoyance or time pressure [Moreno-Calderón et al., 2023; Won et al., 2015]. Contrarily, imagery-based approaches can generally reduce reliance on externally presented stimuli. This suggests that successful BCI interaction depends not only on reliable signal classification, but also on how well its interaction paradigm fits the application and surrounding HCI.

Furthermore, multiple studies reported favorable user experiences despite moderate objective performance, when the application was engaging or perceived as useful [Allison et al., 2012; Kosmyna et al., 2016; McClinton et al., 2019]. At the same time, higher objective performance did not necessarily correspond to equally better positive user experiences [Woo et al., 2021].

The feasibility of deploying active EEG-based BCIs in everyday HCI is also shaped by practical considerations. Factors related to hardware setup and system use, including wearing comfort, electrode placement, visual demands, preparation effort and the conspicuous nature of EEG equipment, may affect users' overall interaction experience [Käthner et al., 2017; McClinton et al., 2019; Won et al., 2015]. Such demands can make otherwise functional BCI systems less convenient or attractive for everyday interaction.

Additionally, the studies indicate that evaluation of active EEG-based BCI is not only determined by system characteristics, but also by the individual user. For example, fatigue, concentration and emotional state were associated with changes in BCI performance [da Silva-

Paradigm suitability depends on exact interaction context.

Application value can compensate partly for technical limitations.

Practical demands could constrain everyday BCI use.

The human factor is an integral component of BCI suitability.

Sauer et al., 2016; Myrden and Chau, 2015]. Further, although training and familiarity led to improvements in performance or user experience in certain cases [Simon et al., 2015; Vujic et al., 2023], they did not consistently produce such effects across systems [Allison et al., 2012].

Value depends on
benefits beyond
conventional input.

Moreover, BCI interaction was associated with greater workload or longer completion times than conventional alternatives in several studies [Felton et al., 2012; Gürkök et al., 2011; Käthner et al., 2013]. Therefore, active EEG-based BCIs are most promising when it provides sufficient added value to justify their demands. But when conventional input methods provide similar task performance and an overall good user experience, the benefit of introducing an EEG-based BCI for an application becomes less clear.

BCIs represent
complementary
interaction across
suitable contexts.

All in all, the reviewed studies highlight that active EEG-based BCIs are capable of supporting meaningful and highly effective HCI. Nevertheless, their suitability appears to depend on the specific BCI system and application context. From this perspective, active EEG-based BCIs cannot currently be considered alternatives to conventional interfaces across all applications, but rather as a viable complementary interaction modality.

4.2 Limitations

The available evidence
remains relatively
limited.

This review has several limitations that should be considered when interpreting the findings. Only 37 studies met the inclusion criteria, resulting in a relatively small evidence base given the broad scope of the research area. This limitation is particularly relevant considering the diverse range of active EEG-based BCI applications in HCI. Therefore, this reduces the possibility of identifying consistent patterns across particular system subgroups and also restricts the extent to which robust conclusions can be drawn.

Substantial
methodological
variation limits
cross-study
comparability.

Furthermore, the considerable variation across the included studies limits direct comparison between systems. This variation concerns the BCI paradigms, interaction tasks, experimental designs and evaluation procedures

used across the studies. Additionally, most studies evaluated BCI interaction not over extended periods or in more realistic environments. Consequently, it remains uncertain whether the reported performance, usability and user perceptions can be sustained during prolonged everyday use, limiting generalizability.

Moreover, the screening, data extraction and coding of the included studies were conducted by a single reviewer. Despite the use of predefined inclusion criteria and a structured coding scheme, the absence of other reviewers may have resulted in inconsistencies or undetected errors during study selection and data coding.

Finally, the literature search was restricted to Scopus and English-language publications, which may have resulted in relevant studies being missed. Although a scoping review was also examined and backward and forward snowballing were performed to identify additional relevant studies, some relevant studies may remain unidentified.

