Towards Practical BCI-Driven Wheelchairs: A Systematic Review Study

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***Abstract*— The use of brain signals in controlling wheelchairs is a promising solution for many disabled individuals, specifically those who are suffering from motor neuron disease affecting the proper functioning of their motor units. Almost two decades since the first work, the applicability of EEG-driven wheelchairs is still limited to laboratory environments. In this work, a systematic review study has been conducted to identify the state-of-the-art and the different models adopted in the literature. Furthermore, a strong emphasis is devoted to introducing the challenges impeding a broad use of the technology as well as the latest research trends in each of those areas.**

***Index Terms*— Assistive technology, brain-computer interface (BCI), electroencephalography (EEG), motor imagery (MI), P300, SSVEP, wheelchair.**

I. Introduction

OVER the past several years, Brain-Computer Interface (BCI) applications have attracted more and more researchers, taking advantage of the advancements in computational capabilities and Machine Learning (ML) science. BCI refers to a system designed to interact with the brain to extract a certain level of valuable information that reflects its complex functions for use in engineering and medical applications. One of the noble goals of BCI is to develop new means of utilizing modern technology to help improve the quality of life of the human being. The field of assistive and restorative technology is a widespread common example.

BCI implementation is often a straightforward process. Having said that, achieving adequate performance for real-life applications remains a challenge [1]. The BCI field has not matured enough to be carried from the research domain to solve real-life problems. Hence, considerable work is still needed to exploit the technology for the wide range of applications BCI can serve. Following is a brief overview of BCI in engineering applications, which is the topic of interest in this review work.

A. BCI in Biomedical Engineering Applications

One of the primary applications of BCI is controlling a screen cursor, hoping to help individuals with limited physical abilities interact with computers without asking for external help. Due to the simplicity of the task, it was one of the first BCI applications to receive attention from the scientific community. Research started more than three decades ago with the work of Wolpaw et al. [2]. It was shown to be a promising application of BCI [3], [4] mainly because of the few commands needed from the subject and the application's lax timing requirements. With that, the application is still arguably limited in its capabilities and lacks the smooth feeling that would allow broad implementation. Hence, it is still open for research to this day. The latest research has succeeded in achieving satisfactory performance from an accuracy perspective (upper 90s) [5], [6]. Nevertheless, the technology still suffers from a number of issues, such as the extra hardware needed to facilitate the system parts (higher cost) [5] or the personalized nature of the model (designed for individual users) [6].

Another active BCI research topic in the restorative technology field is the development of modern, intelligent artificial limbs (prostheses). Limbs share a high level of complexity [7] due to the high number of tasks the artificial limb must be able to perform to imitate the physiological organ. Because of this, prostheses are often constructed using multiple modalities, Electroencephalography (EEG) and Electromyography (EMG), for example [8], or by combining EEG paradigms, such as the work in [9]. Though BCI-based prostheses have been extensively researched, their implementation is still narrow [10]. Therefore, it is one of the current dominant focus areas in the BCI domain.

One equally important application is the design of BCI-driven wheelchairs that are entirely operated by human brain signals. This application can be of extreme help for individuals that rely on wheelchairs to meet their movement needs, particularly for those diagnosed with any type of Motor Neuron Disease (MND). MND is a medical condition that restrains the person's physical motion ability while maintaining a fully functional brain. Symptoms of MND begin to appear gradually and keep developing with time till all skeletal muscle activities become impossible [11]. One of the common types of MND is Amyotrophic Lateral Sclerosis (ALS). Additionally, BCI wheelchairs can be beneficial for individuals diagnosed with any medical condition affecting mobility, such as Spinal Cord Injury (SCI). Every year, around 5000 people are diagnosed with ALS [12] and there were approximately 294,000 active SCI patients in 2020 in the U.S. alone [13]. With 13.7% of the adult population in the U.S. living with a mobility disability in 2020 [14], smart wheelchairs have the potential to improve the quality of life of many people around the globe. Thus, it is

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one of the active research areas in the BCI field, and it is the focus of this study.

B. Neural Activity Measuring Techniques

Brain activity can be explored using different techniques. A main breakdown of BCI's different techniques is based on invasiveness. Invasive techniques require surgical intervention for the placement of certain tools inside the human body. These tools are often microchips. Though this technique offers direct interaction with the brain, it demands substantial human resources such as time, effort, and human skills, which translates into higher costs. As a result, it is less researched compared to non-invasive techniques that do not require such resources.

EEG is among the most non-invasive techniques used in BCI due to its low cost and overall effectiveness in depicting brain activity [15]. It is mainly composed of a headset of electrodes that provides a low-resistance path to the electrical signals generated from the underneath brain activity. These signals are then carefully processed to identify the brain activity associated with signal behavior. Several challenges pertain to EEG that can be intimidating to BCI researchers. First, EEG signals are naturally poor in spatial resolution, in order of a few centimeters [16], [17]. This is mainly due to the way the signals are transferred from the bottom layers of the brain (the source) through the brain tissues to the scalp where the electrodes are placed, this is called the Volume Conduction (VC) effect [8]. VC creates a challenge of mapping the electrodes to the targeted brain region, which already has little known about its functional structure [19]. The temporal resolution of EEG is considerably better, in order of milliseconds [20]. The high nonstationary behavior of EEG causes the technique to be more susceptible to environmental conditions such as surrounding noise, and makes it prone to many artifacts such as eye movement and biological processes inside the body [21], leading to an overall low Signal-to-Noise-Ratio (SNR) [22], [23]. As a result, EEG resembles a signal processing challenge to properly utilize the non-linear distorted brain signals.

Besides EEG, functional Near-Infrared Spectroscopy (fNIRS) is a commonly used technique for characterizing brain activity. It is based on a different methodology than EEG. It detects neural activity by sending an infrared light into the head tissues. This light gets absorbed by the oxyhemoglobin and deoxyhemoglobin [24] and based on this absorption, blood oxygenation levels are estimated [25] and these reflect the neural activity at the cortical location. fNIRS can be portable, easier to implement, and less susceptible to artifacts compared to EEG [26], but it can be more expensive. The two techniques can be coupled together for enhanced performance, such as in the work of [27] and [28]. In addition, medical imaging techniques can be applied with EEG and fNIRS, but those are rarely used for engineering applications due to their complexity and high cost.

C. BCI-Driven Wheelchairs

Compared with other EEG-BCI applications, such as cursor control and prosthesis, wheelchairs are accompanied by higher risks associated with system malfunction. First, this application is time-sensitive; the right command must be issued at the exact right time for proper operation. This is less significant in other applications, while for wheelchairs, this may lead to serious injuries. Also, BCI wheelchairs are expected to operate in a highly dynamic environment with several variations in the surrounding objects every time a task is performed. These are two main challenges specific to the wheelchair application. A separate section is dedicated to discussing the issues of EEG-powered wheelchairs, and since every challenge is an opportunity for progress, some of the most relevant research is introduced as well.

The article is organized as follows. The literature review is described in Section II. Then, the background information that is essential to comprehend the findings, along with some observations are in Section III. Section IV is dedicated to comparing the different approaches followed in the literature, along with a detailed description of the underlying reasons for the observed behavior. Section V is dedicated to introducing the challenges and proposed solutions for EEG wheelchairs. And finally, section VI highlights the conclusions of the study. Note that the acronyms used in this article are shown in Table I.

