

## Review

# The Progress and Prospects of Data Capital for Zero-Shot Deep Brain–Computer Interfaces

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**Abstract:** The vigorous development of deep learning (DL) has been propelled by big data and high-performance computing. For brain–computer interfaces (BCIs) to benefit from DL in a reliable and scalable manner, the scale and quality of data are crucial. Special emphasis is placed on the zero-shot learning (ZSL) paradigm, which is essential for enhancing the flexibility and scalability of BCI systems. ZSL enables models to generalise from limited examples to new, unseen tasks, addressing data scarcity challenges and accelerating the development of robust, adaptable BCIs. Despite a growing number of BCI surveys in recent years, there is a notable gap in clearly presenting public data resources. This paper explores the fundamental data capital necessary for large-scale deep learning BCI (DBCI) models. Our key contributions include (1) a systematic review and comprehensive understanding of the current industrial landscape of DBCI datasets; (2) an in-depth analysis of research gaps and trends in DBCI devices, data and applications, offering insights into the progress and prospects for high-quality data foundation and developing large-scale DBCI models; (3) a focus on the paradigm shift brought by ZSL, which is pivotal for the technical potential and readiness of BCIs in the era of multimodal large AI models.

**Keywords:** brain–computer interfaces; deep learning; Zero-shot learning; industrial landscape; conceptualisation



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## 1. Introduction

Neuralink's 'Telepathy' is a new intrusive brain–computer interaction (BCI) device that places 1024 electrodes in the motor cortex. Unlike non-intrusive EEG technologies, intrusive methods can fully penetrate the brain for deep coverage. This, combined with Telepathy's high electrode count compared to the standard 32 or 64 electrodes for non-intrusive EEG, provides a quality of data unrivalled by non-intrusive means. Furthermore, a vast quantity of data can be gathered by devices embedded in a user, unlike EEG devices, which are typically worn for no more than a day, or MRI machines, which are used for only a couple of hours at a time. The company has also developed a robot to implant their device, making it more scalable and accessible by reducing the need for human expertise during surgery. For these reasons, we believe Neuralink's technology could mark the beginning of large-scale and high-quality data capital collection for BCI applications.

That being said, this technology is still in its infancy. At the time of writing, only two patients have had the Telepathy device implanted, with varying success. Some of the

64 threads came loose in the first patient, although the user was still able to control a cursor with their thoughts. Questions remain as to the safety of this technology, as well as its long-term durability. There is also the cost of the device to consider, as well as the fears people have about having a chip implanted in their brains; these are further barriers to the widespread adoption of this device. For this reason, in this paper, we focus on non-intrusive EEG datasets, which contribute to the majority of existing data capital for BCI applications due to their price and ease of use compared to other brain-imaging techniques. It is also unclear if Neuralink, due to its nature as a private company, will release the data capital it collects to the broader academic community.

The rapid development of deep learning (DL) embraces the prevalence of internet technology. Increasing internet access and availability accumulate large-scale and diverse data, stimulating the demand for efficient computing and data storage. The past two decades have shown a significant shift from theoretical studies toward versatile applications. New commercial needs encounter technical challenges that, in turn, motivate the establishment of new theoretical foundations, such as multimodal [1], multi-task [2], interpretable [3], causality [4], and AI-generated content (AIGC) [5,6]. This paper introduces the industrial landscape (IL) framework, which generally refers to the physical and visual characteristics of areas where industrial activities take place, such as factories, mills, refineries, and other industrial facilities. It can also refer to the broader socioeconomic and cultural impacts of industrialisation on the surrounding environment and communities, including changes to land use, infrastructure, and the built environment. Industrial landscapes can vary widely in appearance and character depending on the type of industry, location, and historical context, and may include features such as smokestacks, silos, pipelines, and rail yards. Recent work has shown the IL framework in the context of data capital [7] to help understand the closed loop of theory–application–need and to identify future trends, limitations, and challenges.

Models and data are the two fundamental pillars of AI development. The origins of AI models lie in logic formalisation [8]. Alan Turing, building on this foundation, introduced the Turing machine and the conceptualisation of AI from a deductive perspective. Deductive or rule-based symbolic systems [9] are characterised by their pursuit of rigour and precision but often sacrifice flexibility and generalisation capabilities. In contrast, inductive methods have evolved to follow a data-driven approach, deriving rules and models from patterns in observed data. Current deep learning (DL) models are primarily grounded in the inductive paradigm, processing empirical perception signals such as vision, natural language, and audio [10]. However, while these models excel at pattern recognition and representation, they are inherently limited to interpreting conscious levels of data, as conceptualised in cognitive theory [11]. According to this theory, an agent's cognition spans four levels: unconsciousness, consciousness, awareness, and meta-awareness. Traditional DL models predominantly operate at the level of behavioural data, reflecting perception and consciousness. Their goal is to align human attention signals (labels) with input data, such as semantic attributes. Despite their progress, supervised learning paradigms, which have dominated AI research for the past two decades, suffer from several limitations. These include issues such as subjective biases [12], vulnerability to adversarial attacks and data poisoning [13], data annotation burdens, and significant ethical concerns [14]. These challenges highlight the constraints of existing methods and the need for more robust approaches. The emergence of self-supervised learning and advances in parallel computing have prompted industrial efforts to pursue a top-down technological approach. This involves leveraging large-scale multimodal interactive data to train powerful DL models that aim to achieve meta-awareness—a higher cognitive representation incorporating knowledge graphs and causal inference [15]. By addressing the divergence in individual

awareness and improving moral generalisation, these models offer a pathway to mitigate bias and ensure more inclusive and fair outcomes. However, this approach relies on the assumption that data collection systems can comprehensively capture diverse users, thereby addressing the challenges of neurodiversity [16].

Emerging BCI technologies have brought new opportunities and challenges, which push the AI and deep learning community to the next level. One aim of this technology is to explain fundamental brain mechanisms beyond perception and consciousness. For example, rapid serial visual presentation (RSVP) displays users with sequential images at high speed (e.g., 10 images per second). In face recognition tasks, users are given a well-known target face to find, e.g., Einstein, before being displayed a high-speed sequence of faces. A promising result is that the P300 signal, which is triggered when a person recognizes a face, can be detected from the BCI signal even when human participants are unaware that the face has been displayed. This shows that signals measured by BCI devices can indeed detect and analyse unconscious level information and suggests that BCI technology could lead AI to a new era by exploring the internal behaviour of brain activities beyond existing cognitive and conscious levels.

In this context, brain–computer interface (BCI) systems represent a critical breakthrough. Unlike traditional methods that primarily rely on behavioural and conscious data, BCI systems have the potential to tap into unconscious levels of cognition, providing a fundamentally new layer of supervision for AI. By integrating neural signals directly from the brain, BCI can reduce the inherent subjectivity of supervised learning and provide richer, more diverse data inputs. This capability not only mitigates bias and enhances fairness but also paves the way for a more comprehensive and accurate alignment of AI systems with human-level cognition, thereby playing an indispensable role in modern AI. Compared to traditional learning paradigms like few-shot and transfer learning, zero-shot learning (ZSL) offers a distinct advantage in BCI applications by eliminating the need for extensive labelled data and enabling generalisation to novel tasks and unseen classes. Few-shot learning requires limited but labelled examples, and transfer learning depends on pre-trained models adapted to new tasks, which can be challenging in scenarios with domain-specific constraints or a lack of domain-aligned data. ZSL, on the other hand, leverages semantic relationships and knowledge transfer to bridge these gaps, making it uniquely suitable for BCIs where obtaining task-specific labelled datasets is often impractical. Beyond healthcare applications, ZSL's potential extends to domains like communication aids, enabling individuals with neuro-disorders to interact seamlessly, and industrial robotics, where adaptive neural control can revolutionise task automation. These capabilities highlight the transformative impact of ZSL in scaling BCIs across diverse real-world scenarios.

However, the key barrier between BCI and contemporary deep learning research is data foundation. The data-hungry nature of deep models requires vast quantities of training data that can only be acquired through large-scale deployment. The polarised situation is that intrusive or fMRI-based data collection can provide high-resolution and reliable results, but are limited by cost and usability. However, low-cost, lightweight, and commercialised devices, such as EEGs, ECGs, and EMGs, are still limited in performance. In this paper, we investigate this problem through the lens of the industrial landscape [7], which provides a new perspective on data capital. This allows us to understand the progress and predict the trend of deep neural network development in BCI domains. The contributions of this paper are threefold:

- First, we use the IL framework to conduct a systematic literature review. We summarise both established and emerging DBCI data capitals which help understand the progress of each identified core technical milestone of DBCI.

- Second, the motivation of this article is to put the development of BCI models into the context of the IL framework. We identify key barriers preventing the development of large DBCI models in terms of devices, data, and applications.
- Third, we point those unaddressed technical challenges towards cutting-edge zero-shot learning techniques. Our findings establish a technical roadmap through inter-sample, inter-person, inter-device, inter-domain and inter-task transfer paradigms, multimodal visual–semantic neural signal models, and data synthesis and signal processing for higher SNR and scalable DBCI device adaption.

This paper is organised as follows. In Section 2, we systematically introduce the research background, the conceptualisation of the industrial landscape, and the current state of DBCI research. In Section 3, we outline our survey methodology and the data we collect. Section 4 discusses the survey results of existing BCI datasets and suggests how the emerging zero-shot neural decoding technique can overcome the barriers identified in the survey. We finalise our discussion and summarise the main findings in the last Section 5.

## 2. Research Background

In this section, we introduce the research background of DBCI to put our review into the context of the industrial landscape [7]. The industrial landscape is a framework that can analyse the industrial trend of both existing digital technologies and AI. Our contribution focuses on making a mapping for DBCI development under the IL framework to understand and predict the progress in parallel with other AI and digital technologies.

To ensure a comprehensive and systematic review of the existing literature on brain–computer interface (BCI) research, a structured search strategy was employed. An initial search on Google Scholar yielded over 28,000 results based on a combination of keywords, including “brain–computer interface”, “brain–machine interface”, “EEG”, “BCI review”, and “BCI survey”. Boolean operators (AND/OR) were used to refine the search, for example, combining terms like “brain–computer interface” AND review and “brain–machine interface” OR “EEG” AND survey to maximise coverage. The search was restricted to papers published between 1986 and 2024, written in English, and focused on journal articles, conference proceedings, and review papers. From this extensive pool, a systematic screening process was conducted to identify 677 relevant papers. The inclusion criteria focused on (1) relevance to BCI research, assessed through titles and abstracts; (2) papers providing foundational insights or discussing recent advancements in BCI technologies, devices, datasets, and applications; and (3) studies addressing key paradigms, such as slow cortical potentials (SCPs), P300, sensorimotor rhythms (SMR), and neurofeedback. This curated selection of 677 papers forms the basis of this review, highlighting milestones, trends, and gaps in BCI research.