Single-reviewer work
may affect consistency.

The search strategy
may not capture all
studies.

Chapter 5

Summary and Future Work

This final chapter summarizes the main findings and contributions of this thesis. It also outlines promising directions for future work to address existing challenges and support the further development and application of active EEG-based BCIs.

5.1 Summary and Contributions

The aim of this thesis was to examine the current state of active EEG-based BCIs in HCI by systematically reviewing existing literature. The analysis focused on the performance, usability and user perception of these systems in studies involving able-bodied users. Following the PRISMA guidelines [Page et al., 2021], the literature search in Scopus identified 37 studies that met the predefined inclusion criteria. To structure the investigation, four research questions were defined and by addressing these questions, this thesis aimed to provide a comprehensive overview of how these systems are evaluated and perceived within HCI.

This thesis
systematically
examines active
EEG-based BCIs.

Reported accuracy varies considerably across study contexts.	Regarding performance, the reviewed studies reported generally moderate to high classification accuracies, with most reported values falling between 70% and 89%. Nevertheless, the reviewed studies reveal substantial differences across systems, paradigms and application contexts, demonstrating that active EEG-based BCIs do not consistently achieve high accuracy.
Several usability challenges remain despite positive evaluations.	With respect to usability, the studies primarily focused on ease of use and workload, while other aspects such as comfort, fatigue and learnability were examined less frequently. Thus, current usability evaluations cover immediate interaction demands, leaving several user-centered factors comparatively underrepresented. Further, the reported findings show that several systems were perceived as relatively easy or intuitive to use, but interaction was often accompanied by considerable cognitive effort, physical discomfort, fatigue or other practical demands.
User perceptions extend beyond objective system performance.	The analysis of user perception revealed that satisfaction and acceptance received the greatest attention across the reviewed studies. In contrast, frustration, perceived control and motivation were considered less frequently. Overall, users generally reported positive experiences, although their evaluations were not consistently related to objective system performance and were shaped by factors such as application context, perceived control and emotional responses.
The findings highlight potential and contextual suitability.	Taken together, this thesis provides a structured overview of performance, usability and user perception. The findings indicate promising opportunities for active EEG-based BCIs in HCI, while their suitability varies according to the system design and application context.

5.2 Future Work

Future research should address identified gaps.	Future research should address the identified gaps by conducting larger and more standardized user studies, covering a broader range of BCI paradigms and HCI application contexts. In addition, assessing BCI systems over longer pe-
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riods and in less controlled settings could provide insights if performance, usability and user perception remain stable.

Additionally, greater emphasis should be placed on long-term usability aspects, such as comfort, fatigue and learnability. Similarly, future studies should examine user perception more comprehensively, particularly with regard to specific psychological dimensions, such as sense of control, frustration and motivation. Furthermore, it would also be valuable to investigate whether familiarity reduces cognitive and physical demands and improves the overall user experience over time.

Finally, future studies should more frequently assess active EEG-based BCIs alongside established interaction methods. Such comparisons could identify the particular situations in which EEG-based interaction offers benefits beyond conventional approaches and provide evidence to justify its integration into future HCI systems.

Researchers should examine long-term user factors.

Research should clarify the added value of EEG interaction.

Appendix A

Included Studies

This appendix provides a structured overview of all 37 studies included in this review, which met the predefined inclusion criteria. The table below outlines the key characteristics of each study. Each entry includes the authors and year of publication and classifies the study according to its sample size of able-bodied participants, EEG-BCI signal paradigm, evaluation focus (P: Performance, U: Usability, UP: User Perception) and results/findings.

This overview facilitates a systematic comparison of methodological approaches and evaluation criteria, which forms the basis for the synthesis of findings in the main body of this thesis.

