Review Article

BIOMEDICAL Journal of Scientific & Technical Research

ISSN: 2574 -1241

DOI: 10.26717/BJSTR.2026.64.010116

Artificial Intelligence (AI) in Neurorehabilitation: Current Status, Challenges, and Future Directions

Xiaomei Wang[1], Yingchun He[1], Ke Wang[1]* and Zhi Yan[1,2]*

[1]Sichuan College of Traditional Chinese Medicine, Mianyang 621000, China

[2]Department of Scientific and Technological Achievement Transformation, Capital Medical University, Beijing 100069, China

***Corresponding author:** : Ke Wang, Department of General Education, Sichuan College of Traditional Chinese Medicine, Mianyang 621000, China

Zhi Yan, Department of Scientific and Technological Achievement Transformation, Capital Medical University, Beijing 100069, China

ARTICLE INFO

Received: February 11, 2026

Published: February 26, 2026

Citation: Xiaomei Wang, Yingchun He, Ke Wang and Zhi Yan. Artificial Intelligence (AI) in Neurorehabilitation: Current Status, Challenges, and Future Directions. Biomed J Sci & Tech Res 64(5)-2026. BJSTR. MS.ID.010116.

ABSTRACT

Stroke, as the leading cause of disability globally, involves a lengthy rehabilitation process, and it is difficult for the therapeutic effect to reach the ideal level. Artificial intelligence (AI) technology presents a novel solution for stroke rehabilitation. This article systematically reviews the core applications of AI technology in stroke rehabilitation, analyzes its challenges and deficiencies at various levels, and anticipates future development from three aspects: multimodal fusion and algorithm optimization, low-cost adaptation and home-based rehabilitation system construction, and data security.

Keywords: Artificial Intelligence; Stroke; Neurorehabilitation; Multimodal Fusion

Abbreviations: GBD: Global Burden of Disease; AI: Artificial Intelligence; ML: Machine Learning; DL: Deep Learning; BCI: Brain-Computer Interface; VR: Virtual Reality; CT: Computed Tomography; MRI: Magnetic Resonance Imaging; CNNs: Convolutional Neural Networks; RNNs: Recurrent Neural Networks; LVO: Large-Vessel Occlusion; mRS: MODIFIED RANKIN SCALE; mPFC: Medial Prefrontal Cortex; DMN: Default Mode Network; FES: Functional Electrical Stimulation; rTMS: Repetitive Transcranial Magnetic Stimulation; SMR: Sensorimotor Rhythm; IMUs: Inertial Measurement Units; EEG: Electroencephalography; fNIRS: Functional Near-Infrared Spectroscopy; tDCS: Transcranial Direct Current Stimulation; TCM: TRADITIONAL CHINESE MEDICINE; EMG: Electromyographic

Introduction

Data from the 2021 Global Burden of Disease (GBD) Study indicate that approximately 69.9 million people are suffering from ischemic stroke, with 7.8 million new cases and 3.6 million deaths occurring each year. Around 80% of patient's experience varying degrees of disability [1,2], rendering stroke the leading cause of disability and the second leading cause of death globally [3]. Stroke exhibits the "five highs" characteristics, namely high incidence, high prevalence, high disability rate, high mortality rate, and high burden, which have become pain-points and challenges in the field of rehabilitation. The primary post-stroke manifestations are disabilities in motor, sensory, cognitive, speech, and swallowing functions, which result in a decline in survival and quality of life and augment the economic and care burden on families and society [4,5]. Rehabilitation therapy is the key to functional recovery after stroke [6]. Active rehabilitation training can, to a certain extent, improve various functions such as movement and cognition, enhance patients' survival rate and quality of life, and minimize the degree of disability caused by stroke. However, despite the certain effects of ordinary rehabilitation therapy, it still encounters issues such as high subjectivity in assessment, insufficient personalized plans, lack of off-hospital rehabilitation support, and outdated technical means [7]. This results in low rehabilitation efficiency and makes it difficult to achieve breakthrough results.