Early work of BCI can be traced back to 1924 [17] when the first-ever electroencephalogram signal was recorded by Hans Berger. Bio–neuro [18] feedback began in the late 1950s. Biofeedback refers to all physiological signals, e.g., blood pressure, heart rate, etc., whereas neurofeedback refers to brain signals only. The first seminal work that provided both a theoretical and technical review of BCI was published in 1973 [19]. Initial research focused on controlling assistive devices. Operant (instrumental) conditioning refers to autonomous functions, e.g., blood pressure and heart rate, which can be manipulated by operant conditions. In 1960 [20,21], Neil Miller conducted the first trial aimed at disrupting the motor system of rats. The experiment extended to blood pressure, urine production, and gut control in [22]. Human learning, in contrast, takes the cognitive dimension into account. Controlling devices with BCI, end-users need to focus their attention throughout the tasks, which is cognitively demanding.

One of the primary applications of BCI lies in the neuro-disorder domain. In particular, locked-in syndrome (LIS), which typically follows a stroke in the basilar artery of the brainstem, is characterised by the retention of vertical eye movements (e.g., looking up and down) [23,24]. LIS can also result from amyotrophic lateral sclerosis (ALS), which leads to the loss of movement or complete motor paralysis. Both LIS and ALS are key target populations for restoring lost functionality through BCI. Compared to traditional voluntary assistive technologies, BCI offers four main advantages. First, slow cortical potentials (SCPs) provide the basis for long-term training, allowing individuals to communicate messages in the absence of peripheral muscular movement. Second, involuntary eye movements associated with LIS present a significant challenge for other assistive technologies, which BCI can bypass. Third, depression caused by LIS often makes it difficult for caregivers to interpret eye movements or spelling codes, which limits communication. Fourth, BCI eliminates the need for questionnaire-based assessments, providing a more direct and efficient interface. A more challenging scenario involves complete locked-in syndrome (CLIS) [25], in which the loss of behavioural output [26] leads to “thought paralysis”. This state, often resembling a vegetative state, poses limitations to operant learning approaches. Despite these challenges, contemporary BCI applications have embraced advancements brought by the AIGC era. For instance, brain painting replaces the traditional P300 matrix with icons representing painting tools, which are controlled by a cursor. This technology has enabled ALS patients to create art independently, without requiring researcher supervision [27,28]. Following painting sessions, satisfaction, joy, and frustration are evaluated by the BCI team, and favourable results have consistently been observed.

Neurophysiology has established key paradigms for BCI signal acquisition, such as slow cortical potentials (SCPs) and P300, which are widely applied in conditions like epilepsy and attention deficit hyperactivity disorder (ADHD). Techniques like voluntary control of alpha activity, sensorimotor rhythms (SMRs), and  $\mu$ -rhythm have been utilised in psychological therapy, behavioural studies, and medicine since the 1950s. Event-related potential (ERP), SMR, SCP, and P300 (a positive potential occurring 300 ms after a stimulus) are frequently implemented with stimuli approaches like the oddball paradigm. For example, a 6x6 letter matrix [29] enables letter selection, while N400 (a negative potential 400 ms after stimulus) is used for face recognition tasks. Operant learning is commonly employed to increase SMR activity (8–15 Hz), which reflects event-related desynchronisation (ERD). ERD was introduced for cursor control in 1991 and later expanded to motor imagery, although it requires users to learn to regulate their brain responses. The S1–S2 paradigm (S1: warning stimulus, S2: imperative stimulus requiring a motor response) is also used, where SCP measures slow EEG shifts, such as contingent negative variation (CNV). For instance, a negative shift occurring 800 ms before finger movement can be observed. SCP shifts are also associated with large negative DC shifts during epileptic seizures, and voluntary SCP modulation may help prevent them. These methods were first implemented for locked-in patients in 1999 [30] and remain foundational for smooth BCI control.

Several traditional barriers are preventing BCI from being widely applied. The first is the signal-noise rate (SNR). SNR reflects the strength of the signal of interest in relation to artefacts like breathing and muscular movement [31]. These noise artefacts remain a fundamental challenge today. Second, BCI training is required for users, decreasing accessibility [32]. In 2010, usability and user-centred design (UCD) set the ISO 9241-210 [33] as the usability standard. This norm requires BCI-controlled applications to be evaluated by user experience in terms of (1) effectiveness, which considers the accuracy and completeness users can achieve; (2) satisfaction, which measures comfort and acceptability while using the device; and (3) usability measurement. The information transfer rate (ITR) is also a key parameter to measure BCI accessibility. From the early work of 2 min per letter [30],



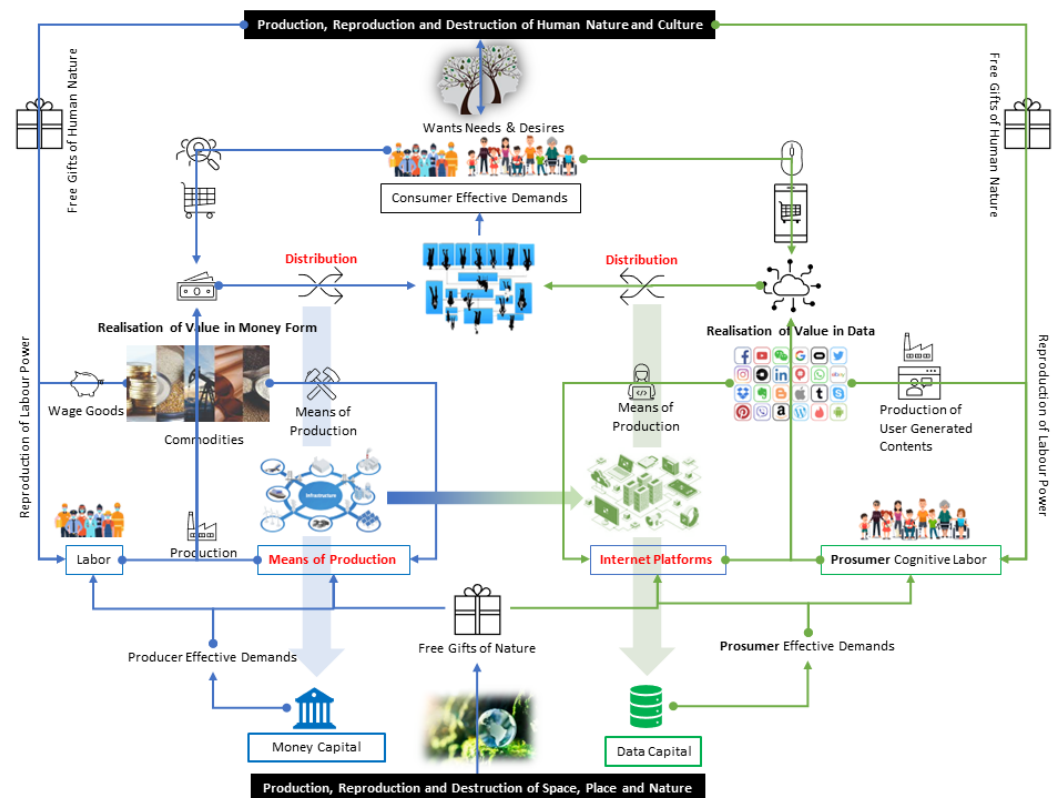
P300-based BCI progressed to 10 letters per min in [34]. However, it is still not suitable for independent home use. Device design is also an important factor. The trend in BCI technology development is moving towards lightweight, cost-effective solutions, ranging from compact RRG amplifiers integrated into caps [35], to artefact rejection techniques for smartphone applications during walking [36], and behind-the-ear designs [37]. We summarise the key milestones as follows:

- 1924: Hans Berger records the first electroencephalogram (EEG) signal.
- 1950s: Bio-neuro feedback was introduced, focusing on physiological and brain signals.
- 1960: Neil Miller demonstrates operant conditioning for controlling autonomic functions, like blood pressure and heart rate, in rats.
- 1973: First theoretical and technical review of brain-computer interfaces (BCIs).
- 1991: Event-related desynchronisation (ERD) is introduced for cursor control.
- 1999: Slow cortical potentials (SCPs) are applied to control devices for locked-in patients.
- 2000s: Development of P300-based BCIs for communication and control tasks.
- 2010: Adoption of ISO 9241-210 usability standards for BCI evaluation, focusing on effectiveness, satisfaction, and usability.
- 2020s: Emergence of advanced applications like brain painting for ALS patients and other neurofeedback-based tools.

The literature review highlights the essential need for advancements in machine learning, communication, and interaction technologies [38]. The key objectives are as follows: (1) reducing training costs for both users and models, (2) developing robust filters to improve signal-to-noise ratio (SNR), and (3) creating transferable and generalised BCI systems that do not require prior calibration. This presents a classic chicken-and-egg dilemma. On the one hand, machine learning, particularly deep learning, requires large-scale data to achieve reliable transferability and generalisation. On the other hand, transferability and generalisation are essential features that must be established before a BCI device can be widely adopted. For instance, no long-term studies involving locked-in patients have been conducted using machine learning. Historically, neurofeedback studies required significant time investments, such as 288 h per user [39], or in 1977, 2.5 years of SMR data collected over 200 sessions. These efforts represent a foundational investment in data capital, which we consider critical for driving progress in models, devices, paradigms, and accessibility. We will further explore how data capital underpins these aspects in the context of the IL framework.

### *Industrial Landscape*

The fast growth of internet companies and new technologies has resulted in a stark contrast to the traditional industrial landscape conceptualisation. The traditional labour theory of Karl Marx conceptualises economic development with key components of labour, value, property, and production relationships. David Harvey [40] provides a modern interpretation with a significant influence on academic and political debates around the world. The work on urbanisation and the political economy of cities has been particularly influential and has been a vocal critic of the neoliberal policies that have shaped urban development in many parts of the world. The work has often addressed the intersections between political economy, social inequality, and environmental degradation. In this paper, we present recent advancements in applying the IL framework to the context of AI and data capital [7]. We provide a consistent illustration of the IL framework, drawing on the work of David Harvey, and extend it to the new contexts of data capital, as illustrated in Figure 1.



