# Neurocybernetic Assistive Technologies to Enhance Robotic Wheelchair Navigation

Poly Rani Ghosh[1*], Maria Afnan[1], Joy Biswas[1]


## Abstract

Millions of individuals worldwide face mobility impairments and rely on wheelchairs for assistance. Yet a significant portion of individuals with severe motor disabilities or insufficient familiarity with conventional interfaces cannot consider powered wheelchairs as a viable solution. Neurocybernetics present a promising solution to this challenge. Neurocybernetics involves exploring how the nervous system interacts with systems, like computers and robots. Through the use of interfaces users can control wheelchairs using neural signals from their brains making navigation more intuitive and effective. Assistive technologies, especially robotic wheelchairs powered by sensors and control systems, are essential for those disabled people, with mobility issues, to live more independently and better lives in their daily life even without the assistance of others. The primary objective of this study is to improve the quality of life for individuals with disabilities who depend on such assistance for their mobility requirements. This article examines some of the cutting-edge neurocybernetic devices that assist people with disabilities, such as brain-computer interfaces (BCIs), algorithms to understand brain signals, and adaptive control methods for wheelchairs. This study proposes a robotic wheelchair which utilizes the human brain signal and undergoes machine learning based classification model with neuromorphic adaptive control. It discusses the key considerations, difficulties, and potential uses of neurocybernetic robotic wheelchairs in real life situations. Additionally, it addresses the ethical, legal, and societal implications of using these technologies and suggests future research areas to advance their creation and use.


**Keywords:** Neurocybernetics, Robotic Wheelchairs. Brain-Computer Interfaces, Assistive Technologies, Mobility Impairments.

## Introduction

Mobility impairments affect millions of people globally, many of whom rely on wheelchairs to maintain their independence and quality of life. However, a significant proportion of individuals with severe motor disabilities or unfamiliarity with conventional powered wheelchair interfaces find themselves excluded from the benefits of these technologies. According to the World Health Organization (2024), around 75 million people worldwide require wheelchairs, but only 5-15% have access to them, reflecting a critical gap in providing mobility assistance to those in need. In this context, advancements in assistive technologies are crucial to address the limitations of traditional mobility aids and meet the diverse needs of users (Morbidi et al., 2022).

Conventional wheelchairs have been the cornerstone of mobility assistance for individuals with impairments, yet they come with limitations. Over the past few decades, researchers have made significant strides in developing powered robotic wheelchairs that

**Significance** | To enhance independence and quality of life through neurocybernetic robotic wheelchairs for individuals with disabilities.

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offer enhanced mobility solutions through automation and sensor-based control systems (How, Wang, & Mihailidis, 2013; Viswanathan et al., 2017). These wheelchairs integrate sensors, control algorithms, and robotic engineering to facilitate safer and more autonomous navigation for users. However, users with severe physical impairments often face challenges in controlling even these advanced systems due to limitations in motor function (Kutbi et al., 2020; Candiotti et al., 2019). As a result, there has been a growing interest in neurocybernetic assistive technologies, which directly bridge the gap between a user's neural activity and robotic control, bypassing the need for traditional interfaces like joysticks or touchpads (Rebsamen et al., 2010; Wolpaw & Wolpaw, 2012).

Neurocybernetics, an interdisciplinary field combining neuroscience, cybernetics, and artificial intelligence, offers a revolutionary approach to assistive technologies by leveraging brain-computer interfaces (BCIs). These interfaces enable direct communication between the brain and external devices, such as robotic wheelchairs, allowing users to control movements with their neural signals (Sinyukov et al., 2014; Ata, 2021). BCIs utilize electroencephalography (EEG) to capture neural activity from the brain, process the signals using machine learning algorithms, and convert them into actionable commands for the wheelchair (Ezeh et al., 2017; Ngo & Nguyen, 2022). The advantages of neurocybernetic systems include more intuitive control, faster response times, and reduced cognitive load, making them particularly suitable for users with limited physical capabilities (Carlson & Demiris, 2012; Erdogan & Argall, 2017).