Since its proposal in 1956, artificial intelligence (AI) has gradually permeated the fields of medical care and rehabilitation medicine, offering a novel technical approach for functional recovery after stroke [8]. In the context of stroke rehabilitation practice, AI technology, leveraging its strengths in data analysis, precise modulation, and multimodal fusion, can conduct a precise assessment of post-stroke functions and formulate personalized rehabilitation plans based on individual patient data. Meanwhile, the AI-supported remote monitoring and intervention system allows patients to obtain continuous and professional rehabilitation guidance outside the hospital and in resource-constrained environments [9-11]. This promotes the transformation of stroke rehabilitation towards a model characterized by "full cycle, wide coverage, and low cost" and constructs a full-course management model of "prevention - assessment - training - follow-up". It has effectively improved the accuracy, efficiency, and accessibility of rehabilitation intervention. Therefore, AI technology has emerged as a crucial enabling tool for propelling the development of the neurorehabilitation system towards precision, personalization, and universality.

AI Applications in Stroke Rehabilitation

Currently, the widely-applied AI in stroke rehabilitation encompasses four core areas: machine learning (ML) and deep learning (DL), brain-computer interface (BCI) technology, virtual reality (VR) technology, and rehabilitation robots.

ML and DL

ML and DL play a crucial role in the precise diagnosis, assessment, and prognosis prediction of stroke [12]. In the acute phase, Computed Tomography (CT) and Magnetic Resonance Imaging (MRI) image data are effectively processed via algorithms such as Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), and lesion features are automatically extracted to enable rapid classification and localization [13]. During the rehabilitation period, ML is employed to integrate multi-source data of patients, including clinical, neuro electrophysiological, and motion sensor data, to discover biomarkers and construct a prognostic model, and to dynamically optimize the rehabilitation plan [14,15]. This technology overcomes the subjectivity of traditional assessment through quantitative analysis, notably enhancing the efficiency of rehabilitation intervention. Its therapeutic effect has been fully validated: The Intelligent Imaging Decision Platform for Acute Stroke developed by Beijing Tiantan Hospital, based on DL algorithms, can complete the automatic analysis of a large number of brain images within minutes, accurately quantifying the range of the ischemic penumbra and the characteristics of infarct volume. The results of the TRACE clinical trial supported by it indicate that this platform can safely extend the thrombolysis time window for large-vessel occlusion (LVO) ischemic stroke patients who meet the assessment criteria of the ischemic penumbra from the traditional 4.5 hours to 24 hours.

By precisely screening the salvageable ischemic "penumbra" areas, it remarkably improves the functional prognosis of patients [16]. The neural functional recovery prediction model constructed by Chen [17]. achieved a prediction accuracy rate of 85% for the modified Rankin Scale (mRS) score of patients with cerebral hemorrhage six months later. Meanwhile, ML cognitive stratification models, such as the NEURO model proposed by Swarnakar [18], can design targeted training protocols for different types of cognitive impairments, including attention deficit and executive disability. This approach can increase the pertinence of cognitive training by 30% and optimize the efficiency of prognosis management.

BCI Technology

BCI, by constructing a closed-loop system of "neural signal acquisition - intention decoding - device control - multimodal feedback", directly activates the motor cortex of the affected hemisphere via motor imagery tasks, directly regulates the central nervous system, and breaks through the limitations of traditional methods. It enhances the active participation of patients, effectively promotes the activation of the motor cortex and the operation of BCI, and facilitates the reorganization of brain functions. It provides a functional reconstruction path for patients with severe paralysis [19-22]. Studies have demonstrated that BCI intervention can significantly enhance the functional connection between the medial prefrontal cortex (mPFC) of the default mode network (DMN) and the motor brain region, and remarkably improve the Fugl-Meyer score of the upper limb [23]. This suggests that BCI can not only activate the locally affected hemisphere but also promote the functional recovery of the whole brain and support the interhemispheric compensation mechanism. BCI combined with functional electrical stimulation (FES) can achieve precise synchronization of "motor intention - muscle contraction", strengthen the neural connection between the motor cortex and the lower extremity muscle groups, significantly improve the walking speed and endurance of patients, and enhance the quality of life [24]. Immersive BCI-VR training combined with repetitive transcranial magnetic stimulation (rTMS) can significantly enhance the motor function and cortical excitability of the upper limbs [25]. Moreover, BCI can effectively enhance patients' concentration during the training process, providing a neuromodulation basis for improving cognitive impairment after stroke [26].

