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Progress in Non-Invasive Cognitive Brain-Computer Interface and Implications for Mind-Uploading

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ABSTRACT

Mind-uploading, the vision of transferring human consciousness into a digital realm, relies on a profound comprehension of the brain and cutting-edge technology. Non-invasive cognitive Brain-Computer Interfaces (BCI) offer a promising avenue for delving into neural activity and bridging the brain-machine gap. This research explores the potential of non-invasive cognitive BCI in realizing mind-uploading through a systematic literature review (SLR), analyzing recent research that focuses on its current progress and implications for mind-uploading. The SLR unveils significant strides in non-invasive cognitive BCI, demonstrating increased precision in recording and decoding cognitive processes and fostering a deeper understanding of these processes. This progress is attributed to a diverse range of emerging feature extraction and decoding methods, transforming subtle neural signals into interpretable commands. Notably, advancements in signal processing and neuroimaging techniques enhance communication speed and clarity between the brain and computer. Furthermore, the development of cost-effective methods, frameworks, and hardware holds the promise of broader accessibility to BCI technology. However, significant hurdles remain. The computational demands of current cognitive BCI systems pose a substantial challenge, while the scarcity of high-quality training datasets hampers algorithm development and accuracy. The poor signal quality causes difficulties in recording neural complexity and hampers accuracy. In conclusion, non-invasive cognitive BCI has significant potential to pave the way for mind-uploading. However, its limitations, make their capabilities remain insufficient to fully realize this ambitious vision. This highlights the critical need for sustained research and innovation to bridge the gap between current understanding and the exciting realm of mind-uploading.

1. Introduction

In general, people must have heard, read, or watched science fiction stories. Science fiction stories themselves are fictional stories or stories that do not originate from real stories and are usually set in the future, relate to the development of imaginary science and technology, and are connected to other worlds. One of these science fiction stories can be seen in the film Tron: Legacy from Disney, which tells the story of a young man who enters the virtual world to look for his father [1], or in the television series Upload, which tells the story of a man who transfers his mind or consciousness to a virtual world or computer after his death [2]. These two science fiction movies explore the concept of transferring human consciousness into virtual or digital realms. These fictional narratives, while not directly reflecting real-world capabilities, raise important questions about the feasibility of such technology in the real world.

Mind-uploading, also known as whole-brain emulation, refers to the hypothetical process of transferring the complete cognitive and neural content of a person's mind or consciousness from their biological brain to a digital or artificial substrate, such as a computer. The idea is to create a digital replica of the individual's mind, including thoughts, memories, decision-making and personality. The human mind itself has always been an interesting subject of study for scientists, philosophers, and futurists. With the advent of recent technological advances and advances in neuroscience, the concept of mind-uploading has become an increasingly interesting and debated topic. One technological development that is increasingly advanced and can support this theory, is a technology that can read brain waves called the Brain-Computer Interface (BCI). BCI is direct and sometimes bidirectional communication between the brain and a computer or other external device that does not involve muscle stimulation [3]. One type of BCI that supports the realization of the mind-uploading theory is non-invasive cognitive BCI, which is a type of BCI that can be used to measure and interpret cognitive processes such as attention, memory, and decision-making in the human brain without performing surgery [4], so that does not harm humans. Therefore, BCI has enormous potential for realizing mind-uploading theory, where mind-uploading theory requires a way to digitally record and store all information in the brain, including connections between neurons [5], [6], [7]. Non-invasive cognitive BCI can be used to aid this process by providing a way to measure and record these relationships without harming humans. However, it is still unknown whether the current state of development of non-invasive cognitive BCI has the potential to contribute to realizing the theory of mind-uploading. This is based on previous research that only focused on the potential of non-invasive BCI in rehabilitation [8], and as an aid in daily activities for patients with disabilities [9], its potential as a mind-reading tool [10], and also on the research on mind-uploading that focuses more on the impact and ethics than the potential for mind-uploading to be realized [7], [11]. Therefore, in this research, a systematic literature review (SLR) was carried out to find out whether the current state of development of non-invasive cognitive BCI has the potential to contribute to realizing the theory of mind-uploading.

The possibility of mind-uploading has been the subject of speculation and conjecture, with many researchers and experts stating that it may happen in the near future. However, the implications of such technology are complex and varied, encompassing ethical, social, and philosophical considerations, so the mind-uploading theory has a major impact on human life [5], [6]. Therefore, this SLR is important to be carried out. Because, apart from being able to find out the potential of non-invasive cognitive BCI in realizing mind-uploading theory, this research can also indirectly be used as a basis for identifying and exploring the potential risks and benefits of mind-uploading theory so that humans can be better prepared to use or facing this mind-uploading technology if it becomes a reality, as exemplified in research [12], which conducted an SLR regarding noninvasive electroencephalography (EEG) equipment for assistive, adaptive, and rehabilitative brain-computer interfaces (BCIs) was conducted to analyze the potential risks and benefits of the technology. Apart from that, this SLR is also useful in explaining the current state of development of non-invasive cognitive BCI, so it can be found out what needs to be improved in non-invasive cognitive BCI technology, thereby encouraging the development of this technology, as shown in research [13], which carried out SLR that focus in reviewing research in the field of brain decoding in somatosensory, auditory, and visual cortex areas, providing a comprehensive overview of the current state of affairs in the field of decoding method in BCI and identifying areas that require further development. The research of [12] and [13] shows why this kind of SLR is important to do, as it can be used to determine the potential risks and benefits and also to identify areas that require further development.

Overall, this research aims to explore the possibility of realizing the mind-uploading theory based on the developmental conditions of non-invasive cognitive BCI technology, so it is known what the current condition of non-invasive cognitive BCI technology is and how the current condition of non-invasive cognitive BCI technology can support or hinder the realization of the mind-uploading theory. Apart from that, this research can also be used as a basis for encouraging the advancement of non-invasive cognitive BCI technology as well as a basis for identifying and exploring the potential risks and benefits of mind-uploading theory.

2. Method

This research uses a qualitative method by conducting a systematic literature review to comprehensively investigate the feasibility of realizing the theory of mind-uploading based on the current progress or condition of non-invasive cognitive Brain-Computer Interface (BCI). The systematic literature review in this research conducted using the PRISMA approach, where PRISMA serves as a structured and transparent guideline that enhances the quality and reliability of reporting in systematic reviews [14]. By adhering to the PRISMA guidelines, this research aims to standardize the review methodology, ensuring clarity and consistency in the selection, analysis, and synthesis of relevant studies pertaining to the research topic. The research stages of this paper can be seen in Figure 1.

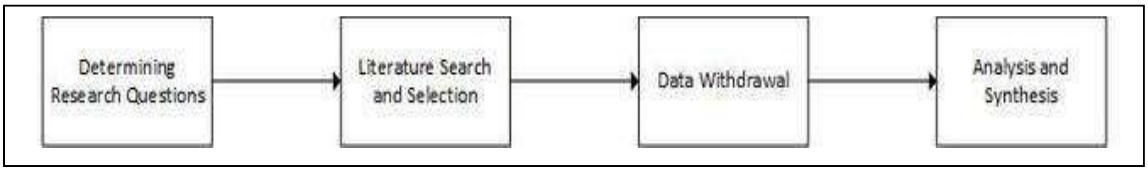

Fig. 1. Research Stages

2.1. Determining Research Questions

The first stage carried out in this research was determining the research question. This research question is used to answer and explain in detail the topic of this research. The research questions used in this research are as follows:

RQ1. How is the current progress of non-invasive Cognitive BCI?

RQ2. What is the implication of the current progress of non-invasive Cognitive BCI for Mind-Uploading?

2.2. Literature Search and Selection

The next stage carried out in this research was a literature search and selection regarding studies that corresponded to the research topic. A literature search for this research was carried out on Google Scholar, Springer, Mendeley Search, and IEEE Xplore databases using the keywords that related to each research question that can be seen in Table 1, and with search limitations based on inclusion criteria, namely has a time period of 2018-2023 (IC2), English language literature (IC3), The literature used is Scopus indexed journal articles or international proceedings (IC4), and is open access (IC5). The inclusion criteria used in this study are as follows:

IC1. The literature used is only that which is related to the research topic or can answer the research question of this study.

IC2. The literature being used has a period from 2018 – 2023.

IC3. The literature being used is only in English.

IC4. The literature being used is Scopus-indexed journal articles or international proceedings.

IC5. The literature being used is Open Access.

Table 1. Keywords for Literature Research

RQ1 Keywords	RQ2 Keywords
Non-Invasive Cognitive Brain-Computer Interface	Neural Information Transfer and Cognitive BCI
Brain-to-Computer Interface Signal Processing	Brain Mapping and Mind-Uploading
Non-Invasive Neuroimaging for BCI	Cognitive BCI and Consciousness Transfer
BCI Decoding Algorithms	Brain-Computer Interface and Memory Transfer
BCI Applications for Cognitive Tasks	Brain Simulation
BCI Frameworks and Tools	BCI Implication for Mind-Uploading
BCI Limitations	
BCI Hardware Innovations	

Next, the results of the literature obtained based on keywords in each database are filtered. This filtering is carried out based on the title, abstract, keyword, and inclusion criteria of IC1. Finally, the results of the screening are then re-checked or quality-checked, by looking at the entire text in each piece of literature that has been previously filtered, so it can be seen whether the literature can answer the research question in this study or is truly appropriate to the research topic or not (IC1). All the literature obtained through re-checking was then used in this research. The PRISMA's flowchart depicting the literature search and selection can be seen in Figure 2.