TABLE I
ABBREVIATIONS

Abbreviation	Full form
BCI	Brain Computer Interface
ML	Machine Learning
EEG	Electroencephalography
EMG	Electromyography
MND	Motor Neuron Disease
ALS	Amyotrophic Lateral Sclerosis
SCI	Spinal Cord Injury
VC	Volume Conduction
SNR	Signal-to-Noise Ratio
fNIRS	Functional Near-Infrared Spectroscopy
PRISMA	Preferred Reporting Items for Systematic review and Meta-Analysis
CSV	Comma Separated Values
DOI	Digital Object Identifier
EOG	Electrooculogram
MI	Motor Imagery
ERD	Event-Related Desynchronization
ERS	Event-Related Synchronization
SSVEP	Steady-State Visual Evoked Potential
ERP	Event-Related Potential
MT	Mental Task
DC	Direct Current
CSP	Common Spatial Pattern
DFBCSP	Discriminative Filter Bank CSP
BP	Band Power
PSD	Power Spectral Density
BPF	Band Pass Filter
SVM	Support Vector Machine
LDA	Linear Discriminant Analysis
FLDA	Functional LDA
SWLDA	Step-Wise LDA
RBF	Radial Basis Function
HKF	Hybrid Kernel Function
CCA	Canonical Correlation Analysis
FBCCA	Filter Bank CCA
RMS	Root Mean Square

II. LITERATURE REVIEW

For many, the work of Millan et al. [29], [30] established the research of BCI for mobility applications. It has kept

TABLE II
THE KEYWORDS AND FILTERS USED FOR THE LITERATURE REVIEW

Web of Science	**Keywords**: ((AB =(BCI) OR TI=(BCI)) OR (AB=(brain computer interface) OR TI=(brain computer interface)) OR (AB=(brain-computer interface) OR TI=(brain-computer interface))) AND ((AB=(Electroencephalogram) OR TI=(Electroencephalogram)) OR (AB=(EEG) OR TI=(EEG)) OR (AB=(brain) OR TI=(brain)) OR (AB=(electroencephalography) OR TI=(electroencephalography)) OR (AB=(electroencephalographic) OR TI=(electroencephalographic))) AND ((AB=(wheelchair) OR TI=(wheelchair)) OR (AB=(wheel chair) OR TI=(wheel chair))) **Filters**: 1) Must be article (not conference proceedings, review articles, book chapters, or data papers or letters) 2) Must be in English
PubMed	**Keywords**: ("BCI"[Title/Abstract] OR "brain computer interface "[Title/Abstract] OR "brain-computer interface"[Title/Abstract]) AND ("EEG"[Title/Abstract] OR "electroencephalogram"[Title/Abstract] OR "brain"[Title/Abstract] OR "electroencephalography"[Title/Abstract] OR "electroencephalographic"[Title/Abstract]) AND ("wheelchair" [Title/Abstract] OR "wheel chair"[Title/Abstract]) **Filters**: None
Scopus	**Keywords**: TITLE-ABS (((BCI) OR (brain AND computer AND interface) OR (brain-computer AND interface)) AND ((EEG) OR (electroencephalogram) OR (electroencephalographic) OR (brain) OR (electroencephalography)) AND ((wheelchair) OR (wheel AND chair))) **Filters**: 1) Must be article (not conference proceedings, review articles, book chapters, or data papers or letters) 2) Must be in English

slowly evolving, resulting in rich literature on all aspects of the model available today. Because of that, and since the target of this study is the practical implementation of BCI wheelchairs, a systematic review was conducted to limit and control the type of articles considered. The search was conducted in accordance with the Preferred Reporting Items for Systematic review and Meta-Analysis-Protocols (PRISMA-P) guideline [31] where the search and consideration criteria are documented for better reproducibility.

A. Search Strategy and Eligibility Criteria

The search was conducted on Mar 16th, 2022, between 9:00 PM and 11:00 PM EST in the following databases: Web of Science, PubMed, and Scopus. IEEE was excluded as it is part of Scopus. The keywords and the Boolean expressions used, along with the applied filters, are shown in Table II. The keywords were chosen to obtain the results specifically related to EEG-driven wheelchairs. Also, the search was limited to peer-reviewed articles written in English. These filters were only available in Web of Science and Scopus. The search was also limited to the article's title and abstract to limit the number of studies acquired. This is a plausible course of action, assuming the articles related to designing BCI wheelchairs would include the keywords BCI, EEG, and wheelchair in their abstracts.

The procedure followed in obtaining the studies considered herein is shown in Fig. 1. The total number of articles retrieved is 417. The papers were exported and downloaded from the three databases in Comma Separated Value (CSV) format. Then, the duplicated articles were removed by Excel using the Digital Object Identifier (DOI) of each. Papers without DOI were removed manually. Next, all manuscripts that are not peer-reviewed or written in any language other than English were removed. These are the ones obtained from PubMed where no filters were available in the search engine (see Table II). Subsequently, the articles that were deemed irrelevant were removed, mainly violating the search guidelines by not being a technical article addressing EEG-driven wheelchairs. Most of these articles studied a specific aspect of EEG-BCI applications, such as new feature extraction

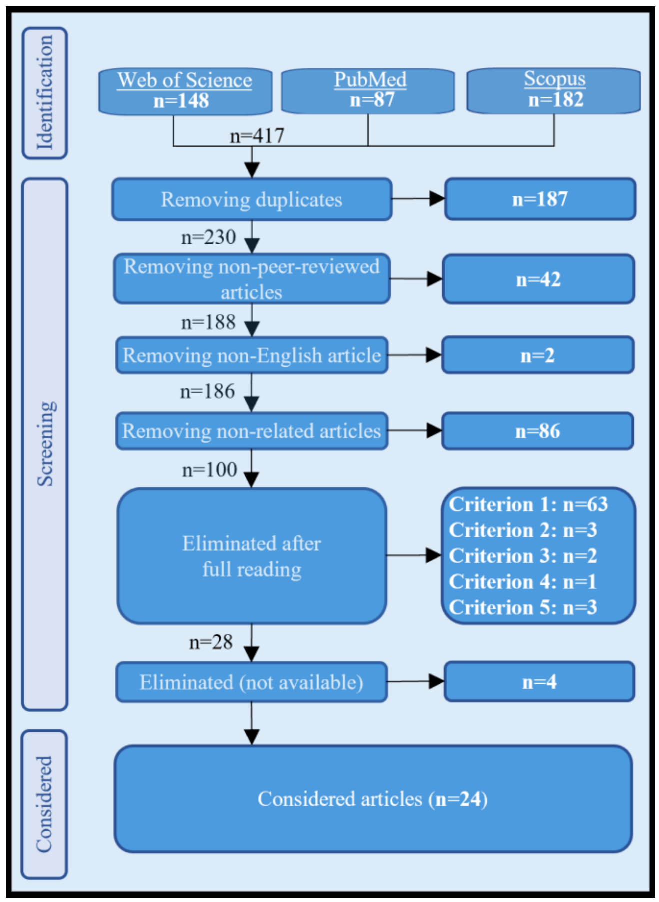

Fig. 1. The stages of Prisma strategy as applied in this work.

or classification techniques. This type of articles frequently mentioned the term "wheelchair" in the abstract as a direct BCI application. After that, the rest of the articles went through a thorough reading step to determine which articles to exclude according to the following five rejection criteria:

- **Criterion 1:** No real-life navigation test using a full-size wheelchair. This is to account for any differences in performance resulting from user fatigue or any variables introduced by the environment or the hardware

design. Hence, studies consisting of virtual (simulated) wheelchairs or small robots in place of wheelchairs were not included.
- **Criterion 2:**The EEG paradigm or acquisition details are not given. These are the articles where significant details about the paradigm used are missing. Such missing details include the EEG acquisition procedure, testing environment, etc.
- **Criterion 3:**No results reported.
- **Criterion 4:**Unclear testing procedure or results.
- **Criterion 5:**Wheelchair results embedded with other functions.