VR Technology

VR constructs a three-dimensional virtual environment, integrates visual, auditory, and somatosensory perceptions, and specifically activates the motor cortex, parietal lobe, and prefrontal network. This enhances the excitability of the cortex and the functional connectivity of brain regions. By regulating the sensorimotor rhythm (SMR) to promote cortical reorganization, it can significantly improve the Fugl-Meyer score and cognitive function of the upper limbs in patients with chronic stroke [27]. The core advantage of VR technology is integrating rehabilitation training into life-related tasks. Through the closed-loop process of "goal setting - action execution - result feedback", it strengthens the neural connection between motor intention and peripheral movements. Ase H, et al. [28] demonstrated through a randomized controlled trial that the Fugl-Meyer score of the upper limb in the family VR task-oriented training group was

DOI: 10.26717/BJSTR.2026.64.010116

significantly higher than that in the traditional rehabilitation group, which enhanced the motor function of the affected limb. Bai Y, et al. [29] demonstrated that virtual tasks, such as "fruit cutting and driving games", can significantly enhance the Fugl-Meyer score and Barthel index of the upper limbs of patients. The underlying mechanism is associated with the activation of synaptic plasticity in the motor cortex through task-specific training. Moreover, VR technology is characterized by portability and remote interaction, which allows stroke patients to access continuous and convenient rehabilitation training, thus overcoming the temporal and spatial constraints of traditional rehabilitation [30].

Rehabilitation Robots

Rehabilitation robots, based on the mechanism of "precise force control - repetitive training - closed-loop feedback", conform to the neural plasticity law after stroke and are the main technical means for the rehabilitation of upper and lower limb functions after stroke [31]. By using force sensors, inertial measurement units (IMUs), and motion capture devices, they can perceive the patient's muscle strength, movement trajectory, joint angle, and movement coordination in real-time. Through standardized and highly repetitive task training, they strengthen the activation of the motor cortex, which promotes the reorganization of damaged neural circuits and interhemispheric functional compensation [32]. Studies have shown that exoskeleton robots can significantly reduce the modified Ashworth score of stroke patients and relieve muscle spasticity [32]; robot-assisted gait training can enhance patients' walking speed, balance ability, and gait coordination, and early intervention can accelerate the functional reorganization of bilateral motion-related brain regions [33]; in addition, exoskeleton robots can also achieve multi-joint collaborative training of fingers, wrists, elbows, and shoulders, thereby improving joint range of motion [34].

AI Limitations in Neurorehabilitation

Although AI boasts remarkable advantages and a well-defined therapeutic effect in the field of neurorehabilitation, it still encounters multiple challenges in clinical transformation and large-scale application.

Technical Aspects: Quality of Signals and Limitations of Model Generalizability

Non-invasive neural signals are susceptible to the influence of electromyography, eye movement, and environmental electromagnetic noise, which causes fluctuations in the accuracy of AI decoding. During VR training, stroke patients encounter an increase in electroencephalography (EEG) artifacts due to head movements, leading to a decline in the accuracy of motor intention decoding. Moreover, there are individual differences in EEG features among different patients, resulting in a decrease in the accuracy of AI models when they are applied across different patients [35]. A substantial amount of personalized data is required for retraining, which raises the application cost. Spatiotemporal alignment and feature fusion of multimodal data represent the core challenges for AI models. Chen, et al. [36] noted that the temporal resolution of EEG fails to match the spatial resolution of functional near-infrared spectroscopy (fNIRS), which renders it arduous for AI to precisely correlate the "neural activity - hemodynamic effect". Moreover, the data formats of different devices lack a unified standard, thereby augmenting the time consumption of data preprocessing. Additionally, the "black-box nature" of AI models makes it tough for clinicians to interpret the biological significance of the results, consequently diminishing clinical trust [35].

Clinical Aspects: Translational Barriers and Insufficient Levels of Evidence

Current AI rehabilitation research predominantly relies on single-center small-sample designs, characterized by a high degree of methodological heterogeneity. Moreover, it excludes patients with multiple underlying diseases, which restricts the generalizability and external validity of the research findings [35]. The majority of AI rehabilitation systems remain in the laboratory prototype phase and are ill-equipped to meet the actual requirements of real-world clinical scenarios. For instance, the electrode-wearing procedure of BCI devices is laborious, and rehabilitation robots demand repeated calibration by professionals, thus impeding their popularization in primary medical institutions. Additionally, the operation interfaces of existing systems are intricate and lack a "one-click" mode in line with clinical work practices, which diminishes the actual willingness and frequency of use among rehabilitation physicians [37,38]. Simultaneously, the acquisition and maintenance costs of high-end AI rehabilitation equipment are substantial, and continuous technical training further exacerbates the application burden on primary hospitals, leading to a low utilization rate of such equipment in actual clinical settings.