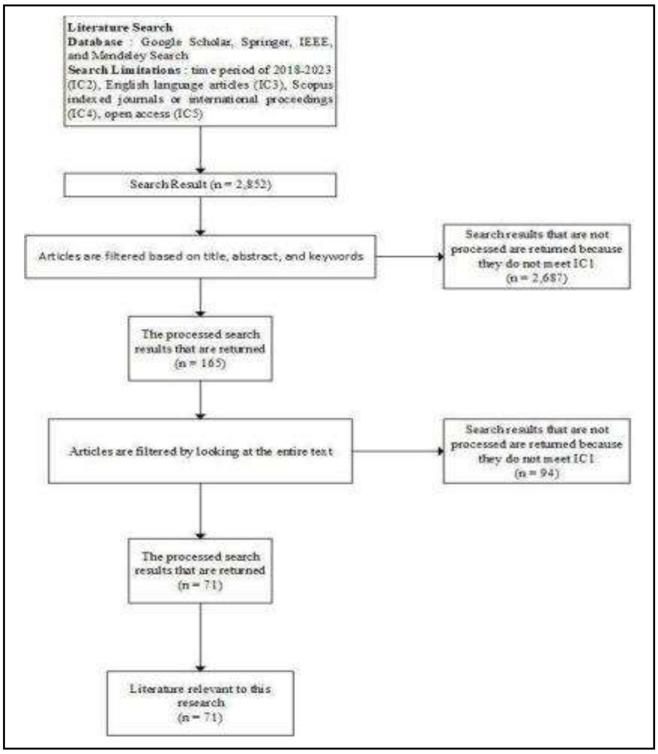

Fig. 2.PRISMA's Flowchart

2.3. Data Withdrawal

The data extraction process is carried out to find data or information that is relevant to the research topic and can answer all research questions that have been determined previously. The relevant data or information is then used in the analysis and synthesis stages later. This data or information was obtained using Atlas.ti software. Atlas.ti itself is computer-based qualitative data analysis software that provides various techniques and functions that enable the analysis, presentation, and explanation of discourse to be carried out systematically, carefully, and transparently [15]. The stages of retrieving data or information using Atlas.ti include the following:

1. Enter all the literature that is being used into the Atlas.ti software.
2. Read the selected literature and code each piece of literature for important data or information related to the research topic or that can answer all the research questions that have been determined previously.

2.4. Analysis and Synthesis

The final stage of this research is analysis and synthesis. The data and information that have been obtained in the previous stages are analyzed and summarized to be able to answer and explain in detail and thoroughly each research question in this study. So that the topic of this research can be discussed in detail. The analysis and synthesis of data or information obtained in the previous stages were also carried out using Atlas.ti software. Analysis and synthesis stages through Atlas.ti software includes:

1. Grouping codes that have been created previously.
2. Create a network that is used to explain the relationship between each previously determined code to answer all research questions.

3. Results and Discussion

3.1. Demographics of Selected Literature

In this literature review, the selected studies that can explain the current progress of non-invasive cognitive BCI development are used to explain how the current development of non-invasive cognitive BCI has the potential to support the realization of mind-uploading, and also explain the limitation of non-invasive cognitive BCI that can hinder the realization of the mind-uploading. The distribution of the selected studies regarding non-invasive cognitive BCI each year shows how interest in non-invasive cognitive BCI changes every year. From Figure 3, it can be seen that there has been a significant increase from 2018 to 2022, which shows that non-invasive cognitive BCI is an interesting topic for researchers. This increase occurs because non-invasive cognitive BCI is useful for helping or improving conditions of people with disabilities [16], along with the potential of non-invasive cognitive BCI, which allows machines to read and interpret thoughts correctly for automatic task implementation [16].

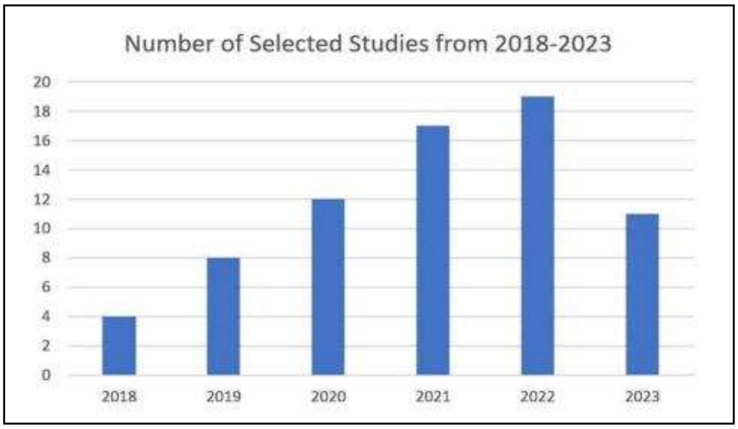

Fig. 3. Distribution of Selected Studies from 2018-2023

Through all the selected studies used in this research, it is possible to know the progress or current condition of non-invasive cognitive BCI, which is shown in Table 2. Through these selected studies, it is known about the latest progress of non-invasive BCI's ability to record and decode human brain signals activity in carrying out cognitive processes along with various supporting factors that increase this progress, such as the development of feature extraction and decoding methods, methods for signal processing, neuroimaging techniques, hardware, low-computation methods, as well as frameworks and tools. However, apart from these supporting factors, some factors hinder the development of BCI's non-invasive ability to record and decode the cognitive processes of the human brain, namely; the signal quality is not good enough, the level of accuracy is still not optimal, the computing cost is quite high, and the limited availability of high-quality datasets in large quantities that can be used to train non-invasive BCI systems. These hindering factors cause limitations in non-invasive cognitive BCI and obstruct the realization of mind-uploading.

Table 2. Condition of Non-Invasive Cognitive BCI

No	Condition	References
1	Non-Invasive BCI Capabilities in Recording and Decoding Cognitive Process	[17], [18], [19], [20], [21], [22], [23], [24], [25], [26], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48]
2	Methods for Feature Extraction and Decoding	[17], [18], [21], [23], [24], [25], [26], [27], [28], [32], [33], [34], [38], [39], [42], [43], [45], [47], [49], [50], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [61], [62], [63]
3	Methods for Signal Processing	[25], [26], [28], [29], [30], [31], [36], [39], [42], [45], [54], [55], [59], [64], [65], [66], [67], [68]
4	Frameworks and Tools	[26], [31], [32], [43], [44], [58], [69], [70]
5	Non-Invasive Neuroimaging Techniques	[26], [32], [46], [48], [54], [55], [56], [57], [58], [59], [63], [66], [67], [70], [71], [72], [73], [74], [75], [76], [77], [78]
6	Hardware for Non-Invasive Cognitive BCI	[75], [79], [80], [81], [82]
7	High Computational Costs	[25], [34], [38], [49], [54], [58], [65], [70]

8	Poor Signal Quality	[19], [21], [22], [26], [29], [34], [36], [37], [40], [41], [42], [45], [46], [50], [54], [55], [57], [63], [64], [65], [67], [71], [74], [75]
9	Suboptimal Accuracy Level	[21], [22], [26], [34], [40], [41], [42], [50], [51], [52], [54], [59], [64]
10	The Quantity of Datasets Exhibiting High Quality is Still Limited.	[58], [59], [63], [77], [83]
11	Low Computational Costs Methods	[49], [52], [63], [65], [67], [68], [72]

3.2. Current Conditions of Non-Invasive Cognitive BCI

In recent years, the field of non-invasive BCI has experienced extraordinary progress, where BCI using various non-invasive neuroimaging techniques has been able to record neural signals related to various kinds of human brain activity. The various types of neuroimaging techniques include;

- Electroencephalogram (EEG)

EEG is a non-invasive neuroimaging technique used to record and measure electrical signals formed due to the activity of neurons in carrying out various kinds of human brain activities, using electrodes attached to the human scalp [55]. The types of electrical signals that can be recorded by EEG include, for example; event-related potentials (ERPs) which are electrical signals formed due to the brain's response to certain stimuli such as images or sounds, where these ERP signals are associated with various cognitive processes that occur in the human brain [56]. This is shown in research conducted by [56] who classified images of human faces, objects, and sounds using ERP to determine the accuracy of ERP in identifying human visual and auditory perception. Through this research, it is known that ERP has a close relationship to human visual and auditory perception based on several ERP components such as N170 and AN which have a high response to human faces, or P2 and LP which have a high response to human voices. Apart from ERP, there is also SSVEP which is a signal that arises due to rhythmic brain activity that occurs in response to continuous flashing visual stimuli [67]. SSVEP itself is associated with various aspects of visual processing, as was done by [32] who used SSVEP to determine which LED panel the research subject was paying attention to, so SSVEP can be used to measure the visual attention of the research subject. These two examples show EEG's ability to record cognitive processes, especially visual and auditory processes. EEG itself is the neuroimaging technique most often used in non-invasive BCI, this is because it has a high level of temporal resolution and is relatively cheap and portable [26], [37], [51], [55], [65], [66], [71], [75]. However, EEG has several disadvantages such as having a low level of spatial resolution and being susceptible to artifacts and noise [26], [37], [51], [55], [65], [66], [71], [75].

- Magnetoencephalography (MEG)

MEG is a non-invasive neuroimaging technique used to record and measure magnetic fields formed due to electrical currents created by neuron activity in carrying out various kinds of human brain activities, using sensors in a protected room [65], [77]. Just like EEG, MEG can also record ERP and SSVEP signals, this is because ERP is a change in electrical activity in the brain that occurs in response to certain events or stimuli, where changes in electrical activity are related to changes in the magnetic field, while SSVEP is brain rhythmic activity that occurs in response to continuous flashing visual stimuli, where this rhythmic activity produces a magnetic field [48], [76]. This is demonstrated by research conducted by [48] who developed a mental spelling system using MEG to record ERP and SSVEP, where subjects can spell words by looking at the appropriate alphabet panel. The mind spelling system achieved an accuracy of 97.7%, which shows MEG's ability to record human brain activity related to cognitive processes and how MEG can be used to decode cognitive process, especially visual processes. MEG itself has a level of temporal resolution that is equivalent to EEG but with a higher level of spatial resolution and is more susceptible to artifacts and noise than EEG, so MEG can be said to be better than EEG [51], [55], [65], [71]. However, MEG is still rarely used because it is not portable and has quite high costs [51], [55], [65], [71].