The reason for applying the five exclusion criteria is to keep this work focused on the practicality aspect of BCI wheelchairs. The insightful papers that were excluded may still be used to explain some methodologies but will not be part of the comparison carried out later. Of what is left (28 articles), 4 papers were not available, 3 because the journal repository is not accessible anymore, and the last one because it has been retracted. The final count for the articles considered is 24. Every step of the literature review process was repeated twice to ensure accuracy.

B. Considered Articles

The articles resulting from the search are shown in Table III sorted by the EEG paradigm used. The most useful details and performance metrics are included in the table as well. The following section will briefly introduce the needed background information to comprehend the information in the table. The performance metrics will be compared in the following section.

III. Observations

EEG is the main modality used in smart wheelchairs. This is mainly due to the large amount of information that can be extracted from the brain due to its complex and essential role in human cognitive and physical activities, and because it does not require any physical activity from the human, which is the main advantage of EEG over EMG, Electrooculogram (EOG), and eye tracking for this type of applications. With that said, EMG, EOG, and eye tracking have been used in conjugation with EEG to leverage the special characteristics of each, such as the work in [32], [33], and [34], respectively. A simplified scheme of the EEG modality as applied in wheelchair control is shown in Fig. 2. More details on the steps in the figure are provided below.

A. EEG Paradigms

EEG signals can be categorized into two groups based on how they are triggered: spontaneous and evoked. While evoked signals only arise when triggered by external stimuli, spontaneous signals are self-generated signals that reflect the human mental and awareness status. Motor Imagery (MI) signals belong to the spontaneous type of signals. They appear on the EEG as a result of mentally performing motor tasks using several body parts, such as the hands, the feet, and the tongue. MI signals are identified by a decrease in brain activity before and while performing motor tasks in a process known as Event-Related Desynchronization (ERD). After the motor task is completed, whether physically or mentally performed, the brain activity returns to normal in a process called Event-Related Synchronization (ERS) [35]. There are spatial differences related to ERD and ERS as well. The tempo spatial characteristics of ERD and ERS have been an open discussion for the last three decades, mainly because of their dependence on the limb used and on the rhythm of interest. MI is mostly associated with two brain rhythms, Beta (β) and Mu (μ) [35]. For hand MI, it is been shown that for ERD, a dominant neural activity exists over the contralateral side of the brain (opposite to the side of the limb used), while ERS shows high activity on the ipsilateral side of the brain, and this is valid for both the β and μ rhythms but it is less evident for β-ERS [36]. For an in-depth view of the ERS and ERD spatial characteristics, the reader is encouraged to review the work of [37], [38], and [39].

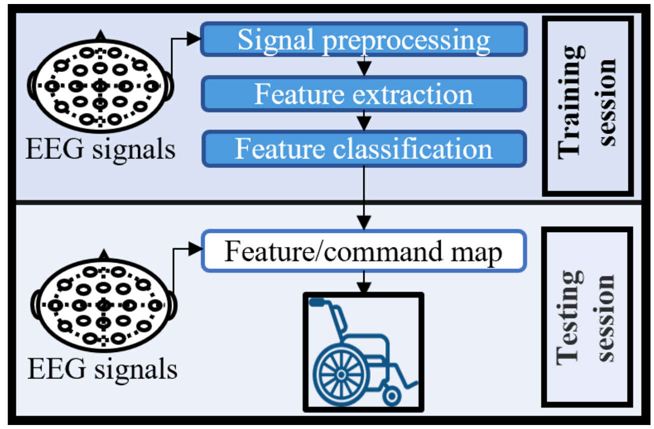

Fig. 2. An overall scheme of EEG-driven wheelchairs.

For evoked signals, two types are often used in BCI: P300 and Steady-State Visual Evoked Potential (SSVEP). P300 is a signal that appears approximately 300ms after the onset of an uncommon stimulus, whether it is visual, auditory, or somatosensory. This type of signals belongs to a group of signals called Event-Related Potential (ERP), which represents the signal behavior in the brain after experiencing an infrequent stimulus. This paradigm is used in BCI by utilizing different stimuli that each flickers with a slight shift from the other. This is to allow linking the signal observed on the EEG with the stimulus chosen by the user. For example, one stimulus can flicker at t_o and every other stimulus n can set to flicker at $t_n + t_o$. The other evoked signal paradigm, SSVEP, is triggered by lighting stimuli. These signals, unlike P300, are periodic, following the periodic stimulus rather than a single spike. The frequencies of the generated signals are integer multiples of the stimulus' fundamental frequency. Hence, it is relatively simple to achieve a high number of commands by using stimuli flickering at distinctive low frequencies.

While both signal types, spontaneous and evoked, are used in the literature, each holds a different set of pros and cons.