**Figure 1.** Comparison between the traditional industrial landscape and the new contexts of digital technology. The new data capital model provides a roadmap to guide the DBCI development.

The driving power in the traditional industrial landscape conceptualisation is money capital, which meets producer-effective demands. This process combines with the “free gifts of nature” to facilitate labour and the means of production. Produced commodities stimulate the realisation of value in monetary form after deducting wage goods and the cost of the means of production. The production, reproduction, and destruction of human nature and culture shape the “free gift” of human nature, as well as fundamental wants, needs, and desires. The resulting consumer effective demands are matched to the realisation of value in money form through marketing activities and create distribution to the producer, consumer, and back-to-money capital. In this IL framework, the key gateways to control the flow of money capital are the means of production and distribution.

In the new contexts of data capital [7], particularly in the era of recent AIGC advancements and large-scale models, internet platforms have emerged as fundamental infrastructure. The updated IL framework is especially valuable for understanding the technical development of contemporary AI, including fields such as computer vision and natural language processing. This framework focuses on the differences and commonalities between the traditional bourgeoisie and the new bourgeoisie, referred to as neo-bourgeoisie. The traditional bourgeoisie owns the means of production and has high fixed costs, while the neo-bourgeoisie owns the means of connection and has low fixed costs. For example, digital products, such as online videos and games are not limited by their physical forms and can serve the scalable needs of customers. The factors involved in production for the traditional bourgeoisie are land, labour, and capital, while for the neo-bourgeoisie, they are data and information. For example, many online services and products are free to use as the owner of a digital gateway can gather valuable data and information. Data can be used to supply further development for business analysis and AI training while information is essential in controlling information distribution and matching market needs. Both data capital and money capital have monopoly power and high economic rents. The

framework also discusses the differences and commonalities between the proletariat and the neo-proletariat. The former is paid for labour hours, while the latter receives free services in exchange for personal data and cognitive workloads.

Our work focuses on analysing the progress and perspective of DBCI technologies in the context of the IL framework. Unlike previous surveys that were technique-driven, this paper provides a hybrid paradigm. Firstly, we derive the survey structure using a scoping review approach and the IL framework. Based on the derived structure, we then match the development of DBCI models and data using the systematic literature review approach. Meta-analysis is also provided to compare key parameters, such as DBCI applications, data statistics, and BCI devices.

### 3. Methodology

#### 3.1. Conceptualisation of DBCI Industrial Landscape

More than 600 BCI survey papers were published between 1986 and 2024. However, none of these surveys has contextualized the technical development of BCI within the industrial landscape, which is crucial to understanding how the factors of data, devices, commercialisation, etc., shape research. Therefore, we introduce the recent IL framework [7] as an initial scoping review to narrow down and identify the following key topics. Our review methodology is summarised in Figure 2. To narrow down the selection of datasets, we employed a further two-stage manual filtering process. In the first stage, we performed a relevance-based screening of the initial 677 papers to identify 229 that aligned with the industrial landscape barriers, specifically focusing on applications, utility, cognitive workload, and data/model ownership. This stage involved evaluating abstracts, keywords, and methodologies for relevance. In the second stage, we conducted a quality assessment of the 229 papers, applying inclusion criteria such as the accessibility of datasets, reproducibility of experimental methods, and overall methodological rigour. This final step reduced the selection to 38 papers that met the highest standards of quality and relevance, forming the basis of our review. This systematic approach ensured that only datasets with substantial value for advancing DBCI research were included. As a result, there are a total of 44 datasets included in this paper. The four barriers, i.e., applications, utility, cognitive workload, and data and model ownership, were derived from the principles and insights outlined in the IL framework. This framework conceptualises the progression of digital technologies and AI through the lens of data capital, a critical resource that underpins innovation, scalability, and economic value in modern industries. In the context of DBCI, these barriers emerge as follows:

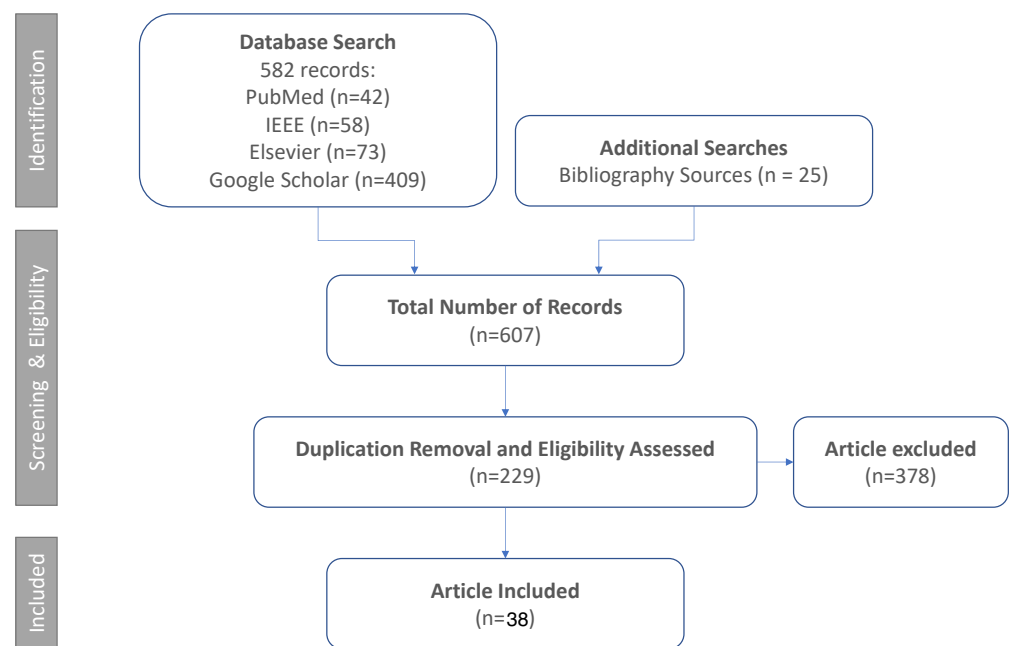
**DBCI applications:** These applications consider the impact of big data and artificial intelligence (AI) on the economic, social, and political systems of the world. AI has increased the ability to produce more for economic growth and development while also making human labour obsolete. This creates a trajectory where capitalism remains the ultimate system, controlling the lives of labour through big data. However, the growth of AI also promotes technological innovation and investment, leading to economic growth. The profit-driven technological singularity of AI creates social challenges and potentially fatal economic impacts under a neoliberal economic system. AI also creates a digital divide and potentially expands existing societal rifts and class conflicts. It is essential to develop policies to protect labour, privacy, trade, and liability and reduce the consequences of AI's impact on employment, inequality, and competition. DBCI may create opportunities for individuals to monetise their personal data and potentially transfer control and ownership to actual data producers in a passive way, i.e., the mind activity and focused time consumption. Application is, therefore, a key parameter in evaluating the maturity and progress of the DBCI industrial landscape.



**The utility of DBCI:** The economic landscape has undergone major changes in the past few decades with the emergence of new internet technologies and the creation of value through business model innovation using data and information. The factors of production have been redefined with data and information being recognised as new variables that have been made possible by technological breakthroughs in information and communications technology. The cost of computing power, data storage, and Internet bandwidth has decreased significantly, enabling the creation of increasingly rich digital information. This has given rise to new phenomena such as big data analytics and Internet platform companies. The democratisation of information and knowledge has also increased the bargaining power of workers and consumers whilst impacting Marxist philosophy in two areas related to the value-creation process. The commodification of cognitive labour is the foundation of the new capitalist system in which modes of control over production, consumption, distribution, and exchanges are very different from earlier forms of capitalism in history. This new economy of capitalist transformation is referred to as ‘cognitive capitalism’ [41]. This work provides empirical evidence supporting the role of cognitive abilities and intellectual resources in driving innovation, productivity, and economic growth. By aligning the discussion of DBCI utility with the principles outlined, we establish a stronger connection between the theoretical framework of cognitive capitalism and the practical implications of DBCI technologies. This addition strengthens our argument and highlights the transformative potential of DBCI within the broader economy and the industrial landscape.

**Value of cognitive workload:** The traditional idea that the value of products and services is measured in labour hours has been challenged by the process of datafication, which involves dematerialisation, liquefaction, and density. Digitisation has made it possible for companies like Netflix to offer on-demand services and gather data on user behaviour. Digital products are also non-rivalrous and non-excludable, which means that they can be used by many individuals at the same time without reducing their availability to others. The availability of free digital services and products also challenges the use of labour hours to value a product or service, as many are provided through advertising or other business models. The concept of the prosumer [7] further undermines the traditional value-creation process. The definition of prosumer originates from the fact that most online content uploaded onto technology platforms today is actually produced by the consumer, free of charge. This means that the traditional value-creation process is rendered obsolete. While existing AIGC technologies have provided the premises for creation, the *cognitive workload* in DBCI provides one step further. The research on cognitive workload can potentially encourage a healthy and fair ecosystem for DBCI and other large models for real-world applications.

**Data and model ownership:** The scoping review discusses how the traditional Marxist dichotomy between bourgeoisie owners of the means of production and proletariat workers has been upended by the emergence of platform-based internet companies. These companies, such as Amazon, Google, and Facebook, do not own the means of production but rather the means of connection to the internet, and they leverage large amounts of customer data to create value. This article also discusses the democratisation of information and the shift in power from traditional owners to individuals and entrepreneurs, as well as the emergence of the sharing economy and the de-linking of assets from value. In the AIGC era, the AI ecosystem is moving from the traditional data capital to the current model capital paradigm, such as ChatGPT. Large-scale deep models, whether they are open-source or not, are no longer accessible to common users for model fine-tuning. Deep model APIs or MLaaS have become dominant practices. In DBCI research, deep learning models are in the early stages of this model capital wave. Our review will discuss the influence of existing data and AI model capitals on the DBCI domain.



**Figure 2.** A total of 607 survey and dataset papers were collected from our initial search. After a screening and eligibility check, we found 229 papers to check whether they significantly contributed to our conceptual framework. As a result, 44 benchmarks from 38 papers are included in this study.