- Functional near-infrared spectroscopy (fNIRS)

fNIRS is a non-invasive neuroimaging technique used to record and measure human brain activity using a sensor installed on the head, where this sensor can emit and record near-infrared rays that can penetrate bones and tissue easily. These near-infrared rays are used to measure changes in oxygenated blood flow caused by human brain activity [26], [46]. This was demonstrated in research conducted by [26] that used fNIRS to record changes in oxygenated blood flow that occurred when performing the operation span (OSPAN) task to measure the capacity of working memory in remembering information, by obtaining an accuracy for the OSPAN vs response category of 91.2% and for the OSPAN vs. rest was 94.7%, which shows the ability of fNIRS to record human brain activity related to cognitive processes and how fNIRS can be used to decode cognitive proccess, especially regarding working memory performance. fNIRS itself has a good level of spatial resolution compared to EEG and MEG but has a worse level of temporal resolution [26], [46], [51], [54], [71], [74]. Just like EEG, fNIRS itself also has a low cost and is portable [26], [46], [51], [54], [71], [74]. However, in contrast to EEG, fNIRS's susceptibility to artifacts and noise is much better than EEG [26], [46], [51], [54], [71], [74].

- Functional MRI (fMRI)

fMRI, like fNIRS, is a neuroimaging technique used to record and measure human brain activity based on changes in oxygenated blood flow caused by human brain activity. fMRI differs from fNIRS, in that fMRI does not use near-infrared light to record these changes, but instead uses strong magnetic fields and radio waves to record these changes and produce detailed maps of brain activity, highlighting the most active area during certain tasks or stimuli. during the scan [57], [58]. This is demonstrated by research conducted by [41], who used fMRI to record and measure changes in oxygenated blood flow in higher-order visual areas, which are areas of the brain that process complex visual information, to decode visual brain activity related to attention to certain objects, obtained an accuracy level of up to 70%, which shows that fMRI can be used to record and decode human brain activity related to cognitive processes, especially visual processes. fMRI itself has the highest level of spatial resolution when compared to other neuroimaging techniques, but its level of temporal resolution is the worst among other neuroimaging techniques [51], [57], [58], [63], [71]. In addition, fMRI itself also requires high costs and is not portable, but it has greater susceptibility to artifacts and noise than EEG [51], [57], [58], [63], [71].

3.2.1. The Cognitive Process Currently can be Recorded and Decoded

By using various non-invasive neuroimaging techniques, BCI can record neuron activity that arises as a result of human brain activity, such as cognitive processes, and translate it into meaningful information. The cognitive process itself is a mental activity used by individuals to obtain, process, store, and use information, so this process is very important in human life. The concept of mind-uploading itself includes the process of transferring or copying the contents of the human mind which also includes cognitive processes. Therefore, a deep understanding of cognitive processes is very important in realizing mind-uploading. Based on the selected studies being used, cognitive processes that can be recorded and decoded by non-invasive BCI using the neuroimaging techniques mentioned above include:

- Visual Process

The visual process is a cognitive process that involves the interpretation and analysis of visual information received through the eyes which makes this process very important in the perception, recognition, and understanding of visual objects. Non-invasive cognitive BCI is now capable of recording and decoding these visual processes, such as visual attention, image reconstruction, or image retrieval. For visual attention itself, there have been various developments, such as research conducted by [32] in 2018, which detected SSVEP and Sensorimotor Rhythms (SMR) to find out how subjects can do multitasking, namely by paying attention to predetermined objects and moving the cursor according to mind's command, where this research obtained an accuracy of 14.2%-59%. This research helps in understanding how the visual process of maintaining the focus of visual attention carried out by the subject occurs while multitasking, this shows that SSVEP can be used to identify visual processes, especially for the visual attention retention process. Apart from that, research conducted by [41] succeeded in decoding the visual attention process with an accuracy of up to 70% using fMRI-based BCI in the higher-order visual area, which is an area of the brain that processes complex visual information, so that recording and decoding in this area can provide more in-depth information regarding visual processes. This shows how higher-order visual areas can be used to identify or decode complex visual processes using fMRI-based BCI.

In 2019, the visual attention process experienced further development, which was shown in the research of [17] who developed a non-invasive BCI system used to monitor variations in sustained attention during certain tasks, where this research obtained an accuracy of 75%-85%, which shows how the process of changing attention from requiring low visual focus to requiring high visual focus when performing a task can be detected using EEG. There is also research conducted by [33] in 2021, which uses fuzzy inference encoding and fuzzy covert state transition diagram methods on its EEG-based non-invasive BCI system to monitor changes in attention that occur during the driving process. Where both methods succeed in explaining how neural states change from one state to another and show the direction of changes in the trajectory of neural states that arise when individuals experience distraction while driving, which shows how EEG signals can decode changes in visual attention processes due to distraction.

Apart from that, there is also the development of various types of gazed-based-spelling non-invasive BCI systems, which are spelling systems based on the user's visual attention to the letters selected on the virtual keyboard. Where visual attention to the selected letters gives rise to brain activity signals that represent the selected letters based on visual attention. This is demonstrated in research conducted by [19] in 2018 which shows how ERP and EOG can be used to classify selected letters from the user's visual attention with an accuracy rate of 97.6%, showing how the use of ERP and EOG can provide more information, to increase the accuracy of the classification. Research conducted by [39] in 2019 also showed the same thing, where she used the SSVEP signal to classify selected letters from the user's visual attention, with an accuracy of 22.62%-100%. Not only that, but MEG can also be used for the same purpose, this was demonstrated in research conducted by [48] in 2021, which used MEG to record ERPs and SSVEPs and translate them into selected words based on the focus of the user's visual attention, with an accuracy of 97.7%. This shows how EEG, EOG, and MEG signals can be recorded and translated by non-invasive BCI to understand how visual attention and visual recognition processes occur.

In 2019, visual reconstruction of objects or images based on human brain activity began to improve, which was shown in research conducted by [44], who used fMRI to record changes in blood flow that occurred in the early visual cortex area when the subject imagine the shape of the letter, then the recording results were successfully used to reconstruct the shape of the letter in visual form, showing that when someone mentally visualizes something, the pattern of neural activity in their early visual cortex resembles, or is related to, the pattern observed when they physically see the same thing. So, this pattern of neural activity in the early visual cortex can be translated to reproduce images with fMRI-based BCI. Apart from that, there was also research conducted by [38] in 2020, which recorded EEG signals produced by the subject to reconstruct images according to the subject's visual perception using generative adversarial networks (GAN), which obtained an accuracy of 78.9 %, this shows how the ERP can be decoded to produce a visual perception that corresponds to the imagined image. In 2021, research conducted by [24] used non-invasive EEG-based BCI to reconstruct attractive facial images based on each subject's perception using GAN, where this research obtained an accuracy of 76% in reconstructing attractive facial images appropriate with the visual perception of the attractiveness of each individual. This further shows how ERP can be used in decoding visual perception specifically related to aesthetic preferences. Apart from reconstructing images, non-invasive BCI can also be used to retrieve desired images through image catalogs. This was demonstrated in research conducted by [18] in 2022, which used EEG signals produced when the subject observed an image, which was then mapped together with visual information taken from the image, where the results of this mapping were used to determine which image corresponds to the decoded visual representation of the EEG signal created when the subject imagines the desired image. This research can help in understanding how visual information is mapped and processed by neural networks in the human brain.

Finally, non-invasive BCI can also be used to evaluate spatial cognition abilities, which was demonstrated in [34] research in 2023, which used permutation conditional mutual information common space patterns (PCMICSP) and convolutional neural networks (CNN) to classify recorded EEG signals generated when remembering building references and routes along a virtual city according to visible route guidance and when subjects repeat the original route based on spatial memory and positioning abilities, to evaluate or classify spatial cognition abilities, obtaining an accuracy of 98%. This shows how EEG can be used in decoding visual-spatial cognition as well as providing insight into how the process of visual-spatial cognition occurs. The progress of non-invasive BCI in recording and decoding visual processes shows how non-invasive BCI can help in understanding how the brain can perceive and process visual information and record and decode

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various complex information contained in visual processes. So, in the context of mind-uploading, it indicates that non-invasive BCI has the potential to provide information and data that can be used to make this visual process replicable in digital form. The timeline for the development of non-invasive BCI capabilities in recording and translating visual processes based on selected studies can be seen in Figure 4.