TABLE III
STUDIES CONSIDERED IN THIS WORK

Paradigm		Control level*	Work, yr.	MI/MT features	Classifier	EEG classifier Training/ sub.***	Navigation test						
							Subjects[1,#]		Test		Performance metric		
							Tot. num.	BCI exp.	Diff. Level**	Rounds /sub[1]	Acc. [%]	Time/ dist. [s/m]	Other
Spontaneous	MI & MT	L	[41], 2018	BP	LDA	160 trials[2]	10H	1	L	2	65.50	18.20[3]	1.48 comm./m
Spontaneous	MI	L	[42], 2018	CSP	LDA	270 trials, subject to user performance[2]	7H	7	I	15	-	13.65[4]	0.02 coll./m 0.11 coll./min 2.25 comm./m 9.88 comm./min
Spontaneous	MT	L[5]	[43], 2017	Statistical features and BP	ANN, SVM & RF	30 trials	3H	-	L	1	-	-	0.37m RMS position error
Spontaneous	MI	L[5]	[44], 2017	BP	LDA	160 trials[2]	9H	1	L	1	76.92	60.65	1.53 time ratio
Spontaneous	MI	L	[45], 2017	CSP	SVM	-	4H	-	L[6]	10	-	5.60	0 coll. 1.05 dist. ratio 1.17 time ratio
Spontaneous	MI	L[5]	[46], 2013	CSP	LDA	120 trials	1	-	L	9	-	-	2.58 coll./min 6.61 comm./min
Spontaneous	MI	L[5]	[47], 2011	BP	LDA	360 trials	2	2	L	4	-	-	0 coll. 4.98 comm./ min
SSVEP		L[5]	[48], 2021	-	CCA	160 trials	8	-	L	1	93.90	8.13	1.8 comm./m 13.24 comm./min
SSVEP		L,H & B[5,7,8]	[49], 2020	-	PSDA	-[2]	5	-	I	1	89.87	-	0.93 comm./min
SSVEP		L	[50], 2013	-	Statistical maximum	80sec session[2]	13 (12H)	0	I	1	96.23	-	21.98 comm./min
P300		L, B[9,10]	[51], 2021	-	LDA	81 trials	13 (7H)	1H	H	1	94.75	-	1.48 comm./min
P300		B[11,5]	[52], 2019	-	LDA	144 trials	5H	-	L	1	79.40	23.55[12]	-
P300		L[5]	[53], 2013	-	Bayesian classifier	3min session	11 (10H)	5H, 1D	H	1	82.50	11.71	0 coll. 1.12 dist. ratio 2.64 time ratio
P300		H[5]	[54], 2010	-	SVM	716 trials	5H	-	L	1	100	-	15s response time
Hybrid	MI& SSVEP	L	[55], 2022	CSP	MI: HKF-RVM SSVEP: CCA	MI: 160 trials[2,13] SSVEP: -	8H	3	H	1	-	-	0.025 coll./m
Hybrid	MI& P300	L	[56], 2017	CSP	LDA	MI: 540 trials P300: 2700 trials	8H	5	I	6	-	14.84	1.47 comm./m 5.81 comm./min 0.05 coll./m 0.27 coll./min
Hybrid	MI& SSVEP	L	[57], 2014	CSP	SVM	MI: 120 trials SSVEP: 3min session Hybrid: 168 trials	3H	3	L	2	-	14.60[12]	0 coll.
Hybrid	MI& SSVEP	L	[58], 2014	CSP	MI: SVM SSVEP: CCA	MI: 60 trials Hybrid: 168 trials	3H	-	L	4	-	14.19[4,12]	0 coll.
Hybrid	MI & P300	L	[59], 2012	CSP	LDA	MI: 180 trials Hybrid: 60 trials	2	-	H	5	-	6.16	0 coll. 1.12 dist. ratio
Multi-modal	MI &EOG	L	[33], 2019	CSP	SVM	360 trials[2]	5H	2	L	3	-	-	.033 Coll./m[12]
Multi-modal	P300 &EOG	H[5] L[5]	[60], 2017	-	Max correlation	34 trials	10 (5H)	-	L	6	-	5.45 7.30	-
Multi-modal	MI, P300& EOG	L	[61], 2014	CSP	EEG: SVM EOG: CCA	EEG: 480 trials	4H	4	H	10	-	7.86	0 coll. 1.13 dist. ratio 1.22 time ratio
Multi-modal	MI, P300 &speech	L	[62], 2014	CSP	P300: SVM MI: SVM	90 trials	5H	-	L	10	-	3.41	0 coll. 1.14 dist. ratio 1.12 time ratio
Multi-modal	Spon. EEG &blinking	L[5]	[63], 2012	BP	None	None	7H	3	L	3	-	20.59	-

[1] Highest number is reported
[2] Certain threshold to qualify for navigation test
[3] Includes two stops
[4] Includes one stop
[5] Equipped with environment detection system
[6] Carried in outdoor environment
[7] Destinations saved when passing by it
[8] Reported results are for hybrid system
[9] Low-level commands to choose destinations
[10] Reported results are for the low-level system
[11] Destinations within sight
[12] Approximated distance
[13] Extra session to determine thresholds (MI and SSVEP)
* L-low, H-high, B-hybrid
** L-low, H-high, I-intermediate
*** None reports using subject-independent classifiers
# H-healthy (no known physical disability), D-physically-disabled

For evoked signals, several cycles are needed to conclude the final decision. This is to ensure robust translation of the response signal. In other words, to mitigate possible noise and artifacts from the environment. This issue is critical as it slows down the command translation process. Also, evoked signals can cause tiring for the eye due to the continuous exposure to flickering sources. While this issue does not exist in the MI paradigm, MI suffers from the high mental workload placed on the brain compared to evoked signals; both P300 and SSVEP do not require performing any mental imagery tasks. One advantage of MI is that it gives the user a full sense of control as the user can issue a command at any time, unlike the evoked signals case where a sequence of stimuli must occur to issue the command. Because of that, MI systems are often called active systems, and evoked signals are called reactive systems. The biggest disadvantage of active systems is the need for extensive user-specific training sessions before the chair is used. This is a result of the non-stationary and noisy nature of EEG signals that cause high variability in response among subjects and across different sessions. This issue necessitates building the classifier using data from the same subject that will be using the classifier in real time at a later stage. The other disadvantage of MI is the limitation on the number of commands, which arises from the limited number of motor activities possible to perform by the user. One solution to this problem is using other biological modalities to perform the commands not achievable by EEG, such as EMG, EOG, and eye movement and position tracking. Lastly, it is believed that user MI training will result in better performance with time as the user adapts to the classifier by receiving several feedback cycles. P300 on the other side is expected to have lower performance with time because of aging [40]. For the above reasons, both BCI systems, active and reactive, have drawbacks that limit their implementation. They also have some unique characteristics that are worth exploring for the potential of transferring the technology to the real world. Table IV shows a side-by-side comparison of the different paradigms.

The three EEG paradigms (MI, P300, and SSVEP) can be used alone, or in a combination of two or three. Any use of multiple paradigms is referred to as hybrid models in this article. EEG can also be combined with other physiological modalities to form what is known as multi-modal BCI systems. From Table III, secondary modalities include speech, and EOG, which is a technique to measure the surface voltage from the eye, mainly triggered by blinking. In addition to the aforementioned EEG paradigms, the work of [63], [43], and [41] used spontaneous EEG signals different from the MI paradigm. In [63], they used the intensity level of the filtered signal in the alpha band. In [43] and [41], they targeted Mental Tasks (MTs) which they are ERS/ERD signals different from MI. In [43], they used math solving, text reading, and relaxing. In [41], mental arithmetic operations and word chains were used. The use of MTs is far less common than MI. From Table III, all paradigms are actively being used, which indicates that no ideal model is determined. With that being said, it is believed that MI provides a better user experience compared to MTs in navigation applications. For example, associating right and left directions with right and left MI is more intuitive than using MTs.

TABLE IV
DIFFERENT PARADIGMS USED FOR EEG-DRIVEN WHEELCHAIRS

	EEG signals		
Types	**Spontaneous** Self-generated	**Evoked** Evoked by external stimulus	
Paradigm	**ERS/ERD(SMR): MI** Generated by executing mental motor movements	**ERP: P300** Generated 300ms after experiencing an infrequent stimulus	**VEP: SSVEP** Generated after experiencing a flickering light source
Method	Every motor task is associated with a different command	The timing of the generated signal is linked to the stimulus	The frequency of the generated signal is linked to the stimulus
Eye fatigue	Lower	Higher	
Mental workload	Higher	Lower	
User training	Extensive	Minimal	
Num. of commands	Limited	Higher	
Setup requirements	Low	Higher	
Control	Full self-control (natural driving feel)	Pseudo self-control (dependent on stimuli)	
Performance with time	Expected to increase with user training	Drops for P300 with aging [40]	

B. Control Methodologies

The control level refers to the method of interaction with the chair. There are two control methodologies commonly used in the literature, these are low-level (asynchronous) and high-level (synchronous). In the first type, the user controls the wheelchair through directional commands. The EEG signals from the user are mapped to directional chair movement commands, such as right, left, forward, etc. For example, a right-hand MI is mapped to a 90° right turn of the wheelchair. High-level systems on the other hand refer to systems where the EEG signals are mapped to destinations rather than directions. The destinations are built-in (pre-programmed) into the model. So, each EEG signal will select a different destination that the wheelchair is capable of automatically driving to it. There is also a third type of control, which is a combination of low and high-level control commands, known as hybrid systems.