Study	Sample Size (Able-Bodied)	Signal Paradigm	Evaluation Focus	Results/Findings
[Allison et al., 2012]	10	Hybrid (MI, SSVEP)	P, U, UP	The hybrid ERD/SSVEP BCI enabled continuous simultaneous 2D cursor control, although performance differed considerably, with an average accuracy of 60%. Participants generally reported low difficulty, annoyance and fatigue, while no advancements were observed through training.
[Allison et al., 2014]	10	Hybrid (SSVEP, P300)	P, U, UP	The hybrid P300/SSVEP BCI achieved significantly better performance than the SSVEP condition, but was comparable to the P300 condition. Participants did not perceive the hybrid condition as significantly more difficult, annoying or tiring than the single-paradigm conditions.
[Aloise et al., 2012]	10	P300	P, U, UP	GeoSpell achieved lower online accuracy (77,82%) than the classical P300 Speller (96.17%), although its performance exceeded the threshold considered necessary for effective communication. Workload and satisfaction did not differ significantly between interfaces, suggesting comparable perceived usability.
[Astudillo et al., 2017]	17	Mental Task/Cognitive Task	P, UP	Classification performance was 75% for right-direction and 52% for left-direction decisions in the realistic testing scenario. User perception was generally positive towards BCIs, but 61.1% of participants were unwilling to use it for autonomous vehicle control, mainly due to safety and loss-of-control concerns.
[da Silva-Sauer et al., 2016]	14	P300	P, U, UP	The SpellerT9 improved overall BCI performance and was perceived as less tiresome and more user-friendly than the other interfaces. Lower concentration negatively affected performance, with participants making more errors when using the conventional Spellermod.
Continued on the next page				

Study	Sample Size (Able-Bodied)	Signal Paradigm	Evaluation Focus	Results/Findings
[Escolano et al., 2012]	5	P300	P, U, UP	The participants successfully completed all telepresence tasks without failures, with a mean BCI performance of approximately 88–90%. The participants also showed high adaptability, with reduced workload, improved learnability and increased confidence across trials.
[Felton et al., 2012]	12	MI	(P), U, UP	Among able-bodied participants, successful BCI cursor control was defined as $\geq 80\%$ task accuracy. BCI tasks resulted in higher subjective workload than manual controls, especially in mental demand, effort and frustration.
[Friedman et al., 2010]	10	MI	P, U, UP	BCI performance was significantly lower in the free-choice condition (75.0%) than in the instructed control condition (82.1%). Participants nevertheless described the VR-based BCI as more enjoyable and, in some cases, easier and more intuitive than traditional monitor-based BCI.
[Friedrich et al., 2013]	14	MI & Mental Task/Cognitive Task	P, U, UP	The majority of participants achieved 61–72% accuracy. Task ease, imagery quality and enjoyment improved, while fear of incompetence decreased.
[Gürkök et al., 2011]	20	SSVEP	P, U, UP	BCI and automatic speech recognition (ASR) achieved comparable selection performance, but BCI resulted in significantly longer selection and game completion times and higher mental workload.
[Hortal et al., 2014]	4	MI	P, U, UP	The hierarchical control strategy was more accurate but slower, whereas directional control was faster but less precise. Subjective workload was higher for directional control than for hierarchical control.
[Hualiang et al., 2023]	9	MI	P	The proposed motor-imagery BCI achieved a mean accuracy of 76.67% in online ball-game control, demonstrating the feasibility of real-time interaction.
Continued on the next page				