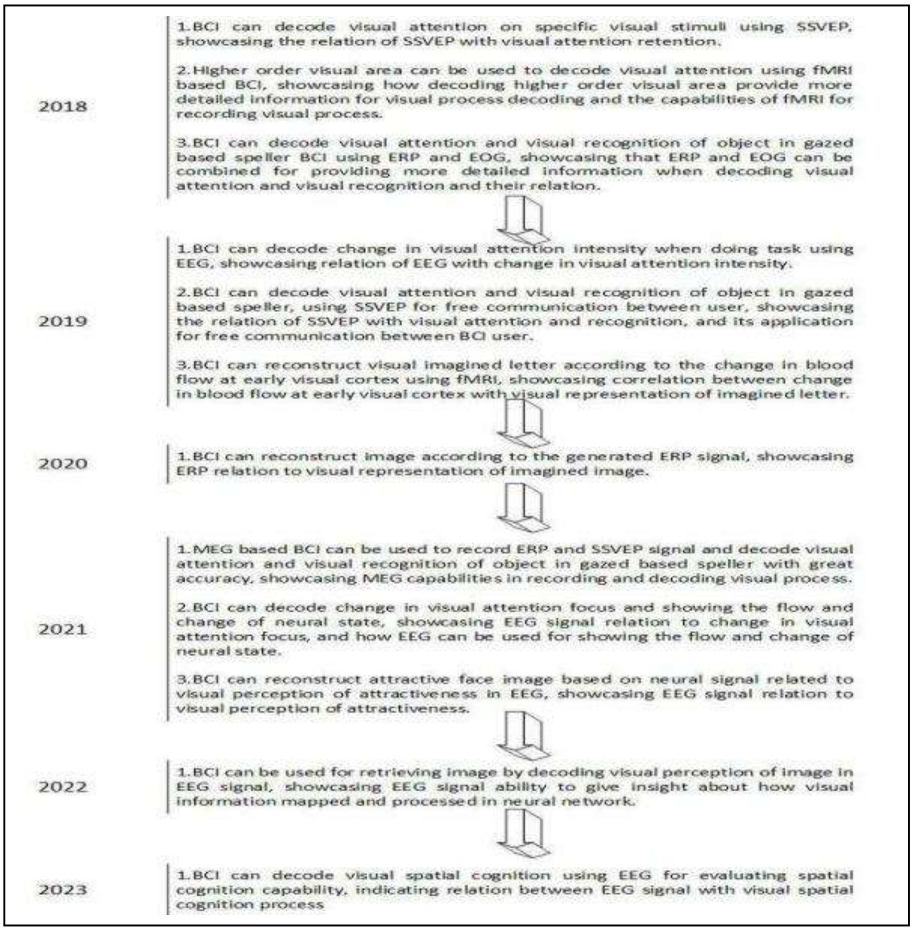

Fig. 4. Timeline of Progress in Non-Invasive BCI for Visual Process

- Speech and Language Process

Speech and language processes refer to a complex set of activities that involve understanding and producing verbal communication, which makes this process very important in the human communication process. Non-invasive cognitive BCI has now progressed quite rapidly so that it can record and decode this process, for example in translating human brain activity related to speech into sentences that can be understood. The progress in recording and decoding speech and language processes is shown in research conducted by [37] in 2020, which shows that there is a relationship between the physical characteristics of spoken language and certain characteristics or patterns in EEG signals related to the brain's response to speech, in which certain characteristics or patterns in the EEG signals recorded in this study are used to translate into understandable sentences with an accuracy rate of 13.2%-71.2%. This shows that EEG can be used to translate human brain activity into sentences that have been thought beforehand. Apart from that, there is also research conducted by [78], which aims to determine the optimal set of MEG channels that can be used to decode imagined and spoken speech via MEG signals, where this research shows that the spatial information underlying decoding related to speech can be revealed through analysis of the optimal MEG sensor arrangement. This shows how MEG can be used to decode brain activity related to speech.

Not only that, research conducted by [42] in 2022, which uses deep neurolinguistic learning to decode EEG signals that appear when imagining the desired word or sentence in real-time into actual words or sentences, then these decoded words or sentences are used as input to control the robot arm, where this research obtained an accuracy of 69.9% -73.5%. This increasingly shows how BCI-based

EEG is getting better at decoding neural signals that appear when imagining words or sentences into meaningful speech or command. Then, research conducted by [29] and [43] in 2022, showed that there were differences in signal characteristics that occurred in human brain activity when imagining tonal and non-tonal words or sentences. In research conducted by [29], EEG was successfully used to classify neural signals related to two different languages, namely English which is a non-tonal language, and Mandarin which is a tonal language, while in research conducted by [43], used EEG to successfully classify Mandarin words or sentences that use tonal and those that don't, because in Mandarin the same sentence or word has different meaning due to whether or not tonal is used. Through these two studies, it can be seen that the EEG signals produced when imagining tonal and non-tonal sentences or words have different characteristics, this shows how EEG can be used to decode neural signals related to language processing.

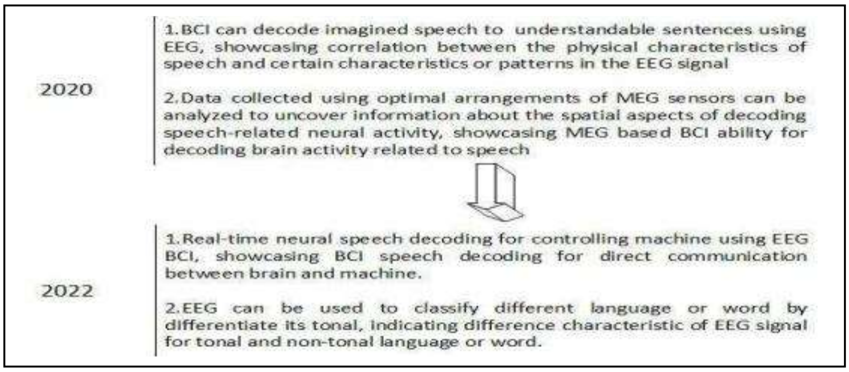

Fig. 5. Timeline of Progress in Non-Invasive BCI for Speech and Language Process

The progress of non-invasive BCI in recording and decoding speech and language processes shows how non-invasive BCI can help in understanding how the brain can produce spoken and written language and also can record and decode various complex information contained in the speech and language process. So, in the context of mind-uploading, this indicates that non-invasive BCI has the potential to provide information and data that can be used to make speech and language processes replicable in digital form. The timeline for the development of non-invasive BCI capabilities in recording and decoding speech and language processes based on selected studies can be seen in Figure 5.

- Working and Long-Term Memory

Memory is a cognitive process that is fully responsible for encoding, storing, and retrieving information needed in various activities or cognitive processes. Therefore, memory facilitates processes such as problem-solving, learning, or decision-making. Recently, non-invasive BCI can be used to record and decode a small part of this memory process, namely working memory and long-term memory. This was demonstrated in research conducted by [30] and [40] in 2020, both of which used EEG to successfully predict whether new vocabulary from the foreign language being studied could be remembered or not. [30] used EEG to record the neural signals formed when learning and remembering German vocabulary on the same day, along with recording the neural signals formed when remembering German vocabulary the following day. The recorded EEG signal is then decoded to predict the possibility of memory retention during the process of learning new vocabulary. This shows how EEG can be used to predict performance and the process of long-term memory in the context of foreign language learning. In contrast to previous research, research conducted by [40] which also used EEG, the neural signals recorded were signals that were formed during learning and remembering English vocabulary on the same day. This shows how EEG can be used to predict performance and the process of working memory in the context of foreign language learning. Both of these studies show a correlation between the EEG signals that appear with memory processes.

Apart from that, there was also research conducted by [26] in 2021, which used fNIRS to measure changes in oxygenated hemoglobin (HbO) and deoxygenated hemoglobin (HbR) levels that occurred when subjects performed OSPAN tasks, to classify the condition of working memory when performing them. In this study, the accuracy rate for OSPAN vs rest was 94.7% and OSPAN vs response was 91.2%, which indicates that fNIRS signals capture different brain activity patterns associated with different working memory and processing loads. This shows how the fNIRS signal correlates with the working memory processes that occur when performing cognitive tasks. Lastly, non-invasive BCI can also be used to increase the working memory capacity of the subject. This was demonstrated through research conducted by [31] in 2023, which used EEG to carry out neurofeedback training to increase the capacity of working memory, where through this research it was found that an increase in alpha brain waves could increase the capacity of working memory. So, even though the research conducted by [31] does not directly decode working memory, the research shows how alpha brain waves that can be recorded by EEG can later be used to provide more information in the working memory decoding process, which makes the working memory decoding process can be more accurate.

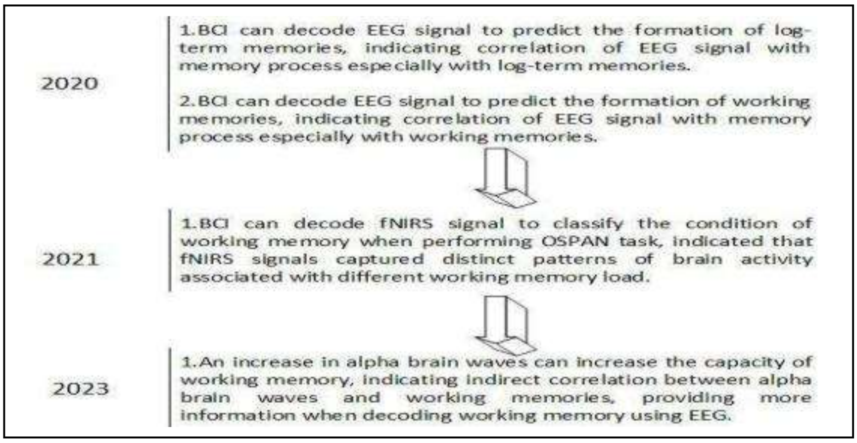

Fig. 6. Timeline of Progress in Non-Invasive BCI for Memory Process

The progress of non-invasive BCI in recording and decoding memory processes, especially working and long-term memory, shows how non-invasive BCI can help in understanding how the brain can carry out the processes of encoding, storing, and retrieving information needed in various cognitive activities, as well as being able to record and decode various complex information contained in the memory process. So, in the context of mind-uploading, this indicates that non-invasive BCI has the potential to provide information and data that can be used to make these memory processes replicable in digital form. The timeline for the development of non-invasive BCI capabilities in recording and translating these memory processes based on selected studies can be seen in Figure 6.