From Table III, most systems adopt the low-level model. This is probably due to the flexibility these systems offer in navigating to unseen places and the fact they do not require external aid. Also, very few articles show an independent high-level system despite its advantage of requiring little mental work and training from the user. This is understandable since it is limited by the list of pre-defined locations; modifying the list would probably need an intervention by someone besides the user. Another reason is the extra equipment required for environment detection and path planning. This is crucial from a cost perspective as accurate path navigation and collision avoidance systems require fast and reliable environment detection equipment implying higher cost, so it is generally less appealing to the audience.

TABLE V
EEG ACQUISITION AND PREPROCESSING DETAILS FOR THE ARTICLES IN TABLE III

Paradigm		Work, yr.	EEG num. of electrodes (region)*	Sampling rate	Wireless/ wired EEG	Use of amplifier	Dry/ wet EEG electrodes	Active/ passive EEG electrodes	Artifact removal technique
Spontaneous	MI & MT	[41], 2018	9 (F, C, P, T)	200	-	Yes	-	-	None
Spontaneous	MI	[42], 2018	31 (F, C, P)	250	-	Yes	-	Active	-
Spontaneous	MT	[43], 2017	14 (F, P, T, O)	128	Wireless	-	Wet	-	Yes (custom)
Spontaneous	MI	[44], 2017	9 (F, C, P, T)	200	-	Yes	-	-	None
Spontaneous	MI	[45], 2017	24	250	Wireless	-	Dry	-	-
Spontaneous	MI	[46], 2013	15 (F, C, P, T)	250	-	Yes	-	-	-
Spontaneous	MI	[47], 2011	10- F, C	250	-	Yes	-	-	-
SSVEP		[48], 2021	8 (O)	-	Wireless	Yes	Dry	-	-
SSVEP		[49], 2020	1 (O)	250	-	Yes	Wet	-	-
SSVEP		[50], 2013	6 (O, F)	240	-	-	-	-	-
P300		[51], 2021	12 (F, C, P, O)	256	-	Yes	-	Active	-
P300		[52], 2019	15- C, P, O.	200	-	Yes	Wet	-	-
P300		[53], 2013	12 (F, C, P, O)	256	-	Yes	-	Passive	-
P300		[54], 2010	15 (F, C, P)	250	-	Yes	-	-	Yes (custom)
Hybrid	MI& SSVEP	[55], 2022	12 (C, P, O)	256	-	Yes	-	-	-
Hybrid	MI& P300	[56], 2017	18 (F, C, P, O)	250	-	Yes	-	Active	-
Hybrid	MI& SSVEP	[57], 2014	SSVEP:4(P, O) MI:11(F, C)	256	-	Yes	-	-	-
Hybrid	MI& SSVEP	[58], 2014	15 (F, C, P, O)	256	-	Yes	-	-	-
Hybrid	MI & P300	[59], 2012	15 (F, C, P, O)	250	Yes	Yes	-	-	-
Multi-modal	MI &EOG	[33], 2019	EEG: 9 (F, C)	250	-	Yes	Wet	Passive	-
Multi-modal	P300 &EOG	[60], 2017	2 (O, C)	200	Wired	Yes	Wet	-	Yes (mean removal)
Multi-modal	MI, P300& EOG	[61], 2014	15 (F, C, P O)	250	-	Yes	Wet	-	-
Multi-modal	MI, P300 &speech	[62], 2014	15 (F, C, P, O)	250	-	Yes	-	-	-
Multi-modal	Spon. EEG &blinking	[63], 2012	Headband	512	Wireless	Yes	-	Active	-

* F: frontal, C: central, P: parietal, O: occipital, T: temporal

C. Data Acquisition

An essential piece of information for BCI systems is the details of the EEG signals acquisition, mainly the number of electrodes and the targeted brain region. This is crucial to assess the feasibility of the technique as setting up EEG can be a tedious process that requires a certain level of experience from the examiner. The data acquisition details and the preprocessing steps for some of the articles in Table III are shown in Table V. The brain signals are extracted using an EEG cap composed of a number of electrodes placed according to a well-established configuration called the 10-20 configuration. While more electrodes may offer greater detail, it entails many practical issues. From Table V, the number of EEG electrodes and their locations differ across the studies as they target different brain signals active in different regions of the brain.

The MI signals are active over the motor cortex [64], [65] located in the central lobe close to the front region. This explains the use of those regions in most studies utilizing the MI paradigm. The entire area surrounding the motor cortex is usually targeted to account for the poor spatial resolution and the possible shift in electrode positions during the cap install. The occipital region works well in showing the visual effects on the brain, making it preferred to use in SSVEP applications. The location to detect the P300 signal depends on the stimulus type whether it is visual or auditory [66].

In addition to the poor spatial resolution of EEG, another fundamental reason for the difference in targeted brain regions in the studies is the lack of a solid understanding of the interconnections between the brain regions and the lack of thorough understanding of the brain functional strategies. Accurate targeting for a brain region lowers the number of electrodes needed, which greatly influences the applicability of EEG in social settings. For instance, the average number of electrodes in the SSVEP case is noticeably lower than it is for MI. This is due to the smaller area of concentration.

D. Signal Processing

A BCI-driven wheelchair system is composed of two parts, as shown in Fig. 2. The first part is the training session, which is a controlled experiment conducted before the navigation test takes place to extract EEG signals from the users. These signals are then downsized via what is called a feature extraction step for use in building and optimizing the ML classifier in a step known as feature classification. Since the classifier is constructed based on subject-specific data, it is called a subject-specific classifier. The second part is the testing session where the navigation test takes place. In this part, the user initiates the commands and classifier performance is reported. The details of each of the steps are out of the scope of this study but below is a brief description of each. The typical EEG preprocessing steps are:

1) Amplification: Amplifying the signal is a necessary step to increase the SNR to help differentiate the brain signal from the environment-induced noise and artifacts. Amplification can be either done at the electrode level using active electrodes (an individual amplifier is located next to each electrode) or after the signals from all channels are transmitted to the processing unit. The use of active electrodes is valuable in that it is carried out before any interference from the neighboring electrodes or nearby external sources of noise occurs. Passive amplification, on the other side, is not able to address electrode interference as it is done on the data transmission level. The brought value of active electrodes is still up for discussion. Though it was shown in [67] that lower power values are noticed using passive electrodes, other studies show comparable noise levels for both types [68], [69]. This should not be surprising as the added value is highly dependent on the interference level and experimental conditions, such as the electrode impedance value [70]. For the studies screened in this work, [42], [51], [56], [63] used active electrodes. Besides [51], no significant improvement is observed. Note that the four studies were conducted in an indoor environment with limited noise sources, so the value of using active electrodes is most likely underestimated herein.