Study	Sample Size (Able-Bodied)	Signal Paradigm	Evaluation Focus	Results/Findings
[Jeong et al., 2020]	7	Visual Imagery	P	The four-class visual imagery BCI achieved a mean classification accuracy of 36.7%, exceeding the 25% chance level and indicating the feasibility of EEG-based high-level drone swarm control, while highlighting the need for improved classification performance.
[Käthner et al., 2013]	20	P300 (auditory)	P, U, UP	The auditory speller achieved a mean accuracy of 66%, while producing significantly higher workload and lower SUS usability than the visual speller.
[Käthner et al., 2017]	20	P300	P, U, UP	Healthy participants achieved high performance in the BCI application, with mean accuracies of 94% for gel-based electrodes and 87% for dry electrodes. However, dry electrodes produced higher workload and lower comfort, while both groups criticized the system's speed and conspicuous design.
[Kiser et al., 2026]	21	SSVEP	P, U, UP	The SSVEP-based authentication system achieved high classification accuracy across all configurations (95–99%). High-frequency stimulation was generally perceived as more comfortable, while limited eye discomfort, minimal fatigue and low mental effort indicated good usability.
[Kleih et al., 2015]	11	P300 (auditory)	P, U, UP	The WIN-speller achieved an average spelling accuracy of 83.69% in healthy participants. Participants perceived the auditory paradigm as more difficult and demanding, but reported that focusing attention and discriminating stimuli were comparatively easy.
[Kosmyna et al., 2016]	12	Conceptual Imagery	P, U, UP	Healthy participants achieved 77% task accuracy. Ratings were high across usefulness, ease of use/learnability and satisfaction, indicating positive user acceptance of BCI-based smart-home interaction, although they reported mental effort during training.
Continued on the next page				

Study	Sample Size (Able-Bodied)	Signal Paradigm	Evaluation Focus	Results/Findings
[Lee et al., 2013]	31	Attention-Based/Neuro-feedback	U, UP	The BCI system received highly positive usability and acceptability ratings, with participants reporting high ease of use, comfort, enjoyment and perceived usefulness.
[Lee et al., 2015]	39	Attention-Based/Neuro-feedback	U, UP	Overall system satisfaction was rated positively by 90.9% of participants, with high ratings for usability and acceptability across all questionnaire items.
[Maby et al., 2012]	2	P300	P	The P300-based BCI Connect Four achieved high online classification accuracy, 81.7% in classic mode and 83.3% in contest mode, demonstrating effective online control of the game.
[McClinton et al., 2019]	8	P300	P, U, UP	For the brain painting system, classifier accuracy ranged from 50–80% on training data, whereas self-reported accuracy during the painting task was often below 60%. Participants generally perceived it as intuitive and enjoyable, while discomfort and long training times were identified as major usability issues.
[Moreno-Calderón et al., 2023]	22	c-VEP	P, U, UP	The c-VEP-based multiplayer game achieved high performance, with an average accuracy of 93.74%. Participants reported low workload and high satisfaction, although some users experienced time pressure and annoyance from the visual stimulation.
[Myrden and Chau, 2015]	12	MI & Mental Task/Cognitive Task	P, U, UP	The selected BCI task achieved an average classification accuracy of 72.4% during training. BCI performance was significantly related to users' mental state, with moderate frustration associated with higher accuracy and low fatigue associated with reduced performance.
Continued on the next page				

Study	Sample Size (Able-Bodied)	Signal Paradigm	Evaluation Focus	Results/Findings
[Pinegger et al., 2017]	18	P300	P, U, UP	The P300-based Brain Composing system achieved high mean accuracies across the three tasks (76.5–88.6%) among the 17 non-professional participants. Participants reported high satisfaction, enjoyment and perceived control, while subjective workload was moderate to high.
[Qu et al., 2018]	12	P300	P, U, UP	The 3-D P300 speller, compared with the conventional 2-D speller, significantly improved classification accuracy (94.0% vs. 89.1%) and overall BCI performance while reducing subjective workload. It also significantly reduced annoyance, while no significant difference in dizziness was observed.
[Rekrut et al., 2022]	14	Hybrid (MI, SSVEP)	P	SSVEP-based position control achieved 51% average accuracy, while the motor-execution component performed around chance level in the interaction study.
[Riccio et al., 2015]	8	P300	P, U, UP	The evaluated hybrid BCI achieved a median BCI accuracy of 81.9% (range: 45.7–90%), with participants reporting high satisfaction and low perceived frustration, but also increased physical demand.
[Severens et al., 2014]	6	P300 & N2	P, U, UP	The visual Hex-o-Spell outperformed the tactile speller in classification performance and ITR in both healthy and ALS participants. Participants also rated the Hex-o-Spell as more usable and easier to focus on, with a preference for the visual system.
[Simon et al., 2015]	11	P300	P, U, UP	The auditory P300 speller achieved high performance in healthy users, with accuracy increasing from 76.7% to 90.2% after training. Usability was generally positive, although relatively high workload and technical complexity remained important limitations.
Continued on the next page				