The integration of neurocybernetics with assistive robotics has opened new possibilities for improving the independence and quality of life for individuals with disabilities. While previous studies have explored various aspects of robotic wheelchairs, including safety, ergonomics, and usability (Morales et al., 2018; Vailland et al., 2021), this paper focuses on a novel neurocybernetic model that utilizes advanced BCIs, signal processing, and adaptive control techniques. Specifically, it proposes a machine-learning-based classification system to interpret neural signals and optimize wheelchair navigation based on real-time feedback and user preferences (Li et al., 2017; Delmas et al., 2021). Additionally, the study highlights the ethical, legal, and societal implications of neurocybernetic technologies, recognizing the importance of addressing concerns about user privacy, consent, and data security (Teodorescu et al., 2021).

This study aims to present a comprehensive overview of the current state of neurocybernetic assistive technologies, focusing on their application in robotic wheelchairs. By discussing the principles, challenges, and future prospects of these systems, this study contributes to the growing body of research on how neurocybernetics can revolutionize mobility assistance. Furthermore, it emphasizes the need for continued interdisciplinary collaboration between neuroscientists, engineers, and healthcare professionals to refine these technologies and make them more accessible to those in need (Jeong et al., 2024; Ghezala, Sentouh, & Pudlo, 2022).

## Materials and Methods

### *Study Design*

This study involves the design, implementation, and evaluation of a neurocybernetic robotic wheelchair system aimed at improving mobility for individuals with disabilities. The system integrates neural signal acquisition, processing, and adaptive control to allow users to navigate a wheelchair using brain-computer interface (BCI) technology. The experimental framework was divided into five key stages: neural signal acquisition, signal processing, feature extraction, adaptive control, and system integration. All experiments were conducted in compliance with ethical guidelines, and informed consent was obtained from all participants (Morbidi et al., 2022).

### *1. Neural Signal Acquisition*

The neural signals required for controlling the robotic wheelchair were acquired using non-invasive Electroencephalogram (EEG) technology. The signal acquisition process involved the following steps:

#### *1.1. Electrode Placement:*

EEG electrodes were attached to the participant's scalp, particularly in areas responsible for motor functions and spatial awareness (e.g., motor cortex). The electrode configuration followed the international 10-20 system, which ensures accurate brain signal acquisition from motor-related regions (How et al., 2013).

#### *1.2. Electrode Type and Configuration:*

High-density silver chloride (AgCl) electrodes were used for EEG signal collection due to their sensitivity and compatibility with motor imagery tasks. For optimal signal acquisition, conductive gel was applied to reduce impedance at the electrode-skin interface. EEG signals were recorded at a sampling rate of 500 Hz with an 8-channel EEG system (Wolpaw & Wolpaw, 2012).

#### *1.3. Signal Amplification and Filtering:*

EEG signals were amplified using a 16-bit bio-amplifier with a gain of 1000x to ensure accurate signal detection. Filtering techniques such as band-pass filtering (0.5 Hz – 100 Hz) were applied to reduce noise and isolate the relevant frequency bands associated with motor imagery, specifically the mu (8–12 Hz) and beta (18–26 Hz) rhythms (Morales et al., 2018; Sumikura et al., 2019; Ata, 2021).

### 2. Signal Processing and Feature Extraction

Once the neural signals were acquired, signal processing algorithms were implemented to extract meaningful features associated with user intent (Kutbi et al., 2020; Devigne et al., 2022; Li et al., 2017).

#### *2.1. Preprocessing:*

The raw EEG data underwent artifact removal to eliminate noise from eye blinks, muscle movements, and other non-neural sources. Independent component analysis (ICA) was used to separate the noise components from the signal, and a notch filter was applied to remove power line interference (50 Hz) (Ezeh et al., 2017; Ngo & Nguyen, 2022; Ata, 2021).

***2.2. Feature Extraction:***

Key features were extracted from the preprocessed signals, including spectral power in the mu and beta bands, which are indicative of motor imagery. Time-frequency analysis was performed using wavelet transforms to capture the dynamic nature of brain activity during wheelchair navigation tasks (Benevides et al., 2011; Podobnik et al., 2017; Wolpaw & Wolpaw, 2012).

***2.3. Dimensionality Reduction:***

Principal component analysis (PCA) was employed to reduce the dimensionality of the EEG data while preserving the most significant features. This step ensured computational efficiency and improved classification accuracy by minimizing irrelevant information (Jeong et al., 2024; de Almeida Afonso & Ferreira Jr, 2023; Candiotti et al., 2019).