2) Sampling: Sampling is needed to convert the signal from analog to digital format for easier processing. As EEG is known for its noisy behavior and fast activity, down sampling the analog signal is usually done without a major loss in accuracy. Of the studies in Table III, 21 studies used a sampling frequency between 200 Hz and 256 Hz, so this is an agreed-upon reasonable sampling frequency that maintains good signal quality without necessitating much computing capabilities.

3) Filtration: Filtration of unwanted frequencies is an essential step for all systems. Depending on the targeted frequency range for the brain signals, the appropriate filters to remove other frequency components are applied. Noise and artifacts of high frequencies are easy to identify and remove since EEG signals are mostly of low frequencies. The general filtering procedure for most of the studies screened is to apply a bandpass filter around the needed frequency range along with a notch filter at 50/60 Hz to remove powerline interference. The bandpass filter usually starts at very slow frequencies larger than 0 to avoid Direct Current (DC) interference and extends to around 30 Hz, this covers $\alpha, \beta, and \gamma$ rhythms in addition to all possible P300 and SSVEP frequencies. The exact filtration range differs in the literature as it is dependent on the noise sources.

E. ML Steps (Feature Extraction and Classification)

1) Feature Extraction: Feature extraction is meant to extract the features that Best represent the signal qualities to reduce the data size with minimal loss in quality.

From Table III, it is evident how the Common Spatial Pattern (CSP) [71], [72] is overwhelmingly dominating the field of MI-BCI. CSP is a powerful spatial filtering technique based on joint diagonalization of the spatial patterns to find a transformation matrix for each of the two classes. The first and last few rows of each matrix are used to maximize the variance in the band power between the two classes. This method is highly dependent on the subject and works with only two classes at a time. Thus, when there are more than two classes, which is often the case, it can be done in a one-versus-all fashion, also known as multi-CSP. This has been applied in [42], [56], [59], and [61]. There have been several modifications to the original algorithm such as the popular Discriminative Filter Bank CSP (DFBCSP) method [73], used in [55]. Moreover, Band Power (BP) features can be used for MI. As the name implies, BP features are the power of the EEG signals in each frequency band [74]. For MTs, many statistical features can be used. In [41], they used four statistical features: mean absolute values, standard, deviation, line length, and the number of zero crossings.

For SSVEP and P300 the process is less critical and not always necessary as the amount of data is far more reasonable compared to MI and it is easier to identify because of the well-defined brain reaction to both paradigms. For SSVEP, since the frequency of the generated signal is known, Power Spectral Density (PSD) can be easily applied to identify a specific frequency, [50] is an example of this technique. For P300 on the other side, the timing of the generated signal is what is known to the operator. Thus, the use of a Band Pass Filter (BPF) targeting the expected time frame of the P300 response is a valid common technique, the work in [59] and [60] utilize this technique.

2) Feature Classification: From Table III, Support Vector Machines (SVM) [75] and Linear Discriminant Analysis (LDA) [76] are the most common techniques used in the literature. LDA is a linear classifier that performs the separation by constructing hyperplanes that minimize the variance within each class and maximize the distance between the two classes' means. It has various variants, such as Functional LDA (FLDA) used in [51], and Step-Wise LDA (SWLDA) used in [52]. SVM is a classifier that imitates transformation to a higher dimension for maximized separability via using kernel functions. In EEG, the Radial Basis Function (RBF) kernel is very common to use, such as in the work of [58], as well as the Hybrid Kernel Function (HKF) used in [55].

Canonical Correlation Analysis (CCA) is commonly used for reactive systems to find the correlation between a reference signal resembling the stimulus and the generated signals, such as in [57]. It can also be used to link the response recorded in training to the actual signal generated while testing. Filter Bank CCA (FBCCA) is a modification of CCA that is better utilized to detect the harmonics of the source fundamental frequency [77] and it was used in [55]. CCA is only one method of finding the correlation between two signals. Other methods can be applied effectively to classify both P300 and SSVEP response signals. For an extensive review of EEG classifiers, the reader is encouraged to peruse the work of Lotte et al. [78].

3) Classifier Training: Classifier training refers to the process of collecting data from the subjects for the purpose of constructing the ML classifier. Classifier training is often a time-consuming process that takes much effort from both the examiner and the user, particularly since training is a subject-specific process. To the best of the authors' knowledge, no one has ever succeeded in using pre-trained BCI models, including all studies in Table III.

In the table, the training sessions conducted in each of the studies are shown. The term "trial" refers to the instance where the user performs a mental task, whether it is an actual mental task in the case of MI and MT or perceiving a stimulus in the case of reactive systems. With a few exceptions, it is clear how many trials are always needed before the experiment takes place. Note that the trials must cover all mental tasks or stimuli presented, which increases the time needed to finish the experiment, especially as this session is repeated for each subject. MI training can last for a few hours, while in reactive systems, it can be carried out in a few minutes.

4) Testing and Performance Metrics: The number of subjects who carried the tasks and their disability status are included in the table. The letter "H" represents healthy participants, meaning that no mobility disability was disclosed by the subject. The letter "D" refers to individuals diagnosed with any type of motor disability. There have been some studies that discuss the difference in BCI performance between healthy and disabled individuals. Hence, having several disabled individuals performing the tests adds credibility to the effectiveness of the proposed model. Whether the difference in performance is driven by physiological or behavioral reasons, this was observed in at least two of the studies in Table III, these are [51] and [60]. Also, the users are classified if they have any experience of any type with BCI applications. This is to weigh the effect of subject training, which is believed to be a determining factor in the overall performance. The work of [55] and [63] confirm this idea while [56] did not show a difference between the two groups. The difficulty level of the test along with the number of rounds performed by each subject are included as well. The difficulty level is included to provide a reference meaning to the results reported. While most articles conducted a relatively easy indoor navigation experiment, some performed more challenging ones by placing obstacles in close proximity to the user's navigation path for example. High-difficulty tasks refer to challenging experiments where the test is usually conducted in tight places and require maneuvering skills to avoid collisions.

The last section of the table presents different performance metrics important to assessing the different designs. First, there are the accuracy values, as achieved during the navigation task. Accuracy is defined as the number of correct commands captured by the classifiers with respect to the total number of commands initiated by the user in real-time. A more universal testing performance metric is the time taken to cross a certain distance [s/m]. Simply, it is the speed reciprocal. Except where noted, the distance and time were taken directly from the papers. More results are shown in the last column of the table. These include the number of collisions and the number of commands per unit of time or distance, the time and distance taken with respect to the optimal minimum values, and also the number of commands which is a valuable metric for assessing the mental workload placed on the user.

IV. Comparison and Detailed Description

As said before, the several major differences in the designs make the comparison between the different studies more challenging. With that, a detailed look at the different articles in Table III is introduced in this section to help shape some conclusions on the methodologies adopted in the literature.