Ethical and Security Aspects: Privacy Risks and Security Threats

EEG, fNIRS, and other types of data contain patients' neural features and cognitive states, which are highly sensitive information. Currently, most AI systems employ "centralized data storage," which poses a risk of data leakage. Moreover, the extraction of "neural features" by AI models might involve patients' cognitive preferences, and the ownership and usage boundaries of these features have not yet been clearly defined [35]. AI-driven closed-loop intervention potentially entails the risk of "overstimulation" [39]. For example, when the parameters of transcranial direct current stimulation (tDCS) are automatically optimized by AI, the absence of real-time monitoring of cortical excitability can result in local overexcitation, leading to headaches and even a reduction in the seizure threshold, along with other adverse reactions. In the scenario of stroke patients undergoing robot training controlled by AI, because the AI overly depends on position signals when judging "motor error" and overlooks the patients' subjective pain, joint pain may emerge.

DOI: 10.26717/BJSTR.2026.64.010116

Sustainable Development Paths of AI Technology

In view of the current deficiencies, future efforts ought to be exerted to foster the sustainable development of AI in the field of neurorehabilitation via coordinated progress in technological innovation, clinical translation, and ethical norms.

Technological Innovation: Advancing Multimodal Fusion and Algorithm Optimization

Strengthen the integration of AI with other state-of-the-art technologies and establish a full-chain rehabilitation system. The integration of "AI + BCI + robot": By decoding the motor intentions of patients through BCI, AI algorithms improve the accuracy of signal decoding and control the motion of the robot. In combination with computer vision to dynamically adjust the robot's trajectory, a closed-loop control of "brain - machine - limb" is achieved, which enhances the rehabilitation effect for patients with severe disabilities. The integration of "AI + digital twin": Construct personalized virtual digital models for patients, simulate the intervention effects of different rehabilitation plans, and select the optimal plan via AI algorithms, thus reducing the costs of clinical trial-and-error. The integration of "AI + integrated traditional Chinese and Western medicine": Centered around the "holistic concept and traditional Chinese medicine (TCM) syndrome differentiation" of TCM, a new intelligent rehabilitation path is constructed.

(1) The correlation between TCM syndrome differentiation and functional deficits: AI is employed to collect information from the four diagnostic methods in TCM, including tongue appearance, pulse condition, and other symptoms. High-dimensional features are then extracted via algorithms, and a database is established to construct a correlation model between TCM syndrome classification and the degree of neurological functional deficits. Simultaneously, wearable sensors are integrated to monitor objective data such as the patient's movement trajectory and electromyographic(EMG) signals in real-time. This provides dynamic feedback on the subtle changes in neurological function during the rehabilitation process, facilitating the transformation of TCM rehabilitation from experience-based to data-driven.

(2) AI-assisted generation of personalized TCM rehabilitation plans: Leveraging the patient's TCM syndrome differentiation and rehabilitation assessment results, AI algorithms are employed to recommend personalized combinations of TCM rehabilitation techniques. Additionally, in conjunction with digital twin models, virtual simulation and therapeutic effect prediction are carried out, thereby achieving a closed-loop path of "syndrome differentiation - treatment - adjustment".

(3) Construction of an intelligent rehabilitation evaluation system integrating traditional Chinese and Western medicine: An evaluation model encompassing multiple dimensions, including TCM syndrome differentiation, functional scales, and EMG signals, is established. Through AI-driven dynamic integration and analysis, a tool for predicting therapeutic effects and prognosis in integrated traditional Chinese and Western medicine rehabilitation is developed, facilitating cross-validation and collaborative development of rehabilitation theories in both systems.