**3. Classification and Control**

***3.1. Machine Learning Model:***

A machine learning classification model was trained to interpret the extracted EEG features and translate them into control commands for the robotic wheelchair. For this study, a Support Vector Machine (SVM) algorithm was used due to its robustness in handling high-dimensional data (Candiotti et al., 2019; Kutbi et al., 2020). The SVM was trained on labeled EEG data from motor imagery tasks (e.g., imagining left or right hand movements) to predict directional commands for the wheelchair (Rebsamen et al., 2010; Ata, 2021).

***3.2. Model Validation:***

The classification accuracy was validated using a 10-fold cross-validation approach (Li et al., 2017). Accuracy, precision, recall, and F1 score were calculated to evaluate the model's performance (Morbidi et al., 2022; Carlson & Demiris, 2012). A threshold of 85% accuracy was set as the minimum standard for reliable wheelchair control (Ngo & Nguyen, 2022).

***4. Adaptive Control Mechanism***

The control system incorporated real-time feedback and adaptive learning algorithms to ensure smooth navigation and user-specific adjustments (How et al., 2013; Teodorescu et al., 2021).

***4.1. Adaptive Learning:***

A reinforcement learning algorithm (Q-learning) was employed to allow the wheelchair to adapt to the user's preferences over time (Morales et al., 2018). The system continuously updated control parameters (e.g., speed, acceleration) based on user feedback and environmental interactions (Erdogan & Argall, 2017). Feedback was provided to the user via a graphical interface showing real-time updates on the wheelchair's position and status.

***4.2. Real-Time Feedback and Calibration:***

The system was calibrated for each user to ensure optimal performance. Calibration involved adjusting the sensitivity of the control commands based on the user's brain activity during initial test sessions. Real-time feedback through visual displays and audio signals allowed the user to adjust their mental focus and improve the accuracy of commands (Jeong et al., 2024).

**5. Robotic Wheelchair Integration**

***5.1. Hardware:***

The robotic wheelchair was equipped with a custom-built control unit that interfaced with the BCI system. The wheelchair had motorized wheels with variable speed control and obstacle detection sensors to assist in navigation. An embedded microcontroller processed the control commands from the BCI and executed appropriate movements (Delmas et al., 2023).

***5.2. Software Integration:***

The control software was developed in Python using the OpenBCI library for EEG data acquisition and signal processing. The control commands generated by the machine learning model were translated into motor control signals, which were sent to the wheelchair via a wireless connection (Podobnik et al., 2017).

**6. Testing Environment**

The experimental setup was tested in both simulated and real-world environments. Participants were first introduced to the system in a virtual simulation to familiarize themselves with the BCI-wheelchair interface. Afterward, real-world trials were conducted in an indoor obstacle course to evaluate the system's performance in navigating complex environments. The participants' performance, ease of use, and mental workload were assessed through self-reported questionnaires and observational analysis (Leblong et al., 2021).

**Statistical Analysis**

Data from the EEG signal classification, user feedback, and wheelchair navigation performance were analyzed using statistical software (SPSS v.26). A paired t-test was performed to compare pre- and post-intervention results, evaluating the improvement in control accuracy and user satisfaction. P-values less than 0.05 were considered statistically significant.

## Results and Discussion

The proposed Neurocybernetic Assistive Model for Robotic Wheelchair Navigation introduces a novel approach to mobility assistance by leveraging brain-computer interfaces (BCIs) and advanced neurocybernetic technologies. The model presents a robust solution for individuals with limited physical abilities, offering them a direct way to control wheelchair movement through neural signals Wu et al., 2018.

***1. Neural Signal Acquisition***

The initial stage in the neurocybernetic process involves acquiring neural signals from the user's brain using Electroencephalogram (EEG) electrodes placed on the scalp. These electrodes capture brain activity related to movement and spatial navigation (Ngo., 2022). The placement and configuration of electrodes are crucial, as they ensure the signals accurately reflect the user's intent for controlling the wheelchair. For this study, standard EEG configurations like steady-state visual evoked potentials (SSVEPs) and event-related potentials (ERPs) were tested. These configurations effectively captured signals linked to motor imagery, which allowed users to control directional movements and stop commands through thought alone (Ata et al., 2021).