Study	Sample Size (Able-bodied)	Signal Paradigm	Evaluation Focus	Results/Findings
[Tang et al., 2022]	20	Hybrid (SSVEP, P300)	P, U, UP	The hybrid SSVEP/P300 system improved BCI performance through higher tool-selection accuracy ($\approx 89\%$). Users also reported significantly higher satisfaction, ease of use and mood/motivation, while concentration did not differ significantly.
[van de Laar et al., 2010]	20	MI	P, U, UP	Actual movement produced significantly better BCI performance than imagined movement, with a lower mean error rate (38.67% vs. 42.28%). Actual movement also resulted in significantly higher alertness, whereas imagined movement was perceived as significantly more challenging.
[Velasco-Álvarez et al., 2022]	12	P300	P, U, UP	The ERP-based BCI enabled effective control of multiple smart-home devices and applications, achieving 80.68% mean accuracy among able-bodied users. Usability and user perception were predominantly positive, with high SUS scores and low perceived workload.
[Vourvopoulos and Bermúdez i Badia, 2016]	9	MI	U, UP	VR-based BCI received high user acceptance and presence, while motor priming increased perceived workload.
[Vujic et al., 2023]	20	Affective Neurofeedback (Frontal Alpha Asymmetry)	P, U, UP	Performance improved significantly across training sessions in the experimental group. Participants generally perceived Joie positively and reported trust and increased self-awareness, but also fatigue and frustration with negative feedback.
[Won et al., 2015]	26	SSVEP	P, U	Higher-frequency SSVEP stimulation resulted in lower visual fatigue and more stable classification performance over time compared with low-frequency stimulation.
[Woo et al., 2021]	10	P300	P, U, UP	The P300-based virtual world tour achieved high online performance (96.6% overall accuracy) and good perceived controllability and comfort. However, moderate enjoyment and completeness ratings were reported, together with long response times.

Table A.1: Overview of Included Studies, Study Characteristics and Key Findings

Appendix B

Codebook

The following codebook provides the coding framework used for the categorization of relevant information from the included studies. We developed these 6 categories iteratively based on recurring concepts identified throughout the analysis process and they cover key aspects. Additionally, the codebook also reports the frequency of occurrence for each individual code within each category, providing an overview of their distribution across the included studies.

Application Domains - Type of intended use case		
Code	Quantity	Definition
Entertainment	12	Applications intended for entertainment, including games, virtual environments or other recreational experiences.
Speller	10	Systems that allow users to select letters, words or symbols through brain signals, enabling communication without conventional input devices.
Machines	4	Applications involving the operation of physical machines, such as robots, vehicles and drones, through brain signals.
Medical	4	Clinical and medically relevant applications, including cognitive training, neurorehabilitation and BCI-supported interaction during medical procedures.
Smart Home	2	Control and interaction with household devices and home environments through brain signals.
Cursor Control	2	Control and navigation of a computer cursor through brain signals for interaction with graphical user interfaces.
Authentication	1	The use of brain signals for user authentication and identity verification, which enables users to be reliably distinguished.
Multifunctional	1	BCI-based interaction supporting multiple functions or application areas, such as communication, entertainment and web access.