Clinical Transformation: Facilitating Personalized and Home-Based Rehabilitation

Design stratified controlled trials for different stroke types and various disease stages to verify the long-term therapeutic effect of AI rehabilitation. Meanwhile, establish an "AI rehabilitation therapeutic effect prediction model" to screen potential beneficiaries based on patients' baseline characteristics and enhance the utilization rate of clinical resources. To facilitate the technology's penetration into grassroots and home settings, it is essential to construct a "low-cost and easy-to-operate" adaptive solution. At the algorithm level, develop lightweight AI algorithms using model compression techniques, transforming complex network architectures into simplified models suitable for mobile devices like phones and tablets, thus reducing the threshold for hardware deployment. At the hardware level, adopt technical substitution approaches to achieve cost control while guaranteeing basic functions. At the scene level, develop portable rehabilitation devices and home AI rehabilitation applications, integrate remote rehabilitation modules, and build an integrated continuous rehabilitation service system of "hospital - community - home" to ensure the continuity and accessibility of rehabilitation intervention.

Ethics and Safety: Establishing Standardized Safeguard Systems

Promote the adoption of technologies such as federated learning and differential privacy to achieve the goal of "data remaining stationary while the model is mobile", thereby reducing the risk of data leakage. Formulate the "AI Data Usage Guidelines for Neurorehabilitation" to clearly define the boundaries of data collection, storage, and sharing. Develop an "AI Security Monitoring Module" to identify abnormal signals in real-time, etc.

Conclusion

AI technology has paved a new way of "precision and personalization" for neurorehabilitation, showcasing remarkable advantages in enhancing motor, cognitive, and other functions. At present, ML, DL, BCI, VR, and rehabilitation robots have attained therapeutic outcomes in various rehabilitation stages. Nevertheless, unstable signal quality, insufficient clinical evidence, limited equipment accessibility, and ethical and safety risks have hindered their large-scale implementation. In the future, it is essential to promote coordinated development through technological innovation, clinical translation, and ethical regulations, systematically overcome the existing bottlenecks, and propel neurorehabilitation towards a more efficient, safer, and more accessible direction.

Funding

This article is supported by the Central Government Guided Local Science and Technology Development Fund Project (Project No.: 2025ZYDF011).

Conflicts of Interest

The authors declare no competing interests.