### 3.2. DBCI Data Capital Liquidation Process

The data asset liquidation process is intrinsically linked to the broader landscape of DBCI applications, encompassing their utility, the value of cognitive workload, and data and model ownership. By systematically evaluating and managing data assets, we can maximise their potential in driving forward DBCI applications, which rely heavily on high-quality and extensive datasets to develop and refine models that enable innovative solutions in healthcare, neurorehabilitation, and beyond. Understanding the utility of DBCI involves assessing the cost-effectiveness and accessibility of devices and paradigms, ensuring that the technology can be widely adopted and utilised. Moreover, the value of the cognitive workload emphasises the importance of accurately measuring and leveraging cognitive data to enhance user experience and productivity, making it crucial to manage and assess data quality effectively. This comprehensive approach to data asset liquidation not only supports the advancement of DBCI technologies but also addresses the multifaceted challenges and opportunities within the industry.

We summarise our assessment factors in Table 1. Specifically, for BCI devices, frequency (Hz) indicates how often signals are sampled per second. Higher frequencies capture finer temporal resolution, which is crucial for tracking rapid brain activities. EEG channels represent the number of electrodes used in data collection. A higher number of channels offers better spatial resolution, capturing data from more regions of the brain. For DBCI Applications, high-frequency and multi-channel devices enable applications requiring precise brain activity mapping, such as neurorehabilitation and emotion recognition. For BCI utility, devices with higher frequency and channel count are more versatile but can be costlier and less portable. Optimising these metrics balances performance and usability in real-world settings. For the value of cognitive workload, accurate frequency and spatial resolution improve the fidelity of cognitive workload measurements, enabling deeper insights into attention, fatigue, and performance. For data and model ownership, high-

resolution devices are often proprietary, with access to raw data or model training pipelines controlled by manufacturers. This raises questions about open standards and accessibility.

**Table 1.** Mapping metrics of devices, data, and applications to the DBCI industrial landscape. Note that trials refer to trials per user.

| Aspect              | Metric         | Why It Is Used                                                                   | Connection to Industrial Landscape                                                                                             |
|---------------------|----------------|----------------------------------------------------------------------------------|--------------------------------------------------------------------------------------------------------------------------------|
| <b>Devices</b>      | Frequency (Hz) | Captures temporal resolution of brain activity.                                  | Enables high-precision DBCI applications, and improves cognitive workload modelling, but is often tied to proprietary devices. |
|                     | EEG Channels   | Indicates spatial resolution of brain activity.                                  | Supports diverse applications, increases utility and workload fidelity, but raises ownership challenges.                       |
| <b>Data</b>         | Length (s)     | Determines duration of captured data for each trial.                             | Supports long-term applications, increases utility, and enhances workload assessment across varied contexts.                   |
|                     | Trials         | Reflects dataset robustness and reliability.                                     | Ensures applicability in diverse scenarios, increases model reliability, and requires careful ownership considerations.        |
|                     | Users          | Represents diversity and generalisability of the dataset.                        | Enables cross-population applications, improves utility, and raises ethical issues about ownership and privacy.                |
| <b>Applications</b> | Stimuli        | Defines the context of recorded brain activity.                                  | Links directly to DBCI use cases, increases task-specific utility, and impacts workload relevance and accessibility.           |
|                     | Task           | Defines the dataset's relevance to specific DBCI applications.                   | Drives model training for targeted use cases, improves cognitive workload insights, and ties to ownership of annotations.      |
|                     | Response       | Determines modalities available for analysis (e.g., EEG, behavioural responses). | Increases flexibility across applications, improves model utility, but raises accessibility challenges due to ownership.       |

The second metric we consider is data. For DBCI applications, longer trial lengths and diverse participant pools make the datasets applicable to a wider range of use cases, such as personalised neurofeedback or cross-cultural studies. For BCI utility, more trials and participants increase the dataset's statistical power but also its complexity and storage requirements. This impacts its usability for researchers and practitioners. For the value of cognitive workload, repeated trials and diverse user data improve the accuracy and generalisability of cognitive workload models, ensuring they work effectively across different scenarios. And, for data and model ownership, datasets with longer trials and diverse users often require substantial investment. Ownership can dictate access, limiting opportunities for public or collaborative research. Specifically, we use length (s) for the duration of each recorded trial, which impacts the total data volume and its utility in capturing prolonged cognitive states. Trials reflect the number of repetitions per user, affecting dataset reliability and robustness. Users indicate the number of participants in a dataset, determining its diversity and generalisability across populations.

Finally, we consider applications in terms of stimuli, task, and response as metrics. The type of stimuli (e.g., visual, auditory) presented to participants defines the context of the dataset and its relevance to specific applications. The task describes what participants were asked to do (e.g., motor imagery, attention tasks), directly linking the dataset to specific DBCI use cases. Response refers to the recorded data types (e.g., EEG signals, behavioural responses), which determine the modalities available for model training and application. For DBCI applications, stimuli, tasks, and responses define the real-world scenarios where the dataset can be applied. For example, datasets with motor imagery tasks are crucial for prosthetics, while emotional stimuli datasets are vital for affective

computing. For utility, datasets with diverse stimuli and task types are more flexible but require sophisticated annotation and preprocessing, impacting ease of use. The value of a cognitive workload is often associated with the stimuli and task types that influence cognitive demands, making these metrics critical for accurately modelling workload and designing adaptive systems. Data and model ownership can be reflected by datasets with complex stimuli and multimodal responses. These datasets are often proprietary due to the cost and effort involved in their collection, limiting broader accessibility and collaboration.

#### 4. Survey Results

Our survey results are summarised in Table 2. The table summarises a comprehensive survey of BCI datasets, focusing on metrics across devices, data, and applications. These metrics provide a valuable foundation for understanding the current landscape of BCI data capital and its alignment with key technical and industrial challenges. Below are the general descriptions of the dataset characteristics based on the metrics presented.

For devices, the datasets span a wide range of sampling frequencies, from low frequencies, such as 128 Hz in the neuromarketing dataset, to very high frequencies, like 2048 Hz in the statistical parametric mapping dataset. High-frequency datasets, such as ThingsEEG-Text (1000 Hz), are ideal for capturing rapid neural dynamics, essential for decoding precise temporal brain activity. Lower frequencies are generally sufficient for static tasks or simple signal processing, such as motor imagery. The number of EEG channels varies significantly, ranging from 1 channel (e.g., synchronised brainwave) to 256 channels (e.g., HeadIT dataset). Multi-channel setups are crucial for high spatial resolution, supporting applications like emotion recognition (SEED dataset) or complex neural decoding (GOD-Wiki).

In the data category, trial durations vary widely, with some datasets focusing on short, event-related trials (e.g., DIR-Wiki (2 s)) and others providing longer continuous recordings (e.g., sustained attention (5400 s)). Shorter trials are suitable for tasks like P300 spellers, whereas longer recordings are necessary for sustained attention or neurofeedback studies. Trials and users: The number of trials and participants reflects the dataset's diversity and robustness. For instance, DIR-Wiki includes 2400 participants, making it highly suitable for inter-person generalisability. ThingsEEG-Text provides 8216 trials per user, supporting inter-sample learning for robust model training. Smaller datasets, like the BCI Competition IV dataset 1 (7 participants), are ideal for exploring targeted applications or algorithms.

For applications, the datasets incorporate a variety of stimuli types, such as visual cues, audio cues, and videos, to simulate diverse cognitive and sensory tasks. For example, HCI Tagging utilises both images and videos for emotion recognition. GOD-Wiki integrates images and text, making it a prime example for visual–semantic decoding applications. Most datasets focus on motor imagery, a staple task in BCI research. However, emerging tasks like neural decoding (e.g., GOD-Wiki) and emotion recognition (e.g., SEED, DEAP) indicate a growing interest in expanding the scope of BCI applications. multimodal datasets that include EEG and additional modalities (e.g., EEG, fMRI, image, and text in GOD-Wiki) are increasingly prevalent. These datasets support advanced tasks like zero-shot neural decoding and multimodal integration, critical for expanding BCI applications.

Summary of dataset contributions and support for BCI applications: Overall, motor imagery remains the most common task, providing a benchmark for BCI algorithm development. Novel tasks like neural decoding and emotion recognition reflect the evolution of BCI datasets toward more complex and versatile applications. Datasets with high temporal properties (e.g., ThingsEEG-Text) and spatial resolution (e.g., HeadIT) are critical for improving utility in advanced modelling techniques. Large participant pools (e.g., DIR-Wiki) ensure generalisability across diverse populations. Multimodal datasets

like SEED and HCI Tagging are invaluable for studying cognitive workload in realistic scenarios, enabling adaptive DBCI systems. Datasets with diverse trial designs and stimuli improve the fidelity of cognitive workload modelling. Open datasets like BCI Competition and BraVl promote accessibility and collaborative research. Proprietary datasets with restricted access, particularly those involving high-cost modalities like fMRI, highlight the ongoing need for equitable data-sharing practices.

The diversity and richness of datasets summarised in the table provide a strong foundation for advancing DBCI research. The wide range of device specifications, data configurations, and application contexts ensures that these datasets are well-suited to address the challenges of generalisability, scalability, and adaptability in BCI systems. Next, we provide an in-depth analysis with enhanced insights for each category.