***2. Signal Processing & Feature Extraction***

The second phase focuses on enhancing and interpreting the neural signals using advanced algorithms. Filtering techniques such as linear filtering and spatial filtering were employed to reduce noise and emphasize important brain patterns, ensuring the system reliably decodes user intentions (De Almeida Afonso., 2023). Signal processing techniques extracted essential features from neural data, specifically those related to intended movement, such as spectral power and spatial coherence between brain regions. Using Principal Component Analysis (PCA) and Linear Discriminant Analysis (LDA), the system reduced dimensionality, which enabled the classifiers to quickly and accurately interpret the user's commands (Benevides., 2011).

***3. Classification & Command Generation***

The extracted features were classified using a variety of machine learning algorithms, including Support Vector Machines (SVMs), Random Forests, and Neural Networks, to interpret neural patterns into actionable wheelchair commands. The classifiers demonstrated high accuracy in distinguishing user intents, allowing for smooth and reliable control of the robotic wheelchair. One particularly successful method was the integration of a Genetic Algorithm Back Propagation Neural Network (GA-BPNN), which proved efficient in classifying neural data for real-time command generation (Ghezala et al., 2022).

***4. Adaptive Control***

The adaptive control mechanisms were a crucial component of the system's success, as they allowed the wheelchair to continuously adjust to the user's unique driving style and preferences. Algorithms such as Reinforcement Learning (RL) and Online Learning dynamically updated the wheelchair's control parameters based on real-time user feedback, improving response times and reducing the cognitive burden on users. By incorporating Bayesian Optimization and Meta-Learning, the system fine-tuned control settings to ensure the highest levels of performance, comfort, and safety. The results showed that the adaptive control algorithms significantly enhanced the user experience by allowing for smoother navigation and a more intuitive control mechanism (Del Castillo., 2012).

***5. Real-time Feedback & User Interaction***

One of the most significant advantages of the neurocybernetic model was its provision of real-time feedback to the user. Through visual, auditory, or vibrational feedback mechanisms, users were constantly informed of the wheelchair's status, enabling them to adjust their navigation inputs accordingly. This feedback system played a crucial role in ensuring safe and precise movement, particularly in complex environments like crowded areas or narrow pathways. The ability to receive immediate updates on the wheelchair's movement allowed users to feel more confident and in control (Rebsamen., 2010).

***6. Calibration & Validation***

Extensive testing and calibration ensured that the system accurately translated brain signals into wheelchair control commands. Calibration steps involved fine-tuning the neural signal acquisition and control interfaces, ensuring that the wheelchair responded accurately and consistently to user commands. Validation trials demonstrated a marked improvement in navigation accuracy, responsiveness, and overall user satisfaction (Carlsonw., 2012).

**Challenges & Opportunities**

Despite significant advancements in neurocybernetic robotic wheelchairs, challenges remain in signal accuracy and system robustness. Noise interference, imprecise decoding of neural signals, and variations in user brain patterns posed difficulties during initial phases. However, improvements in signal processing algorithms and adaptive control systems mitigated these issues, making the system more reliable in real-world scenarios (Welpaw., 2012).

Ethical considerations were also discussed, particularly the need to protect user privacy and ensure the safe use of neural data. Additionally, there are concerns about the accessibility and affordability of such advanced assistive technologies for a broader population. Future research should focus on reducing the cost of neurocybernetic systems while improving their ease of use.

**Future Research Directions**

Ongoing research is critical to enhance the effectiveness of neurocybernetic wheelchair models. Long-term studies will provide valuable insights into how the system affects users' daily lives and overall well-being. Continued collaboration between neuroscientists, engineers, and healthcare professionals will drive innovations in assistive technology, allowing people with disabilities to experience greater independence and a better quality of life.

## Conclusion

Neurocybernetic robotic wheelchairs offer a groundbreaking solution for individuals with mobility impairments, providing greater autonomy and control through brain signal integration. By leveraging advanced neural signal processing and adaptive control algorithms, these wheelchairs enable intuitive navigation without manual input. Despite significant progress, challenges such as signal noise, decoding accuracy, and ethical concerns regarding privacy remain. Continued research and collaboration between neuroscience, robotics, and assistive technology are essential to refine this model. Long-term studies and user feedback will further enhance its efficacy, paving the way for more widespread adoption, ultimately improving the quality of life for wheelchair users.

## Author contributions

P.R.G. conceptualized the project, developed the methodology, conducted formal analysis, and drafted the original writing. M.A. contributed to the methodology, conducted investigations, provided resources, visualized the data, J.B. contributed to the reviewing and editing of the writing.

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## Competing financial interests

The authors have no conflict of interest.

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