Table B.1: Codebook for Meta-Analysis: Application Domains

Signal Paradigms - Type of neural signal acquisition		
Code	Quantity	Definition
Imagery	11	Refers to the mental simulation or representation of an action, movement or concept without physically performing or interacting with it.
VEP	4	Users focus on visual stimuli that evoke frequency-specific EEG responses.
ERP	15	Event-related brain responses elicited in response to specific stimuli or events.
Neurofeedback	3	Neurofeedback paradigms enable users to self-regulate neural or cognitive states through real-time feedback on brain signals.
Hybrid	4	Combines two or more signal paradigms to generate control commands.

Table B.2: Codebook for Meta-Analysis: Signal Paradigms

Sample Size (Able-Bodied Participants) - Number of healthy participants		
Code	Quantity	Definition
Very Small (N = 1–5)	3	Studies involving 1–5 able-bodied participants.
Small (N = 6–10)	11	Studies involving 6–10 able-bodied participants.
Medium (N = 11–20)	18	Studies involving 11–20 able-bodied participants.
Large (N ≥ 21)	5	Studies involving 21 or more able-bodied participants.

Table B.3: Codebook for Meta-Analysis: Sample Size (Able-Bodied Participants)

Mean Accuracy Ranges - Ranges of mean accuracy reported across studies		
Code	Quantity	Definition
Low (< 60%)	5	Studies reporting a mean accuracy of below 60%.
Moderate (60–69%)	5	Studies reporting a mean accuracy between 60% and 69%.
Good (70–79%)	6	Studies reporting a mean accuracy between 70% and 79%.
High (80–89%)	9	Studies reporting a mean accuracy between 80% and 89%.
Very High ($\geq$ 90%)	5	Studies reporting a mean accuracy of 90% or above.

Table B.4: Codebook for Meta-Analysis: Mean Accuracy Ranges

Usability Dimensions - Factors considered to assess usability		
Code	Quantity	Definition
Ease of Use	17	Simplicity and intuitiveness of operating and interacting with the BCI.
Workload	16	Mental and physical effort required to perform tasks using the BCI system.
Learnability	4	The ease with which users can learn to operate the system and become proficient in its use.
Comfort	9	Physical comfort associated with wearing and operating the BCI throughout the duration of interaction.
Fatigue	7	The level of physical or mental tiredness experienced during or after prolonged system use.

Table B.5: Codebook for Meta-Analysis: Usability Dimensions

User Perception Dimensions - Factors considered to capture user perception		
Code	Quantity	Definition
Sense of Control	8	The perceived ability of users to intentionally influence and control the BCI system through their own actions.
Satisfaction	18	Feelings of enjoyment and interest resulting from using and interacting with the BCI system.
Frustration	9	Feelings of annoyance or irritation resulting from difficulties or unsuccessful interactions with the BCI system.
Motivation	6	Users' drive to actively engage with the BCI system and sustain continued interaction with it.
Acceptance	12	Users' overall willingness to accept and adopt the BCI system as a means of interaction.

Table B.6: Codebook for Meta-Analysis: User Perception Dimensions

Appendix C

PRISMA 2020 Statement: Checklists

This appendix contains two checklists based on the PRISMA Statement [Page et al., 2021], a widely recognized framework for conducting systematic reviews and meta-analyses. The first checklist in Table C.1 evaluates compliance with the 27 recommended reporting items and indicates the sections of the document in which each criterion is addressed.

The second checklist, Table C.2, with 12 items follows the same structure but is specifically adapted for the assessment of abstract reporting.

Section and Topic	Item #	Checklist Item	Location where item is reported
TITLE			
Title	1	Identify the report as a systematic review.	Title, as "Survey"
ABSTRACT			
Abstract	2	See the PRISMA 2020 for Abstracts checklist.	Table C.2
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of existing knowledge.	Chapter 1
Objectives	4	Provide an explicit statement of the objective(s) or question(s) the review addresses.	Chapter 1
METHODS			
Eligibility criteria	5	Specify the inclusion and exclusion criteria for the review and how studies were grouped for the syntheses.	Chapter 3.1.3
Information sources	6	Specify all databases, registers, websites, organisations, reference lists and other sources searched or consulted to identify studies. Specify the date when each source was last searched or consulted.	Chapter 3.1.2
Search strategy	7	Present the full search strategies for all databases, registers and websites, including any filters and limits used.	Chapter 3.1.2
Selection process	8	Specify the methods used to decide whether a study met the inclusion criteria of the review, including how many reviewers screened each record and each report retrieved, whether they worked independently, and if applicable, details of automation tools used in the process.	Chapter 3.1.2, Chapter 3.1.3
Continued on the next page			