**Table 2.** Summary of BCI datasets surveyed, classified into devices, data, and applications categories. The columns under “Devices” (e.g., frequency and channels) highlight the technical capabilities of each dataset, which contribute to their utility and cognitive workload studies. The columns under “Data” (e.g., length, trials, and users) reflect the robustness, diversity, and scale of data, essential for generalisability and data ownership considerations. The columns under “Applications” (e.g., stimuli, task, and response) demonstrate the range of BCI applications supported by the datasets, including neurofeedback, motor imagery, and emotion recognition. N/A indicates Not Available.

| Dataset Name                                                                                                                                                                                                                                                                                                                                     | Devices |      | Data |     |     | Application            |               |                                                          |
|--------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------|------|------|-----|-----|------------------------|---------------|----------------------------------------------------------|
|                                                                                                                                                                                                                                                                                                                                                  | Freq    | Chan | Len  | Tri | Use | Stimuli                | Task          | Response                                                 |
| WAY-EEG-GAL( <a href="https://www.kaggle.com/competitions/grasp-and-lift-eeeg-detection/data">https://www.kaggle.com/competitions/grasp-and-lift-eeeg-detection/data</a> ) [42]                                                                                                                                                                  | 500     | 32   | 10   | 328 | 12  | Visual Cue             | Motor Imagery | EEG, EMG, Event Timings, Object Positions, Object Forces |
| GigaDB-EEG-MI ( <a href="http://gigadb.org/dataset/100295">http://gigadb.org/dataset/100295</a> ) [43]                                                                                                                                                                                                                                           | 512     | 64   | 3    | 260 | 52  | Visual Cue             | Motor Imagery | EEG, EMG, EOG, Hand Movement Data, Questionnaire         |
| PhysioNet-EEG-MI ( <a href="https://www.physionet.org/content/eeegmidb/1.0.0/">https://www.physionet.org/content/eeegmidb/1.0.0/</a> ) [44]                                                                                                                                                                                                      | 160     | 64   | 120  | 12  | 109 | Visual Cue             | Motor Imagery | EEG, Annotations                                         |
| Large-scale-EEG ( <a href="https://figshare.com/collections/A_large_electroencephalographic_motor_imagery_dataset_for_electroencephalographic_brain_computer_interfaces/3917698">https://figshare.com/collections/A_large_electroencephalographic_motor_imagery_dataset_for_electroencephalographic_brain_computer_interfaces/3917698</a> ) [45] | 200     | 19   | 3    | 900 | 13  | Visual Cue             | Motor Imagery | EEG                                                      |
| BCI Comp II dataset 1a ( <a href="https://www.bbci.de/competition/">https://www.bbci.de/competition/</a> ) [46]                                                                                                                                                                                                                                  | 256     | 6    | 3.5  | 293 | 1   | Visual Feedback        | Motor Imagery | EEG                                                      |
| BCI Comp II dataset 1b ( <a href="https://www.bbci.de/competition/">https://www.bbci.de/competition/</a> ) [46]                                                                                                                                                                                                                                  | 256     | 6    | 4.5  | 200 | 1   | Visual Feedback, Audio | Motor Imagery | EEG                                                      |
| BCI Comp II dataset 2a ( <a href="https://www.bbci.de/competition/">https://www.bbci.de/competition/</a> ) [46]                                                                                                                                                                                                                                  | 160     | 64   | 30   | 60  | 3   | Visual Feedback        | Motor Imagery | EEG                                                      |
| BCI Comp II dataset 3 ( <a href="https://www.bbci.de/competition/">https://www.bbci.de/competition/</a> ) [46]                                                                                                                                                                                                                                   | 128     | 3    | 9    | 280 | 1   | Visual Feedback        | Motor Imagery | EEG                                                      |
| BCI Comp II dataset 4 ( <a href="https://www.bbci.de/competition/">https://www.bbci.de/competition/</a> ) [46]                                                                                                                                                                                                                                   | 1000    | 28   | 0.5  | 416 | 1   | None                   | Motor Imagery | EEG, Typing                                              |
| BCI Comp III dataset 1 ( <a href="https://www.bbci.de/competition/">https://www.bbci.de/competition/</a> ) [46]                                                                                                                                                                                                                                  | 1000    | 64   | 3    | 378 | 1   | N/A                    | Motor Imagery | ECoG                                                     |



Table 2. Cont.

| Dataset Name                                                                                                                                                                                                                                                                                       | Devices |      | Data  |     |     | Application           |                     |                                                                            |
|----------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------|------|-------|-----|-----|-----------------------|---------------------|----------------------------------------------------------------------------|
|                                                                                                                                                                                                                                                                                                    | Freq    | Chan | Len   | Tri | Use | Stimuli               | Task                | Response                                                                   |
| BCI Comp III dataset 2 ( <a href="https://www.bbc.de/competition/">https://www.bbc.de/competition/</a> ) [46]                                                                                                                                                                                      | 240     | 64   | 2.5   | 92  | 2   | Character Matrix      | P300                | EEG                                                                        |
| BCI Comp III dataset 3a ( <a href="https://www.bbc.de/competition/">https://www.bbc.de/competition/</a> ) [46]                                                                                                                                                                                     | 240     | 64   | 7     | 80  | 3   | Visual Cue, Audio Cue | Motor Imagery       | EEG                                                                        |
| BCI Comp III dataset 3b ( <a href="https://www.bbc.de/competition/">https://www.bbc.de/competition/</a> ) [46]                                                                                                                                                                                     | 125     | 2    | 8     | 40  | 3   | Visual Cue            | Motor Imagery       | EEG                                                                        |
| BCI Comp III dataset 4 ( <a href="https://www.bbc.de/competition/">https://www.bbc.de/competition/</a> ) [46]                                                                                                                                                                                      | 1000    | 118  | 3.5   | 280 | 2   | Visual Cue            | Motor Imagery       | EEG                                                                        |
| BCI Comp III dataset 5 ( <a href="https://www.bbc.de/competition/">https://www.bbc.de/competition/</a> ) [46]                                                                                                                                                                                      | 512     | 32   | 240   | 4   | 3   | Audio Cue             | Motor Imagery       | EEG                                                                        |
| BCI Comp IV dataset 1 ( <a href="https://www.bbc.de/competition/">https://www.bbc.de/competition/</a> ) [46]                                                                                                                                                                                       | 1000    | 64   | 3.5   | 42  | 7   | None                  | Motor Imagery       | EEG, Artificial EEG                                                        |
| BCI Comp IV dataset 2 ( <a href="https://www.bbc.de/competition/">https://www.bbc.de/competition/</a> ) [46]                                                                                                                                                                                       | 250     | 22   | 6     | 576 | 9   | Audio Cue             | Motor Imagery       | EEG, EOG                                                                   |
| High-Gamma ( <a href="https://github.com/robintibor/high-gamma-dataset">https://github.com/robintibor/high-gamma-dataset</a> ) [47]                                                                                                                                                                | 500     | 128  | 4     | 880 | 14  | Visual Cue            | Motor Imagery       | EEG                                                                        |
| Planning-Relax ( <a href="https://archive.ics.uci.edu/ml/datasets/Planning+Relax">https://archive.ics.uci.edu/ml/datasets/Planning+Relax</a> ) [48]                                                                                                                                                | 256     | 8    | 5     | 10  | 1   | Audio Cue             | Motor Imagery       | EEG, EOG                                                                   |
| DAEP ( <a href="http://www.eecs.qmul.ac.uk/mmv/datasets/deap/">http://www.eecs.qmul.ac.uk/mmv/datasets/deap/</a> ) [49]                                                                                                                                                                            | 512     | 32   | 60    | 40  | 32  | Music, Video          | Emotion Recognition | Face Recordings, Questionnaire, EOG, EMG, Blood Pressure, GSR, Respiration |
| HeadIT ( <a href="https://headit.ucsd.edu/studies/3316f70e-35ff-11e3-a2a9-0050563f2612">https://headit.ucsd.edu/studies/3316f70e-35ff-11e3-a2a9-0050563f2612</a> ) [50]                                                                                                                            | 256     | 256  | 218   | 15  | 32  | Audio                 | Emotion Recognition | EEG, ECG, Infra-ocular                                                     |
| Enterface06 ( <a href="http://www.enterface.net/results/">http://www.enterface.net/results/</a> ) [51]                                                                                                                                                                                             | 1024    | 54   | 2.5   | 450 | 5   | Image                 | Emotion Recognition | EEG, fNIRS, GSR, Respiration, Video                                        |
| Neuromarketing ( <a href="https://drive.google.com/file/d/17XhqRXtMWvk8R_iZt-mjn_C0HjqgClaO/view?usp=sharing">https://drive.google.com/file/d/17XhqRXtMWvk8R_iZt-mjn_C0HjqgClaO/view?usp=sharing</a> ) [52]                                                                                        | 128     | 14   | 4     | 42  | 25  | Image                 | Neuromarketing      | EEG, Questionnaire                                                         |
| SEED ( <a href="https://bcmi.sjtu.edu.cn/seed/seed.html">https://bcmi.sjtu.edu.cn/seed/seed.html</a> ) [53]                                                                                                                                                                                        | 1000    | 62   | 240   | 45  | 15  | Video                 | Emotion Recognition | EEG, Eye Movement, Self Assessment Questionnaire                           |
| HCI Tagging ( <a href="https://mahnob-db.eu/hci-tagging/">https://mahnob-db.eu/hci-tagging/</a> ) [54]                                                                                                                                                                                             | 512     | 32   | 135   | 20  | 30  | Image, Video          | Emotion Recognition | EEG, GSR, ECGG, Eye Tracking, Audio, Video, Questionnaire                  |
| Regulation of Arousal ( <a href="https://ieee-dataport.org/open-access/regulation-arousal-online-neurofeedback-improves-human-performance-demanding-sensory">https://ieee-dataport.org/open-access/regulation-arousal-online-neurofeedback-improves-human-performance-demanding-sensory</a> ) [55] | 500     | 64   | 45    | 24  | 18  | Audio, Simulation     | Neurofeedback       | EEG, ECG, EDA, Respiration, Pupil Diameter, Eye Tracking                   |
| BCI-NER Challenge ( <a href="https://www.kaggle.com/c/inria-bci-challenge">https://www.kaggle.com/c/inria-bci-challenge</a> ) [56]                                                                                                                                                                 | 600     | 56   | 10.51 | 340 | 26  | Character Matrix      | P300                | EEG, MEG                                                                   |

Table 2. Cont.