- Cognitive Load

Cognitive load refers to the total amount of mental effort or resources required to perform a task or process information, indicating the allocation and involvement of neurons in carrying out cognitive processes. Recently, non-invasive BCI can be used to record and decode cognitive load. This was demonstrated by research conducted by [25] in 2020, which used EEG and EOG to record neuron signals that appeared when the pilot was flying an airplane. These recording results were then translated using a multiple-feature block-based convolutional neural network (MFB-CNN) to capture local and global features from EEG and EOG signals and classify them into predetermined categories, where this research obtained an accuracy of 75%. This shows the different characteristics of the EEG and EOG signals in each category so that these two signals can be used to determine the cognitive condition of the subject, as well as provide additional information regarding how neuron involvement and allocation are carried out during cognitive processes.

Then there was research conducted by [21] in 2022, which used fNIRS to measure changes in blood oxygen levels in the brain as a result of changes in brain activity caused by simulating high cognitive load tasks, where the results of this measurement were classified using the random forest method to find out whether the subject experiences cognitive fatigue or not. The research obtained accuracy in the range of 6.9%-77.5%. This shows that there are special characteristics that indicate whether the subject is experiencing cognitive fatigue or not in the fNIRS signal so that fNIRS can be used to identify cognitive conditions and provide additional information regarding how neuron involvement and allocation are carried out during cognitive processes. Apart from that, there was also research conducted by [45] who used EEG to classify mental workload and stress levels simultaneously, with accuracy levels of 6.9%-77.5% and 5.9%-84.1% respectively. This shows how EEG signals have specific characteristics that are different for each state of mental workload and stress level, resulting in these two conditions being able to be classified together quite accurately, indicating how EEG signals can provide insight into the neural correlation that indicates stress levels condition or cognitive load and their relation to each other. Finally, there was research conducted by [47] in 2023, which analyzed the topological properties of the brain's functional connectivity network built from EEG data, where the results of the analysis were then used to classify mental workload. This research shows how data from EEG can be used to build functional connectivity networks that reveal large-scale connectivity patterns that tell how neural networks change and interact based on changes in cognitive load when performing certain cognitive tasks, showing how EEG can be used to capture the complexity of neural networks interaction in performing cognitive process.

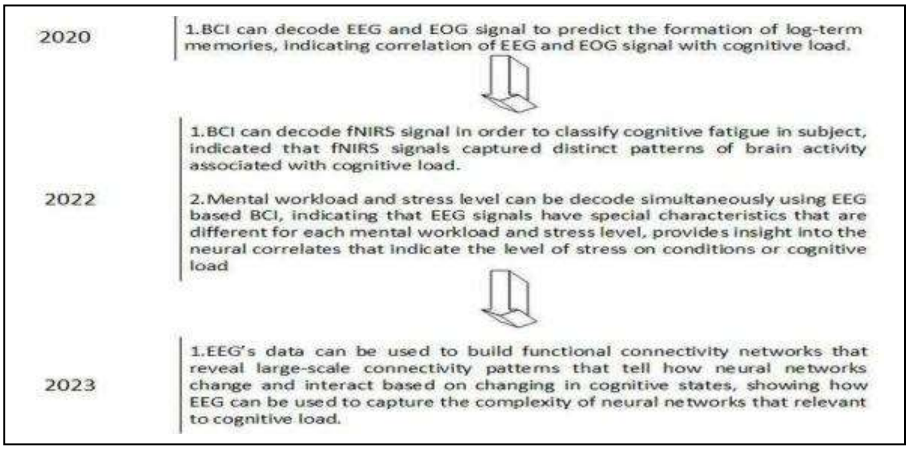

Fig. 7. Timeline of Progress in Non-Invasive BCI for Cognitive Load

The progress of non-invasive BCI in recording and decoding cognitive load shows how non-invasive BCI can help in understanding how neurons are allocated and involved in cognitive processes. So, in the context of mind-uploading, this indicates that non-invasive BCI has the potential to provide information and data that can be used to digitally replicate the process of allocating and involving neurons in cognitive processes. The timeline for the development of non-invasive BCI capabilities in recording and decoding cognitive load based on selected studies can be seen in Figure 7.

3.2.2. Advancement of Factor that Supporting Non-Invasive Cognitive BCI

- Feature Extraction and Decoding Method

The development of various methods that can extract features and decode data or signals obtained from non-invasive neuroimaging techniques greatly supports improving the ability of non-invasive BCI to record and translate the cognitive processes of the human brain. Where these methods can analyze complex and relevant features of neural signal activity that occur from cognitive processes and translate them to understandable information or command with good accuracy. Statistical methods such as analysis of variance (ANOVA), common spatial pattern (CSP), canonical correlation analysis (CCA), principal component analysis (PCA), and t-SNE can be used to analyze the statistical properties of neural signals, providing relevant features for decoding [20], [27], [28], [32], [34], [39], [43], [51], [52], [56], [58], as well as machine learning and deep learning methods such as linear discriminant analysis (LDA), support vector machine (SVM), long short-term memory (LSTM), or convolutional neural network (CNN) which can extract and decode more complex features, are examples of this method [17], [34], [42], [43], [51], [52], [53], [55], [57], [58], [63]. The rapid development of machine learning and deep learning has made it possible to better recognize complex features and provide more accurate decoding accuracy, making it a favorite method to be used [42], [43], [58], [63].

The development of new machine learning or deep learning methods such as MFB-CNN which is a CNN with several feature blocks to extract spectral, temporal and spatial information makes it capable of classifying cognitive load with an accuracy of 61%-75% [25]. The LGGNet method, which integrates all learning blocks to model activity within and between functional areas of the brain, makes it capable of determining levels of attention and fatigue quite accurately [60]. The combination of t-SNE and fuzzy learning (TSK) can increase visual cognitive decoding accuracy up to 81.98% [27].

GAN method that can reconstruct images based on EEG signals with a fairly good level of accuracy [53], [59]. MInd Reading CLassification Engine (MIRACLE) which can classify imagined stimuli with an accuracy level of 70%-96% [62]. As well as the SGLNet method which uses spiking neural networks (SNN), making the architecture of this method more in line with the biological neural networks in the human brain, thus making it better at decoding cognitive processes [49]. All of these methods show progress in the development of methods that can be used to carry out feature extraction and decoding, especially in machine learning and deep learning methods. This progress indicates improvement in ability to decode complex cognitive process and the accuracy of data and information obtained from decoding in non-invasive cognitive BCI. Several examples of feature extraction and decoding methods and their accuracy can be seen in Table 3.

Table 3. Example of Feature Extraction and Decoding Methods

References	Dataset (No of Subjects)	Method	Accuracy Results
[17]	14 Subject	LDA	40.8% - 68.8% (Single Feature Classification) 51.8% - 89.3% (Multiple Feature Classification)
[28]	20 Subject	SVM, LSTM	35.68% (SVM) 39.5% (LSTM)
[60]	Attention Dataset (26 Subject) Fatigue Dataset (27 Subject) DEAP Dataset (32 Subject)	LGGNet	61.2% - 64.5% (Attention Dataset) 89.83% - 90.76 (Fatigue Dataset) 58.85% - 63.07% (DEAP Dataset)
[27]	10 Subject	t-SNE + TSK PCA + TSK	81,98% (t-SNE + TSK) 69.71% (PCA + TSK)
[49]	DEAP Dataset (32 Subject) PhysioNet (109 Subject)	SGLNet	90% (DEAP Dataset) 65% (PhysioNet Dataset)
[25]	7 Subject	MFB-CNN	61% - 75%
[34]	7 Subject	PCMICSP + CNN	98%

- Signal Processing Method

Signals or data obtained from non-invasive neuroimaging techniques are susceptible to noise and artifacts, which can affect the efficiency and accuracy of the decoded information. Therefore, the development of various signal processing methods is very important in increasing the accuracy and efficiency of non-invasive cognitive BCI, where this method can minimize noise and artifacts, as well as provide or select the most relevant features. The distribution of signal processing methods that can be used in non-invasive cognitive BCI can be seen in Figure 8. For example, methods such as the Butterworth bandpass filter which limits the frequency range of the received signal thereby limiting the noise and artifacts received [23], [50], or methods such as independent component analysis (ICA), common spatial pattern (CSP), common average reference (CAR), artifact subspace reconstruction (ASR), and CCA which can separate relevant signals or data from noise and artifacts [28], [31], [39], [42], [45], [55], [84], [85], [86].

Apart from these methods, there are also new methods such as those developed by [68], which are used to detect ERPs in EEG signals so that they can differentiate ERP signals from noise or artifacts, or the ERP-CapsNet method developed by [64], which detects ERP signals using a capsule network makes it possible to distinguish ERP signals from noise or artifacts, thereby increasing the accuracy of character recognition classification by 52%-99%. There is also an image filtering denoising (IFD) method developed by [67], which can reduce noise and artifacts contained in SSVEP from an image analysis perspective. In addition, the EEGNet method with ensemble learning developed by [66], which can classify SSVEPs with a better accuracy rate than the CCA method, which is around 81%, shows how this method can distinguish SSVEPs from noise and artifacts. The Common cross-spectral patterns (CCSP) feature extraction method combines spectral and spatial patterns based on cross-spectral density (CSD) so that it can obtain more relevant features accurately, making it able to reduce the amount of noise and artifacts present [52]. Or the data analysis method developed by [65], which can minimize noise and reduce data dimensionality from MEG signals. These new methods show how signal processing methods continue to develop to improve the signal quality of non-invasive cognitive BCI