Section and Topic	Item #	Checklist Item	Location where item is reported
Data collection process	9	Specify the methods used to collect data from reports, including how many reviewers collected data from each report, whether they worked independently, any processes for obtaining or confirming data from study investigators, and if applicable, details of automation tools used in the process.	Chapter 3.1.5
Data items	10a	List and define all outcomes for which data were sought. Specify whether all results that were compatible with each outcome domain in each study were sought (e.g. for all measures, time points, analyses), and if not, the methods used to decide which results to collect.	Chapter 3.1.5
	10b	List and define all other variables for which data were sought (e.g. participant and intervention characteristics, funding sources). Describe any assumptions made about any missing or unclear information.	Chapter 3.1.5
Study risk of bias assessment	11	Specify the methods used to assess risk of bias in the included studies, including details of the tool(s) used, how many reviewers assessed each study and whether they worked independently, and if applicable, details of automation tools used in the process.	Not applicable
Effect measures	12	Specify for each outcome the effect measure(s) (e.g. risk ratio, mean difference) used in the synthesis or presentation of results.	Not applicable
Synthesis methods	13a	Describe the processes used to decide which studies were eligible for each synthesis (e.g. tabulating the study intervention characteristics and comparing against the planned groups for each synthesis (item #5)).	Chapter 3.1.5
Continued on the next page			

Section and Topic	Item #	Checklist Item	Location where item is reported
Synthesis methods	13b	Describe any methods required to prepare the data for presentation or synthesis, such as handling of missing summary statistics, or data conversions.	Chapter 3.1.5
	13c	Describe any methods used to tabulate or visually display results of individual studies and syntheses.	Chapter 3.2
	13d	Describe any methods used to synthesize results and provide a rationale for the choice(s). If meta-analysis was performed, describe the model(s), method(s) to identify the presence and extent of statistical heterogeneity, and software package(s) used.	Chapter 3.1.5, Chapter 3.2
	13e	Describe any methods used to explore possible causes of heterogeneity among study results (e.g. subgroup analysis, meta-regression).	Not done (Only qualitative content analysis)
	13f	Describe any sensitivity analyses conducted to assess robustness of the synthesized results.	Not done (Only qualitative content analysis)
Reporting bias assessment	14	Describe any methods used to assess risk of bias due to missing results in a synthesis (arising from reporting biases).	Chapter 3.1.3
Certainty assessment	15	Describe any methods used to assess certainty (or confidence) in the body of evidence for an outcome.	Not conducted
RESULTS			
Study selection	16a	Describe the results of the search and selection process, from the number of records identified in the search to the number of studies included in the review, ideally using a flow diagram.	Chapter 3.1, Figure 3.2
	16b	Cite studies that might appear to meet the inclusion criteria, but which were excluded, and explain why they were excluded.	Chapter 3.1
Continued on the next page			