A. Spontaneous Paradigm

All MI studies utilize the low-level BCI model, which should not be surprising due to the limited possible number of MI tasks. Of the seven studies, only two report accuracy values: 65.50% and 76.92% for [41] and [44], respectively. Both studies used band power features with an LDA classifier. The data acquisition, training, and navigation tests are also similar as they both are coming from the same group of researchers. Though the reported accuracy exceeds the chance level, 50% and 25%, respectively, they are lower than acceptable for practical applications. The low accuracy values are reflected in a long time needed to finish the experiments. For [41], the average of 18.20 s/m is a high value, especially considering the simple navigation task of moving in a short straight line with two stops along the route. The short-distance route along with the needed stops resulted in a high number of commands. Though the accuracy is better in [44], the time/distance metric is much higher due to the collision detection mechanism that was automatically activated many times to avoid collisions in the tight corridor used for navigation. In both studies, the authors believe that the main driver of the poor performance is the low accuracy values reported in the calibration session; most participants scored in the 70s and 80s range. This is despite the fact that the users with error exceeding 30% were removed from the navigation experiment and claimed

BCI illiterate. BCI literacy is a condition where the subject cannot produce mental tasks with accuracy above 70% [79]. In [47], a similar system is proposed but less practical as every command moves the chair to a new point of a grid covering the testing area. This operation is less smooth as it requires a high number of commands to travel between places (around one command every ten seconds for the navigation task reported). In [46], CSP features are used to train an LDA classifier, which is a common combination in the literature. The model was only tested using one subject for an easy task and similar mental work to what is reported in [47] was needed. The installed collision avoidance system was able to avoid all collisions with a rate of 2.58 collision per minute. Based on the given testing area geometry, the speed reciprocal is expected to be very high.

The work in [42] is one of the promising studies utilizing MI. 31 active electrodes were used to collect the signals, which is on the high end. A CSP-LDA combination is used for users with some level of BCI experience who went through reasonable training before performing an indoor path navigation task with one waypoint 15 times. The number of commands turned out high as the task required several turns along the way and because of a few collisions that occurred along the way. On average, the chair needed 13.65 seconds to cross one meter of distance including the stop point. Though this is a high number, the authors believe thee results of this study are truly reflective of the paradigm used as it was carried out with several subjects in a non-trivial task and several meaningful results are reported.

The work in [45] is the only work to conduct the navigation task in an outdoor environment. This is of extreme significance to assess the environmental effect on the overall performance. With noting that the signals were acquired with 24 dry electrodes and a typical SVM classifier is used to process the CSP features, an impressive 5.60 s/m on average was needed to perform an intermediate-level task of moving between objects in an open space. The other results are encouraging as well. Note that the time ratio is obtained by using a fixed 0.2 m/s chair speed as a reference and the distance ratio is the ratio of the distance taken to the lowest distance between the start and end points.

Lastly, the single use of MTs was tested in [43]. The use of a combination of classifiers exceeded the accuracy values obtained from the single classifiers and was able to reach a 90% limit. Unfortunately, it is hard to analyze the overall system performance by only knowing the Root Mean Square (RMS) position error, but this study has shown potential in the combined use of classifiers.

B. Evoked Signal Paradigms

The work shown in [48] and [50] use the SSVEP paradigm for operating the wheelchair. They place several electrodes in the occipital region to capture the signal resulting from the lighting stimuli. The first note to make is the high accuracies achieved compared to MI which is expected for evoked signals. The speed reciprocal is approximated to be in the range between 18 s/m and 40 s/m for [50]. The results are based on four different tasks performed by several individuals ranging between 4 and 13 per task. Based on the high number of participants and considering the slow SSVEP paradigm, it should not be surprising to have this high s/m ratio. The same metric in the other study [48] is decent. This is mainly due to the easy navigation task performed. From both articles, it is also clear how the number of commands is noticeably high compared with MI. With that, it is expected to induce a lighter mental workload on the user as these commands resemble gazing at the stimuli and not performing actual mental tasks.

The other study of SSVEP is [49]. The model created for this work can be used in low, high, and hybrid formats. The main paradigm is the low-level paradigm where the user initiates control commands in the form of directions to the chair. While traveling using that paradigm, the user is able to program a specific location to be saved for later use in a high-level fashion. The test conducted is a hybrid test composed of two tasks, one carried in low and one in high level. Such a system solves one of the biggest drawbacks of high-level systems, which is the need for external aid to enter new destinations.

The results using the P300 model are expected to be comparable to those of SSVEP. The work in [53] achieved a satisfactory performance when using P300 in a low-level fashion for a challenging task (1.12 distance ratio, and 2.64 time ratio). Accuracy (82.5%) is within expected as well.

The work of [54] shows a typical high-level system utilizing the P300 response. All commands were translated successfully (100% accuracy), and this is expected because of the limited number of commands needed in high-level systems. On average, 15 seconds were needed to initiate the command from the user. Once initiated, the wheelchair automatically drives to the pre-defined destination.

The work of [52] shows a hybrid model where the user initiates low-level commands to choose a destination of the ones shown on the monitor. This system was particularly created for short-distanced destinations. This control scheme has resulted in the system being slower than expected. This raises a question on the feasibility of using high-level commands and whether it is easier to navigate to destinations within sight using directional commands. A similar control methodology is applied in [51]. The results in the table are obtained by applying the low-level scheme. It is obvious that the accuracy achieved is more than satisfactory, especially when noting that the participants were a mix of healthy and disabled individuals. Note that the signals are obtained using active electrodes as well. The low number of commands is because a large portion of the route is a straight path.

C. Hybrid Models

Hybrid models refer to models of more than one EEG paradigm. The work shown in [56] and [59] are similar as both utilize combining the MI and P300 paradigms to navigate the wheelchair by directional commands. Both studies use the CSP-LDA combination and conduct relatively challenging navigation tasks in tight corridors. Both also provide satisfactory results, but neither drastically outperforms other work in the literature. With that in mind, it is worth mentioning that the use of multiple paradigms may offer new capabilities that are not necessarily reflected in the results. One example of this is the use of the evoked signal paradigm to control the chair speed while dedicating MI for issuing the navigation commands, such as in [59]. Another possible use is for enhanced decision robustness.

Combining MI with SSVEP for low-level systems was tested in the work of [55]. For a challenging task, the rate of collisions is one per forty meters, which can be seen as acceptable considering the difficulty of the task. As well, it is worth noting that high classification accuracy values were achieved in the study (above 90%) for both MI and SSVEP.

The work shown in [57] and [58] is resulting from the same group of researchers utilizing very similar systems. The results of both show comparable performance obtained by conducting simple navigation tasks. The metrics reported do not show a major increase in performance compared to some of the single paradigm articles in the table.

D. Multi-Modal Models

Multi-modal models refer to models of more than one modality. Here, EEG is always one of the two. The work shown in [63] extracts the signals using a headband sensor rather than an EEG cap. While this is a more practical approach, it is limited by the area it covers. In this work, the intensity of the α rhythm as well as eye blinking signals appearing on EEG are taken as features. This approach resulted in a high s/m metric for a simple navigation task.

In [62], human speech was used to initiate the stop command, P300 to start the chair, and MI for the navigation commands. The test is a very simple one in a half-circle path carried out ten times per each of the five subjects. The s/m achieved is the lowest one seen in the literature. This positive result is further confirmed by the optimal time and distance ratios. Note that this exceptional performance is compromised by the technical challenges of facilitating the different modalities used.

Another common modality to use with EEG is EOG. It is considered a different modality in this study because it requires a different action besides mental activity. In [33], MI is combined with EOG. The number of collisions per meter is around 1/30m which is close to [55]. In [60], the P300 was combined with EOG. It is applied in both low and high-level fashion. Both were separately tested. It is clear that the low-level system is slower as expected because of the higher number of commands needed. Note that both results are satisfactory compared to the other studies in the table. Lastly, both P300 and MI are combined in [61]. A challenging task was conducted by four experienced subjects and good results were achieved.