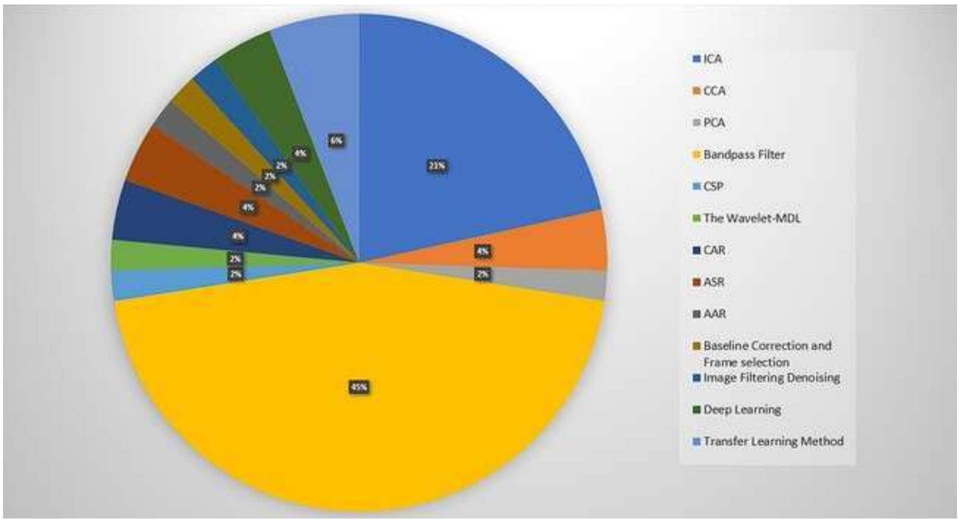

Fig. 8. Distribution of Signal Processing Methods

- Neuroimaging Technique

The development of neuroimaging techniques also improves the ability of non-invasive cognitive BCI to record and decode cognitive processes. The development of this technique helps expand the range of brain activity that can be recorded and decoded. EEG is the most commonly used technique because of its affordability, portability, and high temporal resolution, but other techniques such as MEG, fNIRS, and fMRI can be used as an alternative to EEG, because they provide superior spatial resolution, thus allowing accurate localization of brain activity [26], [37], [46], [51], [54], [63], [71]. Apart from these techniques, new techniques such as eye-tracking and EOG have emerged as a complement or more portable alternative to existing techniques, where they record eye movements and the electrical signals that arise as a result of these movements, thus providing additional data from visual processes, making it a good complement to EEG [19], [72], [73], [87]. Hybrid techniques that combine two different neuroimaging techniques, such as EEG with fNIRS or EEG with MEG, can increase temporal and spatial resolution, thus providing more in-depth information on the cognitive processes that occur [54], [76], [88]. OPM-MEG is an improvement over traditional MEG, which makes MEG more portable and increases its spatial resolution [78]. Finally, there is hdEEG, which is an improvement on EEG, where hdEEG uses a larger number of electrodes (128-256 electrodes) to increase its spatial resolution and make it less susceptible to noise and artifacts [59], [70], [89], [90].

- Framework and Tools

The emergence of various frameworks and tools has had a significant impact on the non-invasive cognitive BCI research landscape. Frameworks such as the Integrated Development Environment for EEG which is focused on developing EEG-based BCI [69], or BCI 2000 for developing various BCI modalities such as EEG, fNIRS, or fMRI-based BCI [49], [91]. As well as tools that can be used to facilitate the data processing and analysis process, such as easyfMRI and BrainVoyager for fMRI [44], [58], EEGLab which focuses on EEG [31], [43], RT-NET for processing and analyzing hdEEG data in real-time [70], and MATLAB which can be used for various modalities [32], [43], [65], [92]. All of these methods provide increased accessibility by allowing researchers with varying levels of expertise to participate in BCI development, increased efficiency by facilitating rapid prototyping and development, accelerated pace of research, and customizability that gives researchers the ability to adapt frameworks and tools to specific needs, thereby encouraging innovation. This has resulted in a significant increase in the rate of development of non-invasive BCIs, providing valuable data and insights into human brain function.

- Low Computational Cost Method

The development of various methods that have low computational costs also supports increasing the capabilities of non-invasive cognitive BCI, where these methods enable more efficient and real-time data processing, handle complex tasks or large amounts of data, and increase energy efficiency. This makes non-invasive cognitive BCI better at carrying out multiple and complex processes and also making it more efficient and practical, which makes it able to be integrated and accessed easily in everyday life. These methods include feature extraction and signal processing methods such as CCSP which uses a fast Fourier transformer that can effectively reduce computational complexity and time delay [52], SGLNet which uses SNN, which has been proven to be more computationally efficient than artificial neural networks (ANN), because of its event-driven processing architecture [49], or simple machine learning methods such as logistic regression, LDA, and SVM which are not as complex as deep learning methods [65]. Signal processing methods such as bandpass filters have a simple design because they only require a few parameters, which represent fewer calculations and a smaller memory footprint, thereby reducing computational costs [93], or the method developed by [68] which can detect ERP signals with a fairly high level of accuracy but with low computational costs, due to an agile approach in characterizing and detecting ERP variables. Finally, there are neuroimaging techniques such as EEG, fNIRS, eye-tracking, or EOG which use simple signal acquisition techniques and produce simpler signals, known to have low computational costs [46], [63], [72], [73], [75].

- Hardware Improvement

The development of various types of hardware also supports increasing the capabilities of non-invasive cognitive BCI in recording and decoding cognitive processes, especially in terms of increasing signal quality and length of use of non-invasive cognitive BCI [75], [80], [94]. This is shown in the development of various types of electrodes that can be used in EEG, which are shown in Table 4. For example, wet electrodes which have a low signal impedance which results in good signal quality but have a short usage time, or dry electrodes which can be used for a longer period of time become an alternative to wet electrodes, although the signal impedance is lower than wet electrodes [75], [80]. Then there is also the emergence of the semi-dry electrode to overcome the shortcomings of the wet and dry electrode, where the semi-dry electrode combines the advantages of each wet and dry electrode so that the semi-dry electrode has a signal impedance that is almost equivalent to the wet electrode and has a usage time that can be longer than dry electrodes [75], [80]. Apart from electrodes, there is also the emergence of programmable metasurfaces that can manipulate or control electromagnetic waves in non-invasive BCIs, where the use of programmable metasurfaces allows sending brain messages wirelessly between operators thereby facilitating direct text communication [79], [95], [96]. This indicates the possibility of using programmable metasurfaces in non-invasive BCIs to later be able to communicate directly with the digital brain.

Table 4. Types of Electrodes That Can Be Used in EEG

No	Name	Advantages	Disadvantages
1	Wet Electrode	Low Impedance, Good Signal Quality	Not Suitable for Long Term Use, Can Cause Skin Irritation, Need Conductive Gel, Long Preparation Time
2	Dry Electrode	Low Preparation Time, Not Causing Skin Irritation, Don't Need Conductive Gel, Suitable for Long Term Use	High Impedance, Low Signal Quality
3	Textile Electrode	Not Causing Skin Irritation, Impedance Comparable to Wet Electrode, Comfortable to Use	Can Provide Low Signal Quality if Subject Has Thick Hair, Vulnerable to Damage Because of Washing and Tear
4	Capacitive Electrode	Don't Need Skin Contact, Comfortable to Use, Resistant to Artifact or Noise	High Impedance, Low Signal Quality
5	Semidry Electrode	Low Impedance Compared to Dry Electrode, Suitable for Long Term Use, Comfortable to Use, Not Prone to Causing Skin Irritation	High Impedance Compared to Wet Electrode, Need Conductive Gel

3.2.3. Limitation of Non-Invasive Cognitive BCI

- High Computational Cost

In carrying out recording and decoding, non-invasive cognitive BCI requires various methods that are quite complex to get accurate results, where the application of this complex method requires quite large computing capabilities, this causes latency problems which can hamper data processing in non-invasive cognitive BCI, causing non-invasive cognitive BCI to be inefficient [25], [54], [76], [88].

Not only that, the human brain has 100 billion neurons that produce various neural signals when carrying out activities [22], so non-invasive BCI produces a large amount of data to be analyzed and decoded in real time. This also causes a fairly high level of computing in non-invasive cognitive BCI. Various kinds of low computational cost methods have been developed, but high computational costs in non-invasive cognitive BCI remain. One of the causes of this is that methods that have a higher level of accuracy are still a priority, whereas methods with high accuracy generally have high computational costs due to their complexity.

For example, MFB-CNN method that uses seven convolutional blocks to obtain high-level features from EEG data in classifying mental states, where MFB-CNN obtains an accuracy level of 75%, this accuracy is higher than methods with simpler architectures than MFB-CNN such as SVM [25]. The use of these seven convolutional blocks shows an increase in the number of parameters and complexity of the architecture, resulting in a high computational rate. Hybrid neuroimaging techniques that combine two modalities such as EEG with fNIRS, can be used to provide more in-depth data for the process of classifying human brain activity, where classification using this method obtains an accuracy of 70.57% - 92.16%, this accuracy is greater compared when only using EEG or fNIRS separately [54]. Combining EEG and fNIRS data involves aligning and synchronizing signals from multiple modalities, a process that is computationally demanding, especially when handling data from different levels of temporal and spatial resolution [54], [76], [88]. Not only that, low-cost computational methods may also be good for use in certain populations or tasks only [97]. This causes a shift in the use of low computational cost methods to high computational cost methods. High computational costs also cause the development of non-invasive cognitive BCI to be difficult and require quite large costs, this is because it requires quite expensive hardware or technology in its development, thus limiting its accessibility and hindering widespread adoption, especially in areas with limited resources.

- Difficult in Recording Neural Complexity

Recording neural complexity is a significant challenge in the field of non-invasive cognitive BCI, where non-invasive methods such as EEG, fNIRS, or fMRI have limitations in capturing the complex and multidimensional nature of neural activity [46], [71], [74]. These techniques generally have poor signal quality, which is demonstrated by lacking the spatial or temporal resolution necessary to precisely identify specific brain regions involved in complex cognitive processes or capture the rapid and dynamic interactions of neural networks involved in cognitive processes when compared with invasive techniques, limiting its ability in capturing all of the detailed data or information needed for decoding cognitive process as a whole [46], [71], [74]. Apart from that, non-invasive BCI is also very susceptible to noise and artifacts, where this noise and artifacts can obscure weak brain signals that are relevant to cognitive processes, making it difficult to decode complex information [51], [71], [74]. Non-invasive BCI also only records brain activity through the outermost parts of the brain, so deeper structures, hidden beneath the cortex, remain largely inaccessible, limiting understanding of their role in cognitive processes [51], [71]. Finally, the activity of neural networks in the brain when carrying out cognitive processes can be different for each individual [98], this makes the development of a BCI system that can record and interpret all neural activity accurately in various populations very difficult.