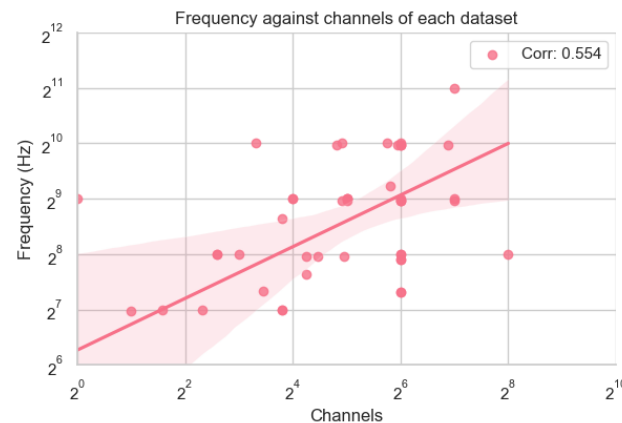
| Dataset Name                                                                                                                                                                                                                                                                             | Devices |      | Data |           |     | Application      |                 |                         |
|------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------|------|------|-----------|-----|------------------|-----------------|-------------------------|
|                                                                                                                                                                                                                                                                                          | Freq    | Chan | Len  | Tri       | Use | Stimuli          | Task            | Response                |
| Face-House ( <a href="https://purl.stanford.edu/xd109qh3109">https://purl.stanford.edu/xd109qh3109</a> ) [57]                                                                                                                                                                            | 1000    | N/A  | 0.8  | 300       | 7   | Image            | Neural Decoding | ECoG, ERPS              |
| Synchronised Brainwave ( <a href="https://www.kaggle.com/datasets/berkeley-biosense/synchronized-brainwave-dataset">https://www.kaggle.com/datasets/berkeley-biosense/synchronized-brainwave-dataset</a> ) [58]                                                                          | 512     | 1    | 319  | 1         | 30  | Video            | Neural Decoding | EEG                     |
| Target vs Non-target ( <a href="https://github.com/plcrodrigues/py.BI.EEG.2014a-GIPSA">https://github.com/plcrodrigues/py.BI.EEG.2014a-GIPSA</a> ) [59]                                                                                                                                  | 512     | 16   | 300  | 3         | 64  | Character Matrix | P300            | EEG                     |
| Impedance ( <a href="https://erpinfo.org/impedance">https://erpinfo.org/impedance</a> ) [60]                                                                                                                                                                                             | 1024    | 10   | 1.5  | 1280      | 12  | Text             | Neural Decoding | EEG, EOG                |
| Sustained Attention ( <a href="https://figshare.com/articles/dataset/Multi-channel_EEG_recordings_during_a_sustained-attention_driving_task/6427334/5">https://figshare.com/articles/dataset/Multi-channel_EEG_recordings_during_a_sustained-attention_driving_task/6427334/5</a> ) [61] | 500     | 30   | 5400 | 2.5       | 27  | Simulation       | Driving         | EEG, Questionnaire      |
| Dryad-Speech ( <a href="https://datadryad.org/stash/dataset/doi:10.5061/dryad.070jc">https://datadryad.org/stash/dataset/doi:10.5061/dryad.070jc</a> ) [62]                                                                                                                              | 512     | 128  | 105  | 20        | 92  | Audio            | N400            | EEG                     |
| SPIS Resting State ( <a href="https://github.com/mastaneht/SPIS-Resting-State-Dataset">https://github.com/mastaneht/SPIS-Resting-State-Dataset</a> ) [63]                                                                                                                                | 256     | 64   | 300  | 1         | 10  | None             | Resting State   | EEG, EOG                |
| Alpha-waves ( <a href="https://zenodo.org/record/2348892#.Y2ZRYOzP23I">https://zenodo.org/record/2348892#.Y2ZRYOzP23I</a> ) [64]                                                                                                                                                         | 512     | 16   | 10   | 10        | 20  | None             | Resting State   | EEG, Questionnaire      |
| Music Imagery Retrieval ( <a href="https://github.com/sstober/openmiir">https://github.com/sstober/openmiir</a> ) [65]                                                                                                                                                                   | 400     | 14   | 11.5 | 12        | 10  | Music            | Music Imagery   | EEG                     |
| EEG-eye State ( <a href="https://archive.ics.uci.edu/ml/datasets/EEG+Eye+State">https://archive.ics.uci.edu/ml/datasets/EEG+Eye+State</a> ) [66]                                                                                                                                         | 128     | 14   | 117  | 1         | 1   | None             | Eye state       | EEG                     |
| EEG-IO ( <a href="https://gnan.ece.gatech.edu/eeg-eyeblinks/">https://gnan.ece.gatech.edu/eeg-eyeblinks/</a> ) [67]                                                                                                                                                                      | 250     | 19   | 3.5  | 25        | 20  | N/A              | Eye state       | EEG, Annotations        |
| Eye State Prediction ( <a href="http://suendermann.com/corpus/EEG_Eyes.arff.gz">http://suendermann.com/corpus/EEG_Eyes.arff.gz</a> ) [68]                                                                                                                                                | N/A     | 14   | 117  | 1         | 1   | None             | Eye state       | EEG, Video, Annotations |
| Classifying Phonological Categories ( <a href="https://pdfs.semanticscholar.org/5480/d270cc92b284e8ee7db7c6af8a3dec58e163.pdf">https://pdfs.semanticscholar.org/5480/d270cc92b284e8ee7db7c6af8a3dec58e163.pdf</a> ) [69]                                                                 | 1024    | 64   | 2100 | 1         | 8   | Text, Audio      | Speech Imagery  | EEG, Video, Audio       |
| MNIST Brain Digits ( <a href="http://mindbigdata.com/opendb/index.html">http://mindbigdata.com/opendb/index.html</a> ) [70]                                                                                                                                                              | 161     | 11   | 2    | 1,206,611 | 1   | Image            | Neural Decoding | EEG                     |
| ImageNet Brain ( <a href="http://www.mindbigdata.com/opendb/imagenet.html">http://www.mindbigdata.com/opendb/imagenet.html</a> ) [70]                                                                                                                                                    | 128     | 5    | 3    | 14,012    | 1   | Image            | Neural Decoding | EEG                     |

Table 2. Cont.

| Dataset Name                                                                                                                                                          | Devices |      |       | Data |        | Stimuli             | Application                 |                                 |
|-----------------------------------------------------------------------------------------------------------------------------------------------------------------------|---------|------|-------|------|--------|---------------------|-----------------------------|---------------------------------|
|                                                                                                                                                                       | Freq    | Chan | Len   | Tri  | Use    |                     | Task                        | Response                        |
| EEGLearn ( <a href="https://github.com/pbashivan/EEGLearn/tree/master/">https://github.com/pbashivan/EEGLearn/tree/master/</a> ) [71]                                 | 500     | 64   | 3.5   | 240  | 13     | Text                | Neural Decoding             | EEG                             |
| Deep Sleep Slow Oscillation ( <a href="https://challengedata.ens.fr/challenges/10/">https://challengedata.ens.fr/challenges/10/</a> ) [72]                            | 125     | N/A  | 10    | 1261 | N/A    | None                | Slow Oscillation Prediction | EEG, Sleep Stage, Time Sleeping |
| Genetic Predisposition to Alcoholism ( <a href="https://archive.ics.uci.edu/ml/datasets/EEG+Database">https://archive.ics.uci.edu/ml/datasets/EEG+Database</a> ) [73] | 256     | 64   | 1     | 120  | 122    | Image               | Neural Decoding             | EEG                             |
| Confusion During MOOC ( <a href="https://www.kaggle.com/datasets/wanghaohan/confused-eeeg">https://www.kaggle.com/datasets/wanghaohan/confused-eeeg</a> ) [74]        | 2       | 1    | 60    | 10   | 10     | Video               | Education Feedback          | EGG, Questionnaire              |
| TUH EEG Corpus ( <a href="https://isip.piconepress.com/projects/tuh_eeg/">https://isip.piconepress.com/projects/tuh_eeg/</a> ) [75]                                   | 250     | 31   | 167   | 1.56 | 10,874 | None                | Seizure Detection           | EEG, Clinician Report           |
| Predict-UNM ( <a href="http://predict.cs.unm.edu/">http://predict.cs.unm.edu/</a> ) [76]                                                                              | 500     | 64   | 3.6   | 200  | 25     | Medication, Audio   | Neural Decoding             | EEG                             |
| ERP CORE ( <a href="https://erpinfo.org/erp-core">https://erpinfo.org/erp-core</a> ) [77]                                                                             | 1024    | 30   | 600   | 6    | 40     | Image, Video, Audio | Face Perception             | EEG, ERP                        |
| Statistical Parametric Mapping ( <a href="https://www.fil.ion.ucl.ac.uk/spm/data/">https://www.fil.ion.ucl.ac.uk/spm/data/</a> ) [78]                                 | 2048    | 128  | 1.8   | 172  | 1      | Image, Audio        | Face Perception             | EEG, fMRI, MEG, sMRI, EOG       |
| GOD-Wiki ( <a href="https://figshare.com/articles/dataset/BraVL/17024591">https://figshare.com/articles/dataset/BraVL/17024591</a> ) [79]                             | N/A     | N/A  | 3     | 590  | 5      | Image               | Neural Decoding             | fMRI, Image, Text               |
| DIR-Wiki ( <a href="https://figshare.com/articles/dataset/BraVL/17024591">https://figshare.com/articles/dataset/BraVL/17024591</a> ) [79]                             | N/A     | N/A  | 2     | 2400 | 3      | Image               | Neural Decoding             | fMRI, Image, Text               |
| ThingsEEG-Text ( <a href="https://figshare.com/articles/dataset/BraVL/17024591">https://figshare.com/articles/dataset/BraVL/17024591</a> ) [79]                       | 1000    | 64   | 0.235 | 8216 | 10     | Image               | Neural Decoding             | EEG, Image, Text                |

#### 4.1. Device

The scatter plot in Figure 3, illustrating the relationship between frequency (Hz) and the number of EEG channels, was generated using the dataset information provided in the table. Both frequency and channel data were transformed into a log-2 scale to allow for a more interpretable comparison across datasets with varying magnitudes. The dataset “Confusion During MOOC”, which had an unusually low frequency of 2 Hz, was excluded to avoid distortion of the plot. The x-axis represents the log-2 of the number of channels, while the y-axis represents the log-2 of the frequency. Each point on the scatter plot corresponds to a dataset, allowing us to visualise the distribution and clustering of datasets based on their device configurations. This approach highlights key patterns and outliers in the data, such as datasets with exceptionally high temporal or spatial resolution, facilitating deeper analysis of trends in DBCI devices.



**Figure 3.** The frequency of each dataset plotted again the number of channels on a log-2 scale. The Confusion During MOOC (<https://www.kaggle.com/datasets/wanghaohan/confused-eeg>) [74] dataset was an outlier with a frequency of only 2 Hz, and so was cut off from this graph.

Analysing the scatter plot reveals several notable trends and insights into the current state of device metrics in DBCI datasets. The majority of datasets cluster around 32–64 channels and 128–512 Hz frequencies, reflecting the most common experimental setups in EEG research. This range balances temporal and spatial resolution, making it suitable for general-purpose applications such as motor imagery, emotion recognition, and cognitive workload studies. A few datasets stand out as outliers. For example, HeadIT features an exceptionally high number of channels (256), which enhances spatial resolution and is particularly valuable for advanced applications like high-resolution neural decoding or emotion recognition. On the other hand, datasets like Enterface06 (1024 Hz) and statistical parametric mapping (2048 Hz) offer exceptionally high temporal resolution, enabling precise tracking of rapid neural dynamics. These high-frequency datasets are critical for applications such as speech imagery, real-time neurofeedback, or fine motor control.