V. Challenges and Future Trends

The main challenges of EEG-driven wheelchairs that prohibit a wider use of the technology are introduced below.

A. Lack of Standardized Testing

EEG-driven wheelchairs have many variables contributing to their final performance. To that end, a unified strategy to test the final product is a tricky task and under no circumstances a single metric would be sufficient to describe all details of the system. The metrics used in the literature are introduced in Table VI.

While accuracy, is a preferred metric in a lot of BCI applications, it has limited significance in high-level/hybrid systems as the number of commands issued in such systems is limited. Thus, the time/distance metric is believed to be a more thorough representation of system performance. This metric is not commonly used in the literature (the values reported in Table III were calculated by the authors). The metric though does not adequately account for any stop points along the route or the difficulty level of the navigation path. Additionally, the ratios of actual time and/or distance with respect to the minimum values help assess how close the developed model is compared to regular wheelchairs. The number of collisions is essential to ensure system safety. In short, there are several metrics to report. Excluding some of them may produce incorrect or faulty conclusions. In our opinion, all metrics in Table VI must be reported to avoid inaccurate conclusions. If these are reported, a good indication of the overall performance is possible, regardless of the navigation task.

The mental workload of the paradigm is another critical factor to consider. The direct way to assess the workload is by observing the number, duration, and type of tasks performed. Some researchers prefer using the well-established NASA task load index [80], while others come up with their own assessments, such as the work of [81]. The use of surveys is also possible. And lastly, a more systematic signal-based way is possible by studying the brain activity by means of ML, similar to the work of [82], [83], and [84].

B. Issues With the MI Paradigm

Due to the many advantages of MI over reactive systems, it is believed to have a real potential to become applicable in real-life settings. One of the biggest drawbacks of MI is the extensive training preceding the experiment. It is widely accepted and intuitive to believe that longer training sessions would generate better results. Classifier training is not only critical as it increases the requirements of the model, but it acts as a major barrier to commercial BCI wheelchairs since the user needs to train the model and cannot obtain it pre-programmed.

The other main issue with training is that it should be carried out for each subject. This is a tiring step for potential disabled users. This becomes more concerning knowing that the motor neuron abilities of MND patients keep changing with time [12]. In addition, there have been several studies that show age as a responsible factor for changing the brain signals behavior with time [85]. All of this indicates the instability of current approaches. To that end, the authors believe that adopting dynamic MI models where little-to-no user-specific data is required will boost the applicability of such systems.

A dynamic classifier is a classifier that needs a minimal amount of information from the user and keeps adjusting its parameters based on data obtained in real-time. This will eliminate the training session and results in a classifier more adaptable to different subjects and conditions. Reducing the training time holds high significance that extends beyond wheelchairs to several BCI applications. Recent work that started to discover this area includes [86], [87]. In the studies, the concept of transfer learning was deployed where only a small data set is needed from the targeted user and promising results of equal and even exceeding other user-specific training models were achieved, which shows a positive trend towards building robust universal classifiers.

One other limitation is the small number of achievable commands with adequate accuracy. Most researchers target the use of up to three MI movements, these are both hands and feet. If a wheelchair design requires a higher number of commands, these can be achieved by another modality or EEG paradigm.

C. Issues With Evoked Signals Paradigms

One of the challenges of P300 and SSVEP is the non-intuitive way the chair is being controlled which may cause hesitancy from potential users to use the technology. Also, these systems require extra equipment to be mounted on the chair to facilitate having the stimulus. As well, since these paradigms are often applied in a high-level fashion, they require expensive equipment for path planning and obstacle avoidance. And most importantly, the long response time in these models is hard to overcome as it is an artifact of the design itself.

Another issue for P300 models is the possibility of reduced performance with time as the eye gets used to the stimulus. Hence, the stimulus needs to be periodically changed. More crucially, both P300 and SSVEP are tiring to the eye, but the extent of this issue is still largely unexplored.

D. EEG Impracticality

One major challenge of EEG-based BCI is its impracticality as it is notorious for its potential hiccups. First, the use of a large array of electrodes increases the risk of individual electrode failure. Second, if wet electrodes are used, this requires frequent gel filling, which is a time-consuming process and cannot be done by the disabled individual. Also, it can be challenging to effectively attach the cap to the user's scalp and establish a secure connection, this is often the case for users with thick hair. These reasons make it hard to apply EEG in normal life situations and make it unappealing in social settings. In recent years, the industry started introducing modern easy-to-set-up EEG headsets. Examples are [88] and [89]. Although these are limited in their spatial coverage, they prove the possibility of building light and easy-to-use EEG headsets, especially if the targeted brain region is small. Thus, a huge step towards easier use of EEG would be examining the possibility of reducing the number of electrodes by fully capturing the brain activity by a selected number of electrodes. This is dependent on our understanding of the functional behavior of the brain. If fully understanding the brain functions is a lengthy and challenging process, then applying ML concepts to utilize the number and location of EEG electrodes would be a cheaper, easier alternative. Several studies have shown the validity of this approach, such as [90] and [91].

TABLE VI
COMMON PERFORMANCE METRICS USED WITH

Metric	Indication	Notes
Accuracy	Classifier performance	Less indicative for high-level and hybrid control systems
Time/distance	Overall general performance	Unsuitable to handle stops
Normalized num of commands	Mental workload	Commands have a different meaning based on the paradigm used
Normalized num of collisions	Control system effectiveness	The presence of control system should be disclosed
Training time	Generalizability and classifier rigidness	Less critical for reactive systems
Time ratio	Overall general performance	-
Distance ratio	Overall general performance	-
Performance over time	System durability	-

The other main issue of EEG is the low SNR [22], [23] which makes distinguishing the useful signal a challenging task, especially in a highly noisy environment. The unpredictable noise sources in the outdoor environment make it difficult for this application and this is why all studies in Table III, except for one, were conducted indoors with limited noise artifacts. Noise sources include lighting, motion, and any surrounding electrical devices. Some other noise sources are internal, generated from the biological systems inside the human body such as the hemodynamic continuous operation [21], [92]. These artifacts and noise sources can be easily removed when a great difference exists between their range of operation and the typical frequencies of brain signals. Before a robust filtration method is available, it is hard to imagine a successful transition of EEG to the outside environment.

VI. CONCLUSION AND STUDY LIMITATIONS

This review examined 24 peer-reviewed articles related to EEG-driven wheelchairs, with an emphasis on the feasibility of the current models. This article detailed the different approaches available in the literature, as well as the background material needed to understand the theory underlying the technology. The substantial differences among the models leave many open-ended questions about the best strategies moving forward. The article highlighted the pros and cons of the different systems and the needed improvements in the fields of data science, neuroscience, and signal processing to overcome the current challenges for wider implementation of the technology.

Although PRISMA guidelines were followed in conducting the review, there remains the possibility of human error in data collection and/or interpretation. This is one of the work's limitations. Another limitation is the possibility that some articles are missing owing to the search strategy employed. Having stated that, the authors are not aware of any relevant work that meets the search criteria but was not included herein. Finally, the nature of this review research prohibited a thorough overview of the methodologies used in the articles from being included. Thus, an interested reader is encouraged to refer to the original articles for detailed information.

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