- Suboptimal Accuracy

Despite significant progress in non-invasive cognitive BCI, suboptimal accuracy is still an obstacle. This is shown in Table 3, where several feature extraction and decoding methods used in several studies still obtain a range of accuracy levels that are still less than optimal. This suboptimal accuracy can be caused by two factors, namely signal quality and limited high-quality dataset.

First, signal quality in non-invasive BCI is still far from perfect. Non-invasive methods such as EEG, MEG, fNIRS, and fMRI have a level of spatial and temporal resolution that is not good enough, this causes a lack of detailed data that can be used to understand and decode cognitive processes so that the level of accuracy becomes less reliable [46], [71], [74]. Hybrid neuroimaging methods can indeed be used to increase the temporal and spatial resolution of each combined method. However, the spatial and temporal characteristics of the various imaging modalities may not be perfectly aligned, thus creating challenges in combining and interpreting the data coherently [54], [76], [88]. Misalignment can affect the accuracy of spatial localization and temporal dynamics, causing less accuracy. Apart from that, non-invasive BCI is also very susceptible to noise and artifacts, where this noise and artifacts complicate the decoding method in interpreting the data obtained, causing inaccurate accuracy [51], [71], [74]. Signal processing methods can indeed be used to remove existing noise and artifacts, but this method can make errors in identifying noise and artifacts from relevant data, which causes the loss of important data or information used in the decoding process [54], [64].

Second, good quality datasets with high amounts of data, which can be used in non-invasive cognitive BCI training are still limited [58], [63], [99]. Small datasets can indeed provide a fairly good level of accuracy. However, small datasets only provide small variations in brain activity, this can lead to poor generalization capabilities of feature extraction and decoding methods so that these methods only work well for certain cognitive tasks or populations and may not apply well to other tasks or populations [26], [34], [49], [60], [63], [77], [83], [100]. Although there is an increase in the number of freely available datasets [58], [63], these datasets may be limited to only a few specific cases, and larger datasets may be needed to improve the performance of non-invasive cognitive BCI [63], [99].

3.3. Implication for Mind-Uploading and Its Future Direction

Mind-uploading, also known as whole-brain emulation and mind copying or transfer, is the hypothetical process of transferring a person's mind including memory, decision-making, attention, knowledge, thoughts, personality, and consciousness, into a digital substrate or computer [5], [101]. This process involves scanning and encoding the entire neural structure and brain information, then translating it into a digital format that can be run on a computer simulation [7], [102]. Therefore, to be able to realize mind-uploading, a technology that can record and decode all neural structures and brain information from all existing brain processes is needed [5], [7], [101], [102]. Especially the cognitive process, which is one of the main processes in the brain that plays a role in regulating how to obtain, store, use, and manipulate information, is an important part of being able to build a digital brain to realize mind-uploading.

Non-invasive BCI is a technology that can detect and translate brain activity without having to physically enter the brain, so this technology has the potential to help realize mind-uploading [22], [51], [102]. This technology has experienced very rapid development due to the development of various factors that support this technology. As shown in Figure 9, the development of feature extraction and decoding methods facilitates non-invasive BCI to be able to find features that are most relevant to ongoing brain activity, which the features then can be translated into accurate and meaningful information, data, or commands. [34], [51], [58], [63]. The development of signal processing methods facilitates non-invasive BCI in improving signal quality and analyzing the obtained signals [52], [64]. The development of neuroimaging techniques facilitates non-invasive BCI with sensors that can record complex brain activity signals with good quality [74], [76], [78]. The development of frameworks and tools facilitates the development of non-invasive BCI systems so that the system does not need to be created from scratch [31], [49], [70]. The development of hardware and low computational cost methods facilitates improving BCI's non-invasive capabilities, such as increasing BCI computational capabilities or improving signal quality, and also improving BCI wireless communication capabilities [52], [68], [79], [80].

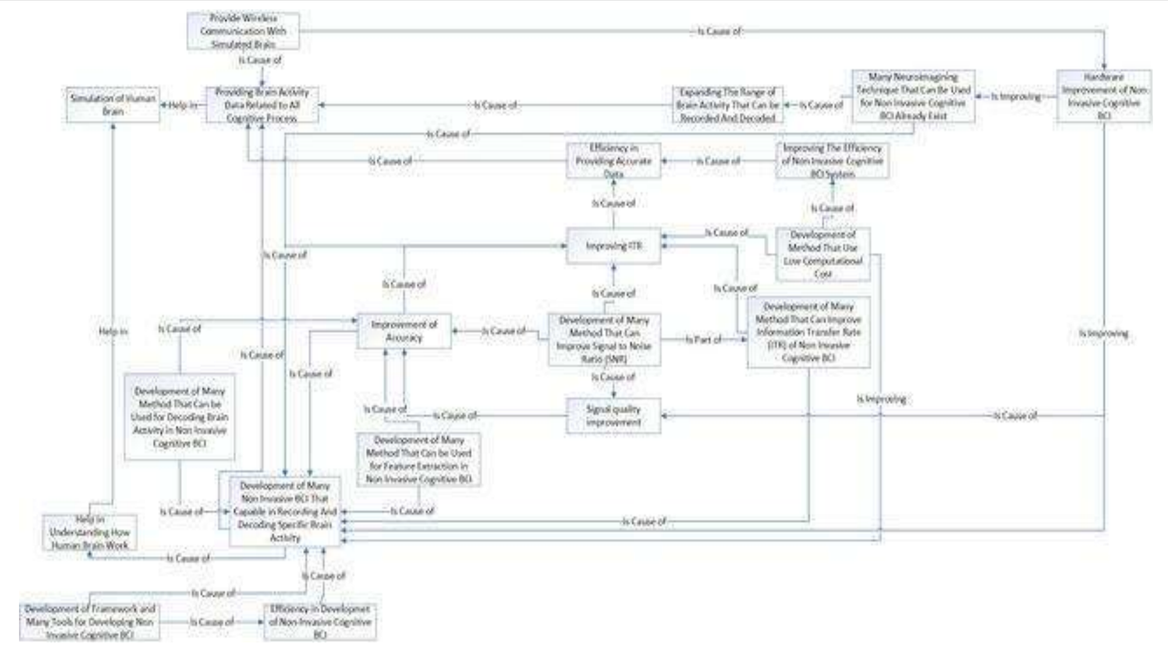

Fig. 9. Relationship of Factor that Improve Non-Invasive BCI and The Implication for Mind-Uploading

The development of various supporting factors makes non-invasive BCI capable of recording and decoding cognitive processes that play an important role in various brain activities, such as memory, decision-making, memory, and even consciousness [22]. Cognitive processes such as visual, speech and language, working and long-term memory, and cognitive load can now be recorded and translated by non-invasive BCI, making non-invasive BCI has the potential to be used to collect detailed brain data related to these cognitive processes in large quantities, providing valuable information for understanding cognitive processes and potentially creating accurate models of cognitive processes for mind-uploading [7], [22]. In addition, non-invasive cognitive BCI can be used for direct communication between users, showing its possible use as a communication channel between the digital brain and the outside world, which allows for interaction and feedback, which has the potential to enrich the experience of the digital brain [7], [39], [79].

Even though non-invasive cognitive BCI has experienced rapid development to be able to record and decode various kinds of cognitive processes, the limitations of this technology still prevent it from being able to fully assist in realizing mind-uploading. As shown in Figure 10, high computational cost is still a problem even though low computational cost methods exist, this is due to the displacement of low computational cost methods with high computational cost methods that focus more on high accuracy [25], [54]. Apart from that, the large amount of data that must be recorded and decoded by non-invasive cognitive BCI to be able to provide accurate and detailed information for building cognitive process models that are the same as the original is also one of the main causes [22]. This makes the process of developing an efficient and accurate non-invasive cognitive BCI difficult. Apart from that, this also limits the capabilities of non-invasive cognitive BCI in recording, processing, and decoding all complex neural network activity in cognitive processes, making it currently impossible to process and represent all cognitive processes of the human brain, so that information or data required for mind-uploading still cannot be fully fulfilled [7], [25], [54], [76], [88], [102].

Difficulty in recording neural complexity caused by low signal quality encompassing noise and artifacts as well as inadequate spatial and temporal resolution, restricts access to deeper brain structures, along with differences in neural network activity in the brain in carrying out cognitive processes in each individual also hindering the full usage of no-invasive cognitive BCI in realizing mind-uploading [46], [51], [71], [74], [98]. This causes the data or information that can be captured to only be a small and outer part of all existing cognitive processes and makes it difficult to record more complex cognitive processes such as memory encoding and retrieval, decision-making, and even consciousness, so that the data or information is still not completely sufficient to build cognitive process models identical to the original for mind-uploading [46], [51], [71], [74], [98]. Lastly, suboptimal accuracy caused by poor signal quality and the limited high-quality datasets with large amounts of data that can be used for non-invasive cognitive BCI training affects the ability of non-invasive cognitive BCI to capture and translate brain signals accurately in a new situation or context that is different from the training data being used is become poor, making the decoded cognitive process data and information unreliable, so that the cognitive process model built for mind-uploading can be different compared to the original [34], [46], [49], [63], [71], [74].