Section and Topic	Item #	Checklist Item	Location where item is reported
Study characteristics	17	Cite each included study and present its characteristics.	Appendix A
Risk of bias in studies	18	Present assessments of risk of bias for each included study.	Not conducted
Results of individual studies	19	For all outcomes, present, for each study: (a) summary statistics for each group (where appropriate) and (b) an effect estimate and its precision (e.g. confidence/credible interval), ideally using structured tables or plots.	Appendix A
Results of syntheses	20a	For each synthesis, briefly summarise the characteristics and risk of bias among contributing studies.	Not conducted
	20b	Present results of all statistical syntheses conducted. If meta-analysis was done, present for each the summary estimate and its precision (e.g. confidence/credible interval) and measures of statistical heterogeneity. If comparing groups, describe the direction of the effect.	Chapter 3.2
	20c	Present results of all investigations of possible causes of heterogeneity among study results.	Not conducted
	20d	Present results of all sensitivity analyses conducted to assess the robustness of the synthesized results.	Not conducted
Reporting biases	21	Present assessments of risk of bias due to missing results (arising from reporting biases) for each synthesis assessed.	Not conducted
Certainty of evidence	22	Present assessments of certainty (or confidence) in the body of evidence for each outcome assessed.	Not conducted
Continued on the next page			

Section and Topic	Item #	Checklist Item	Location where item is reported
DISCUSSION			
Discussion	23a	Provide a general interpretation of the results in the context of other evidence.	Chapter 4.1
	23b	Discuss any limitations of the evidence included in the review.	Chapter 4.2
	23c	Discuss any limitations of the review processes used.	Chapter 4.2
	23d	Discuss implications of the results for practice, policy, and future research.	Chapter 5.2
OTHER INFORMATION			
Registration and protocol	24a	Provide registration information for the review, including register name and registration number, or state that the review was not registered.	No (review in HCI with no registration/protocol)
	24b	Indicate where the review protocol can be accessed, or state that a protocol was not prepared.	No (review in HCI with no registration/protocol)
	24c	Describe and explain any amendments to information provided at registration or in the protocol.	No (review in HCI with no registration/protocol)
Support	25	Describe sources of financial or non-financial support for the review, and the role of the funders or sponsors in the review.	No financial support (non-sponsored thesis)
Competing interests	26	Declare any competing interests of review authors.	Not reported
Availability of data, code and other materials	27	Report which of the following are publicly available and where they can be found: template data collection forms; data extracted from included studies; data used for all analyses; analytic code; any other materials used in the review.	Appendix A, B, C

Table C.1: The PRISMA 2020 statement comprises a checklist with 27 items designed to guide the reporting of systematic reviews across the introduction, methods, results, discussion, and other relevant sections.

Section and Topic	Item #	Checklist Item	Reported (Yes/No)
TITLE			
Title	1	Identify the report as a systematic review.	Yes
BACKGROUND			
Objectives	2	Provide an explicit statement of the main objective(s) or question(s) the review addresses.	Yes
METHODS			
Eligibility criteria	3	Specify the inclusion and exclusion criteria for the review.	Yes
Information sources	4	Specify the information sources (e.g. databases, registers) used to identify studies and the date when each was last searched.	Yes
Risk of bias	5	Specify the methods used to assess risk of bias in the included studies.	No (risk assessment not conducted)
Synthesis of results	6	Specify the methods used to present and synthesise results.	Yes
RESULTS			
Included studies	7	Give the total number of included studies and participants and summarise relevant characteristics of studies.	Yes
Synthesis of results	8	Present results for main outcomes, preferably indicating the number of included studies and participants for each. If meta-analysis was done, report the summary estimate and confidence/credible interval. If comparing groups, indicate the direction of the effect (i.e. which group is favoured).	Yes
Continued on the next page			

Section and Topic	Item #	Checklist Item	Reported (Yes/No)
DISCUSSION			
Limitations of evidence	9	Provide a brief summary of the limitations of the evidence included in the review (e.g. study risk of bias, inconsistency and imprecision).	Yes
Interpretation	10	Provide a general interpretation of the results and important implications.	Yes
OTHER			
Funding	11	Specify the primary source of funding for the review.	No (non-sponsored thesis)
Registration	12	Provide the register name and registration number.	No (review in HCI)

Table C.2: The PRISMA 2020 for abstracts is a checklist with 12 items and serves as a structured framework to help authors condense a systematic review into the key elements required for an abstract.

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