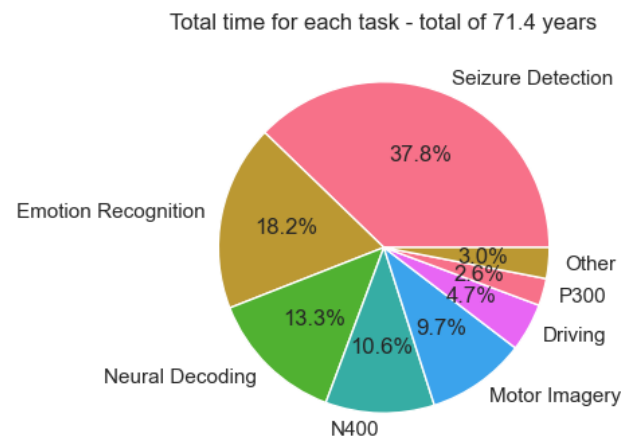
Interestingly, there is a moderately positive correlation of 0.554 between the frequency and number of channels. This trend could be explained if the bandwidth of devices has improved over time, meaning more modern devices have both a higher frequency and a larger number of channels. Alternatively, assuming the bandwidth of devices increases with price, this trend could be explained by the financial limitations of the groups gathering data instead. As this survey does not record the price or release data of the devices used in each dataset, we are unable to provide a definitive answer to this question. This highlights a limitation of our study and we leave it to future work to investigate how the prices of BCI devices have changed over time.

From an industrial landscape perspective, the clustering of datasets—at around 32–64 channels and 128–512 Hz frequencies—reflects the standardisation of EEG devices. This standardisation ensures compatibility and widespread usability across research and clinical settings, contributing to the utility of these devices. However, datasets that rely on higher-channel and higher-frequency devices often involve proprietary equipment, raising challenges related to data and model ownership. Furthermore, datasets with extreme configurations, such as high-channel or high-frequency setups, cater to niche applications but may face scalability and cost-effectiveness challenges in real-world DBCI deployment. Overall, the diversity in device configurations highlights the ongoing need to balance spatial and temporal resolution to meet the varying demands of DBCI applications. While standard configurations dominate due to their general usability, high-resolution setups offer unique opportunities for advanced research, albeit with limitations in accessibility and scalability.

#### 4.2. Data

The pie chart in Figure 4 was created to represent the proportion of accumulated data for each task, such as seizure detection, emotion recognition, and neural decoding, based on the provided formula:

$$time = channels \times trial\ length \times trials\ per\ subject \times subjects$$



**Figure 4.** The fraction of data belonging to each task, measured in years. In total, the datasets we looked at had 71.4 years of data. Tasks with less than 1.5 years of data were merged into ‘Other’.

This formula calculates the total recording time for each dataset in years by multiplying the number of EEG channels, the length of each trial, the number of trials per subject, and the number of subjects. The datasets were then grouped by task, and the total recording time for each task was summed. Tasks with less than 1.5 years of data were combined into the “Other” category to simplify the visualisation. The total accumulated data across all tasks was 71.4 years, and the pie chart shows the fraction of this total for each task. We summarise our findings according to the IL framework:

**Applications:** The pie chart analysis highlights the dominance of seizure detection, accounting for 37.8% of the total data. This reflects the clinical priority of seizure detection in healthcare, where its applications in epilepsy diagnosis and monitoring are highly established. It is worth noting that the data for seizure detection comes from a single large data set, the TUH EEG Corpus ([https://isip.piconepress.com/projects/tuh\\_eeg/](https://isip.piconepress.com/projects/tuh_eeg/)) [75]. The impressive size of this dataset shows that a large volume of data can be gathered when a device is widely deployed. Furthermore, this is a very diverse dataset with data coming from over 10,000 patients, meaning that a model trained on these data will be robust due to the high inter-subject variability. These factors combined make the dataset well-suited for real-world deployment, showing that seizure detection is a mature task in the DBCI application landscape. On the other hand, tasks like emotion recognition (18.2%) and neural decoding (13.3%) represent expanding frontiers in BCI research. These emerging applications cater to the rising demand for adaptive systems in mental health, emotion-aware technologies, and cognitive analysis, showcasing their growing relevance in the industrial framework. However, tasks like driving (4.7%) and P300 paradigms (2.6%) remain under-represented despite their direct applicability to safety-critical applications and assistive devices, indicating the need for further investment to enhance their practical deployment.

**Utility:** The dataset distribution underscores the significant utility of core tasks like motor imagery (9.7%) and N400 (10.6%) in the DBCI landscape. Motor imagery serves as a cornerstone for neurorehabilitation and prosthetic control, while N400 supports applications in linguistic processing and cognitive workload analysis. Their substantial data representation

highlights their importance for developing reliable and scalable BCI systems. In contrast, the other category (3%) and specialised tasks like driving-related paradigms reflect limited utility due to insufficient data accumulation. Expanding data collection efforts for these under-represented areas could significantly enhance their scalability and integration into diverse real-world applications, fostering a more balanced utility across the DBCI domain.

**Value of cognitive workload:** The significant proportion of datasets dedicated to emotion recognition and neural decoding reflects a growing emphasis on modelling cognitive workload within the DBCI landscape. These tasks enable the development of systems that adapt to users' cognitive and emotional states, supporting advanced applications such as emotion-aware interfaces, cognitive workload management, and mental health monitoring. However, the limited data availability for tasks in the other category suggests missed opportunities for expanding cognitive workload research into less-explored domains. A more diversified dataset ecosystem could provide deeper insights into user cognition and behaviour, enhancing the adaptability and personalisation of DBCI systems.

**Data and model ownership:** The dominance of seizure detection datasets highlights a relatively mature ecosystem for data collection, sharing, and model development in this domain. This maturity offers opportunities to refine data-sharing frameworks, ensuring equitable access and fostering collaborative research. However, the limited representation of lesser-explored tasks, grouped under the other category, presents challenges related to data ownership and accessibility. Addressing these challenges requires the establishment of robust frameworks for data sharing and ownership, particularly for under-represented tasks. This would support a more equitable and innovative landscape for developing open-access datasets and models across the DBCI spectrum.

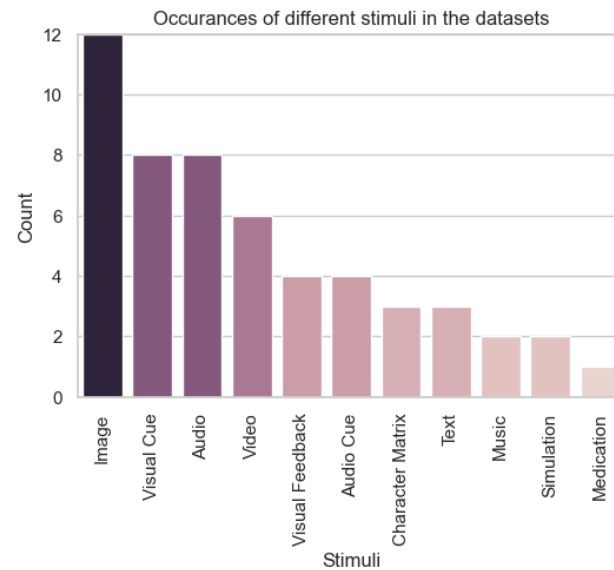
#### 4.3. Application

To analyse the distribution of stimuli, tasks, and responses across datasets, three bar charts were created. For stimuli, the bar chart shows the number of times each type of stimulus (e.g., visual cues, audio cues, video) is featured in a dataset. For tasks, another bar chart represents the frequency of each task (e.g., motor imagery, emotion recognition, seizure detection) in the datasets. For responses, the chart depicts the number of datasets that recorded various responses (e.g., EMG, EOG, fMRI). EEG, being the dominant response type, is excluded from the responses chart to avoid overshadowing other data modalities. In total, the analysis considers 47 datasets that recorded EEG, allowing for a detailed exploration of how stimuli, tasks, and responses are distributed in the DBCI landscape.

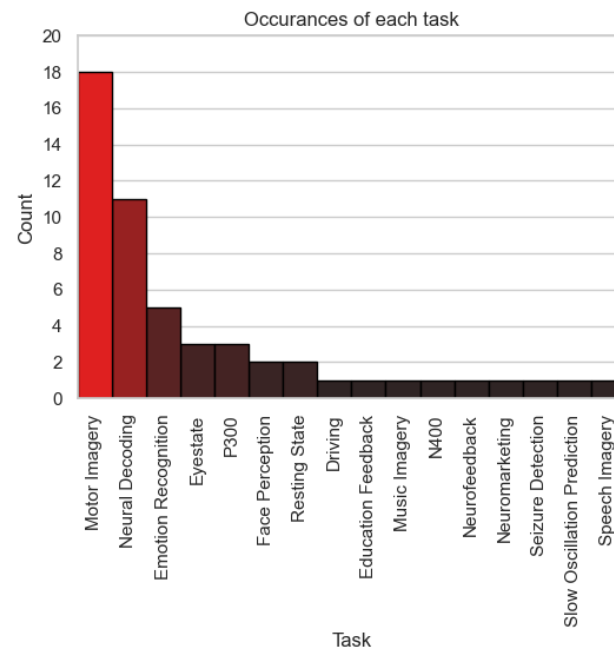
Figure 5 shows that the distribution of stimuli reveals a strong focus on visual stimuli, which dominate the datasets. Visual cues feature heavily in tasks like motor imagery, whilst images appear more in tasks that require more complicated stimuli, like neural decoding and emotion recognition. However, the inclusion of audio cues and video stimuli in several datasets reflects the expanding diversity of applications, such as emotion recognition and cognitive workload assessment, which demand multimodal data to mimic real-world environments. The growing use of diverse stimuli suggests a shift toward broader applicability of DBCI systems, including multimedia interactions and adaptive user interfaces.

The analysis of tasks in Figure 6 underscores the dominance of foundational paradigms, like motor imagery and seizure detection, which are critical for clinical and rehabilitative applications. However, the emergence of tasks like emotion recognition and neural decoding signals the diversification of DBCI utility into consumer-oriented applications, such as mental health monitoring and cognitive enhancement tools. These trends indicate that DBCI research is moving beyond traditional clinical use cases toward more general-purpose systems that align with evolving user needs and technological capabilities.