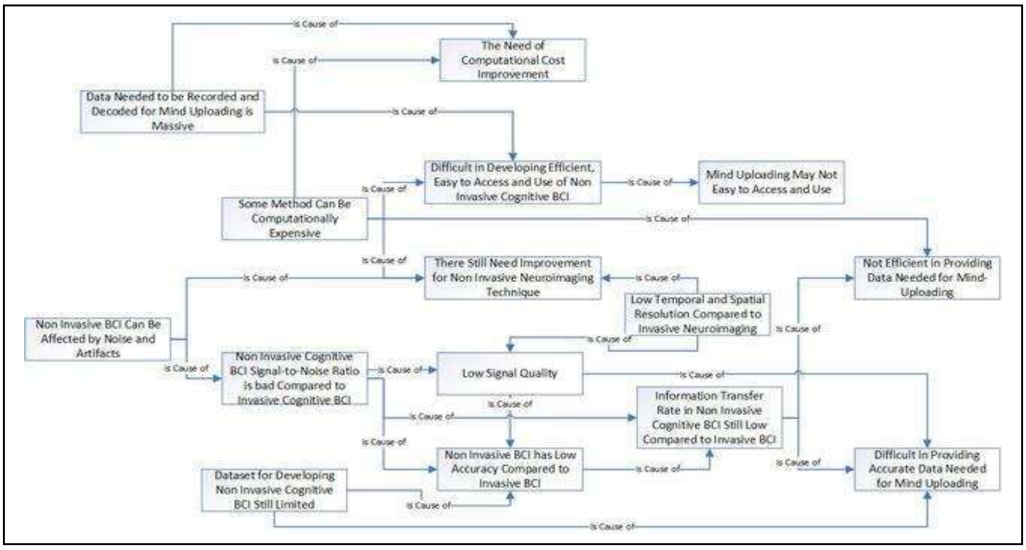

Fig. 10. Relationship of Limitation that Hindering The Realization of Mind-Uploading

For non-invasive cognitive BCI to fully support the realization of mind-uploading, existing limitations must be overcome along with increasing the capabilities of the current non-invasive cognitive BCI. Therefore, the direction of development of non-invasive cognitive BCI in the future, as shown in Table 5, can be carried out. Where, by synergistically pursuing this future direction, non-invasive cognitive BCI can make significant progress in achieving its ultimate goal of understanding the human mind and even potentially bridging the gap between biological and digital in the field of mind-uploading.

Table 5. Future Direction of Non-Invasive Cognitive BCI for Realizing Mind-Uploading

Methods	Description	Purpose
Future Improvement of Deep learning Algorithm	Deep learning algorithms are capable of learning complex patterns [51]. Future improvement of these architectures that are capable of learning complex patterns becomes more essential. For example, Developing and using novel SNN models that are designed to be more biologically plausible [49], or models that mimic or leverage certain features of the brain's structure, like EEG-Graph-Net proposed by [23], can potentially help extract subtle nuances in brain activity that map to specific thoughts or intentions. Other than that, in data-sparse regions, where there is limited training data, traditional models may struggle to make accurate predictions and can become overconfident in their estimation, so developing and using models that can provide reliable predictions in data-sparse regions, like Bayesian-CNN proposed by [50], can be the solution. Finally, Deep learning algorithms trained on large datasets can also identify and remove artifacts more effectively than traditional filtering methods, thus improving signal quality [34], [64], [66].	Improving Accuracy, Generalizability, Signal Quality and Decoding Complex Cognitive Process.
Exploring new brain imaging modalities or developing higher-resolution imaging modalities	Investigating the capability of emerging neuroimaging technologies like High-Density Diffuse optical tomography (HD-DOT) that can create a 3D image of brain activity may provide better information and data for decoding brain activity [103]. Other than that, developing neuroimaging techniques that can provide better spatial and temporal resolution and can	Improving Signal Quality and Improving Recording of Complex Cognitive Process.

	penetrate deeper structures that are hidden beneath the cortex, can also provide more detailed information [46], [71], [74].	
The Use and Improvement of Transfer Learning Method	Transfer learning serves the purpose of leveraging knowledge gained from one task or domain to improve the performance of the BCI in another, potentially more complex task or domain [45], [61], [104]. So, transfer learning can be used for improving accuracy, significantly reducing the training time, and data needed for new applications [45], [61], [104]. Development of transfer learning methods like low-dimensional subject representation-based transfer learning (LDSR-TL) proposed by [61], can obtain the low-dimensional subject representations such that the subjects with similar brain dynamics can be identified, providing more detailed data for decoding and improving generalizability.	Improving Accuracy and Generalizability, also Overcoming Data Scarcity for Training.
Further Research in Recording and Decoding other Cognitive Process	Current non-invasive cognitive BCIs can record and decode various cognitive processes like working and long-term memory, visual perception, speech and language processing, and even cognitive load. However, unlocking the full potential of this technology requires further research into more complex areas like auditory processing, decision-making, and memory retrieval/encoding. While some aspects of memory, such as working memory and long-term memory, have been studied using non-invasive BCIs, these are mostly initial investigations and focus on specific aspects like successful encoding or recognition of simple stimuli, so further research is needed to understand these processes comprehensively [30], [35], [40]. For example, exploring areas like decoding auditory spatial attention and imagined musical pitch demonstrates the early progress made in recording and decoding auditory processes [23], [28]. Additionally, progress has been made by the researcher in using EEG to detect how cognitive capabilities change because of aging [20], [36]. These advancements provide valuable insights and more information about the brain's cognitive functioning and even help in understanding the nature of consciousness.	Mapping the Cognitive Landscape and Developing Complete Models of Cognition
Integration of Quantum Computing Chip and Cloud Computing	High computational cost still becomes a problem in non-invasive cognitive BCI even though low computational cost already exists, this is because low computational cost may only be able to be used for certain tasks [97], making high computational cost more preferable [25], [54]. The sheer amount of data generated by 100 million neurons that need to be recorded and decoded also contributes to this problem [22]. Thus, restricts the capabilities of non-invasive BCI because of limited processing power, making BCI technology less accessible and hindering widespread research and development. Quantum computing chips can process massive data and perform complex calculations in a matter of seconds compared to classical computers, providing more processing power of non-invasive cognitive BCI, potentially speeding up complex algorithms processes used in non-invasive cognitive BCI [81], [94]. Other than that, cloud computing can also provide high computing resources, moving the computational load from local devices to powerful cloud servers, so they can run and speed up the computationally intensive tasks [82].	Improving Computational Capability and Real-Time Process
Collaborative Efforts to Collect Diverse and Representative Datasets and Development of Synthetic Data	Although there is an increase in the number of freely available datasets [58], [63], these datasets may be limited to only a few specific cases, and larger datasets may be needed to improve the performance of non-invasive cognitive BCI [63], [77], [99]. Therefore, ongoing efforts to increase the availability of datasets that contain large amounts of data with good quality need to be made. Collaborative efforts between researchers by exchanging or sharing anonymized data responsibly can accelerate research progress and benefit the broader scientific community, expanding the available datasets [58], [63], [77], [99]. Other than that, using synthetic data generation techniques like GAN for generating synthetic EEG signals can also expand the available datasets that can be used for training, highly beneficial in improving the accuracy, convergence rate, and generalization capabilities of non-invasive cognitive BCI [83].	Overcoming Data Scarcity for Training.

4. Conclusion

Non-invasive cognitive BCI has experienced very rapid development. This is demonstrated through various improvements in various factors that support non-invasive cognitive BCI. Improvements in various supporting factors include the development of feature extraction and decoding methods, signal processing, neuroimaging techniques, frameworks and tools, low-cost computational methods, and hardware. These things make non-invasive cognitive BCI now capable of recording and decoding several cognitive processes such as visual process, speech and language, working and long-term memory, and cognitive load, by simplifying the process of developing a non-invasive cognitive BCI system and increasing its capabilities in accurately recording and decoding the cognitive processes that occur. This ability gives non-invasive cognitive BCI the ability to provide insight as well as information and data that potentially can be used in building models of the human brain, especially the cognitive process part, becoming a bridge in sending cognitive information into digital format.

However, although non-invasive cognitive BCI has the potential to support the realization of mind-uploading, currently it cannot be fully used in realizing mind-uploading. This is because there are still limitations in non-invasive cognitive BCI, such as high computational costs, difficulty in recording neural complexity, and suboptimal accuracy. This limits the ability of non-invasive cognitive BCI to provide accurate and reliable cognitive process data and information and currently only able to record and decode the smallest part of each cognitive process, causing non-invasive cognitive BCI to still not be able to in-depth and thoroughly record and translate all neural network interactions that occur in each cognitive process and make it difficult to record and decode more complex cognitive processes such as decision-making, knowledge, and memory retrieval and encoding. This results in the lack of accurate data or information needed to build a digital cognitive process model for mind-uploading.

In the future, improving non-invasive cognitive BCI can focus on improving deep learning algorithms, exploring or developing new neuroimaging techniques, using and developing transfer learning techniques, continuing research to record and decode other complex cognitive processes, applying quantum computing chips and cloud computing, or continuous collaboration and use of synthetic data to improve datasets, to overcome existing limitations and increase the capabilities of non-invasive cognitive BCI. With such continuous innovation and exploration, non-invasive cognitive BCI can offer more valuable additional knowledge and can fully contribute to realizing mind-uploading, thereby increasing our understanding of the human brain to an unprecedented level.

Meanwhile, this research specifically examines the potential for realizing mind-uploading based on recent progress in non-invasive cognitive BCI. However, mind-uploading requires a complete understanding of the human mind or brain, therefore it requires exploration of other brain processes. Therefore, future research could address recent progress in non-invasive BCI that are capable of recording and deciphering motor, emotional, affective, and subconscious or unconscious processes, along with their implications for mind-uploading. This is important for assessing the feasibility of non-invasive BCI in realizing mind-uploading in a way that not only covers cognitive abilities but also the entire spectrum of human brain processing experience.

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