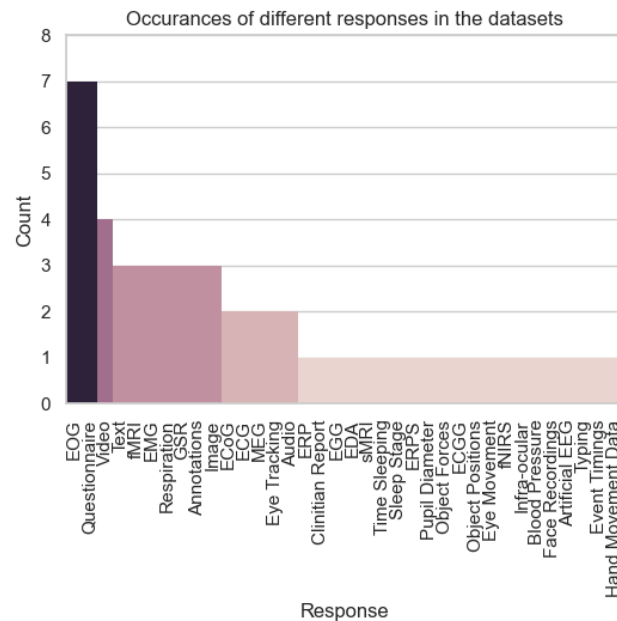


**Figure 5.** Bar chart showing the number of times each stimulus is featured in a dataset.



**Figure 6.** Bar chart showing the number of times each task is featured in a dataset.

The response data in Figure 7 highlight the inclusion of multimodal recordings, such as EOG, EMG, and fMRI, alongside EEG. The use of these additional modalities supports the modelling of complex cognitive and emotional states, which are critical for understanding cognitive workloads in diverse scenarios. For example, datasets incorporating fMRI and EOG responses provide high-resolution insights into brain activity and eye movements, respectively, enriching the development of adaptive and context-aware DBCI systems. This multimodal approach aligns with the growing emphasis on cognitive workload evaluation, ensuring that systems can dynamically respond to users' mental states.



**Figure 7.** Bar chart showing the number of times each response is featured in a dataset. EEG was removed as the other data became dwarfed. In total, we looked at 47 datasets that recorded EEG.

Finally, the growing inclusion of alternative responses such as EMG and fMRI indicates a diversification of data modalities, which has implications for data and model ownership. Proprietary restrictions associated with high-cost modalities like fMRI may limit accessibility and collaboration. On the other hand, the widespread use of EEG reflects a more open ecosystem, promoting data sharing and model development. Addressing ownership challenges for multimodal datasets is crucial for fostering equitable innovation in the DBCI domain.

#### 4.4. Zero-Shot Neural Decoding for Prospective DBCI

The analysis of DBCI data capital highlights a critical turning point in addressing limitations in devices, data, and applications. While traditional deep learning and machine learning approaches often face challenges with limited resources and generalisability, prospective zero-shot neural decoding (ZSND) [79] techniques offer transformative potential. ZSND enables models to generalise to unseen tasks and novel classes without requiring extensive labelled data, making it a pivotal approach for scaling DBCI applications. Recent advancements in ZSND leverage large-scale, multimodal datasets from adjacent fields, such as natural language processing (NLP) and computer vision (CV), to enhance generalisation across domains. This ability to bridge domains and tasks is critical for addressing the barriers identified in the DBCI IL framework:

- **Applications:** ZSND extends the reach of DBCI systems by enabling flexibility in adapting to diverse and novel use cases, such as neurofeedback, emotion recognition, and motor control, without retraining.
- **Utility:** The incorporation of transfer learning and pre-trained multimodal models reduces reliance on expensive and proprietary datasets, enhancing scalability and reducing costs.
- **Cognitive workload:** By enabling adaptive and user-independent neural decoding, ZSND reduces the cognitive demands on users, facilitating broader accessibility and usability.
- **Data and model ownership:** ZSND aligns with the open-sourced large AI models and multimodal publicly available datasets and fostering collaborative research for ethical and inclusive model development.

ZSND techniques enable DBCI systems to generalise across unseen samples, individuals, devices, domains, and tasks without extensive retraining. These capabilities are made possible by cutting-edge frameworks such as BraVL, which integrates brain activity with visual and linguistic information through trimodal learning approaches. The use of multimodal data ensures that models can transfer knowledge effectively, mitigating the following challenges:

**The inter-sample and inter-person transfer** ZSND datasets, such as DIR-Wiki (with 2400 participants) and ThingsEEG-Text (with 8216 trials per participant (10 participants)), provide the diversity necessary for robust inter-person generalisation. These datasets enable models to adapt to neural variability across individuals, a critical requirement for DBCI applications such as personalized neurorehabilitation. Inter-sample transfer is enhanced by the trial-level richness of datasets, as seen in ThingsEEG-Text, which captures high temporal resolution (1000 Hz) data across multiple conditions.

**Inter-device and inter-domain transfer** By incorporating multiple modalities such as EEG, fMRI, image, and text, ZSND datasets bridge the gap between invasive and non-invasive techniques, facilitating inter-device adaptability. For example, BraVL supports the alignment of brain signals recorded via EEG or fMRI with visual and semantic stimuli, ensuring models remain functional across diverse hardware environments. Inter-domain transfer is critical for applying DBCI systems in new contexts, such as transitioning from laboratory settings to real-world applications. The multimodal design of GOD-Wiki and DIR-Wiki exemplifies how datasets can support cross-domain learning.

**Inter-task transfer** Neural decoding tasks in datasets like GOD-Wiki and ThingsEEG-Text demonstrate the capability of ZSND techniques to generalise across tasks. Models trained on image decoding tasks can seamlessly adapt to semantic decoding tasks due to shared latent representations. This inter-task flexibility is crucial for multi-purpose DBCI systems, enabling applications ranging from motor imagery control to emotion recognition.

**Utility enhancement** frameworks like BraVL leverage multimodal data integration to create robust visual–semantic neural signal models. These models align brain activity with both visual and linguistic information, expanding the scope of DBCI applications to include cognitive workload assessment, attention monitoring, and adaptive feedback systems. The inclusion of high-resolution data (e.g., 64-channel EEG in all datasets and 1000 Hz sampling in ThingsEEG-Text) enables advancements in signal processing techniques to improve signal-to-noise ratio (SNR). Enhanced SNR is essential for the scalable adaptation of DBCI devices in real-world environments.

Beyond the ZSND techniques, the high-quality data published have also established a foundation for DBCI progression. Our proposed metrics highlight the contributions of the datasets to the IL framework, as follows:

- **Devices:** High-frequency datasets, such as ThingsEEG-Text, ensure precise temporal resolution for decoding dynamic neural activity. The consistent use of 64-channel setups across datasets provides the spatial granularity necessary for diverse applications.
- **Data:** Datasets like DIR-Wiki, with its 2400 participants, address the need for diversity in neural data, improving inter-person generalisability.
- **Applications:** Multimodal stimuli in GOD-Wiki and DIR-Wiki datasets, including image and text, expand the applicability of DBCI systems to multimodal tasks. Neural decoding tasks recorded in these datasets align directly with the practical needs of applications such as neurorehabilitation, cognitive monitoring, and emotion recognition.

Overall, our work establishes a roadmap for DBCI research by identifying key barriers and demonstrating how ZSND techniques and dataset metrics address them. ZSND datasets and techniques enable generalisation across diverse stimuli and tasks, expanding

the applicability of DBCI systems. The inclusion of diverse participants and trials increases dataset reliability and usability, supporting scalable and robust model training. Multimodal data and advanced signal processing improve the fidelity of workload modelling, ensuring adaptive and context-aware systems. While proprietary aspects of devices and datasets remain a challenge, open frameworks like BraVL and publicly available datasets mitigate access barriers, fostering collaboration and innovation.

While ZSND techniques and datasets provide significant advancements, further work is needed to fully realise the potential of DBCI systems. Future efforts could focus on (1) Expanding modalities: Incorporating additional data modalities such as MEG or wearable EEG devices to enhance data diversity and usability. (2) Self-supervised learning: Leveraging unsupervised techniques to reduce dependency on large-scale annotated data, improving efficiency and scalability. (3) Standardisation: Establishing universal standards for dataset annotation and evaluation to enable seamless integration and benchmarking across research groups. By leveraging ZSND techniques and metrics, this roadmap provides a clear pathway for overcoming barriers and advancing the industrial framework of DBCI systems.

## 5. Conclusions

In this work, we introduce the IL framework for data capital to understand and evaluate the development of the DBCI domain. This framework highlights how data capital is established within the DBCI domain, identifying four key barriers: applications, utility, data and model ownership, and cognitive workload. We further demonstrate how publicly available datasets can be assessed through metrics categorised into devices, data, and applications. Using this measurement approach, we identified and analysed 53 top DBCI datasets to reflect the progression of the DBCI industrial landscape. Moreover, we emphasised the role of emerging techniques, such as zero-shot neural decoding, which has shown significant potential in mitigating the barriers by enabling more generalisable, scalable, and efficient utilisation of DBCI data.

While our study provides a comprehensive assessment of the current state of DBCI data capital, further work is needed to address the limitations and expand the scope of this research. Future directions include exploring the integration of additional data modalities, such as fMRI or MEG, into the IL framework to ensure a more holistic understanding of data capital. Additionally, the framework can be extended to evaluate existing DBCI models and accessibility challenges associated with data and model ownership. Advancements in self-supervised learning [80] and federated learning [81] techniques also present opportunities for enhancing data capital by improving data efficiency and privacy. Lastly, establishing an open standard for dataset annotation and evaluation could foster collaboration across academia and industry, accelerating innovation in DBCI applications.

To address equitable data-sharing while balancing privacy and accessibility, we propose the adoption of federated learning frameworks in the future to enable collaborative research without exposing sensitive raw data, adherence to robust data privacy protocols such as anonymisation and compliance with GDPR, and the establishment of tiered access models to share sensitive datasets under controlled conditions. Additionally, incentivizing open science practices through funding agencies and journals and creating a centralised data commons for high-quality open-access datasets, e.g., BCI Competition, can promote collaboration while safeguarding privacy. These measures ensure ethical data-sharing, foster inclusivity, and accelerate innovation in DBCI research.

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D.O.; writing—review and editing, T.M., J.E.T.W. and Y.L.; visualisation, Y.L. and J.E.T.W.; supervision, W.M. All authors have read and agreed to the published version of the manuscript.

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