References

1. Hou S, Zhang Y, Xia Y, Liu Y, Deng X, et al. (2024) Global, regional, and national epidemiology of ischemic stroke from 1990 to 2021. Eur J Neurol 31: e16481.
2. Liu J, Xu A, Zhao Z, Ren B, Gao Z, et al. (2025) Epidemiology and future trend predictions of ischemic stroke based on the global burden of disease study 1990-2021. Commun Med (Lond) 5: 273.
3. Swartz RH, Longman RS, Lindsay MP, Lund R, Ganesh A, et al. (2025) Canadian Stroke Best Practice Recommendations Advisory Committee, in collaboration with the Canadian Stroke Consortium, Canadian Neurological Sciences Federation, and CanStroke Recovery Trials Platform. Canadian Stroke Best Practice Recommendations: Vascular cognitive impairment, (7th Edn.,), practice guidelines update, 2025. Alzheimers Dement 21: e14324.
4. Maggio MG, Corallo F, De Francesco M, De Cola MC, De Luca R, et al. (2024) Understanding the family burden and caregiver role in stroke rehabilitation: insights from a retrospective study. Neurol Sci 45: 5347-5353.
5. Anandakumar J, Ja Mai H, Bv Riblet N, Waseem H (2024) Telehealth interventions for stroke management and rehabilitation in low- and middle-income countries: A scoping review. J Clin Neurosci 130: 110906.
6. Winstein CJ, Stein J, Arena R, Bates B, Cherney LR, et al. (2016) Guidelines for Adult Stroke Rehabilitation and Recovery: A Guideline for Healthcare Professionals from the American Heart Association. American Stroke Association. Stroke 47: e98-169.
7. Todhunter-Brown A, Sellers CE, Baer GD, Choo PL, Cowie J, et al. (2025) Physical rehabilitation approaches for the recovery of function and mobility following stroke. Cochrane Database Syst Rev 2(2): CD001920.
8. Lee D, Yoon SN (2021) Application of Artificial Intelligence-Based Technologies in the Healthcare Industry: Opportunities and Challenges. Int J Environ Res Public Health 18: 271.
9. Al Kuwaiti A, Nazer K, Al-Reedy A, Al-Shehri S, Al-Muhanna A, et al. (2023) A Review of the Role of Artificial Intelligence in Healthcare. J Pers Med 13: 951.
10. Senadheera I, Hettiarachchi P, Haslam B, Nawaratne R, Sheehan J, et al. (2024) AI Applications in Adult Stroke Recovery and Rehabilitation: A Scoping Review Using AI. Sensors 24: 6585.
11. Sumner J, Lim HW, Chong LS, Bundele A, Mukhopadhyay A, et al. (2023) Artificial Intelligence in Physical Rehabilitation: A Systematic Review. Artif Intell Med 146: 102693.
12. Liu H, Meng T, Qie R (2026) Machine learning in stroke and its sequelae: a narrative review of clinical applications and emerging trends. Int J Med Inform 208: 106245.
13. Al Askar A, Buchireddygari D, Middi BVSR, Ravishankar S, Namidis I, et al. (2025) The Role of Artificial Intelligence and Machine Learning in the Assessment, Diagnosis, and Prediction of Cerebral Small Vessel Disease. Cureus 17: e93376.
14. Deng Q, Yang Y, Bai H, Li F, Zhang W, et al. (2025) Predictive Value of Machine Learning Models for Cerebral Edema Risk in Stroke Patients: A Meta-Analysis. Brain Behav 15: e70198.
15. Senadheera I, Hettiarachchi P, Haslam B, Nawaratne R, Sheehan J, et al. (2024) AI Applications in Adult Stroke Recovery and Rehabilitation: A Scoping Review Using AI. Sensors (Basel) 24(20): 6585.
16. Xiong Y, Campbell BCV, Schwamm LH, Meng X, Jin A, et al. (2024) TRACE-III Investigators. Tenecteplase for Ischemic Stroke at 4.5 to 24 Hours without Thrombectomy. N Engl J Med 391(3): 203-212.
17. Chen D, Zhao Z, Zhang S, Chen S, Wu X, et al. (2025) Evolving Therapeutic Landscape of Intracerebral Hemorrhage: Emerging Cutting-Edge Advancements in Surgical Robots, Regenerative Medicine, and Neurorehabilitation Techniques. Transl Stroke Res 16: 975-989.
18. Swarnakar R (2025) Brain-Computer Interfaces in Rehabilitation: Implementation Models and Future Perspectives. Cureus 17: e88873.
19. Grefkes C, Fink GR (2020) Recovery from stroke: current concepts and future perspectives. Neurol Res Pract 2: 17.
20. Sánchez-Cuesta FJ, Arroyo-Ferrer A, González-Zamorano Y, Vourvopoulos A, Badia SBI, et al. (2021) Clinical Effects of Immersive Multimodal BCI-VR Training after Bilateral Neuromodulation with rTMS on Upper Limb Motor Recovery after Stroke. A Study Protocol for a Randomized Controlled Trial. Medicina (Kaunas) 57: 736.
21. Zhang M, Zhu F, Jia F, Wu Y, Wang B, et al. (2024) Efficacy of brain-computer interfaces on upper extremity motor function rehabilitation after stroke: A systematic review and meta-analysis. NeuroRehabilitation 54: 199-212.
22. Lv S, Ran X, Xia M, Zhang Y, Pang T, et al. (2025) Classification of left and right-hand motor imagery in acute stroke patients using EEG microstate. J Neuroeng Rehabil 22: 137.
23. Grigoryan KA, Mueller K, Wagner M, Masri D, Pine KJ, et al. (2025) Short-term BCI intervention enhances functional brain connectivity associated with motor performance in chronic stroke. Neuroimage Clin 46: 103772.
24. Biswas P, Dodakian L, Wang PT, Johnson CA, See J, et al. (2026) A single-center, assessor-blinded, randomized controlled clinical trial to test the safety and efficacy of a novel brain-computer interface controlled functional electrical stimulation (BCI-FES) intervention for gait rehabilitation in the chronic stroke population. BMC Neurol 24(4): 200.
25. Cantillo-Negrete J, Rodríguez-García ME, Carrillo-Mora P, Arias-Carrión O, Ortega-Robles E, et al. (2025) The ReHand-BCI trial: A randomized controlled trial of a brain-computer interface for upper extremity stroke neurorehabilitation. Front Neurosci 19: 1579988.
26. Yuan Z, Peng Y, Wang L, Song S, Chen S, et al. (2021) Effect of BCI-Controlled Pedaling Training System with Multiple Modalities of Feedback on Motor and Cognitive Function Rehabilitation of Early Subacute Stroke Patients. IEEE Trans Neural Syst Rehabil Eng 29: 2569-2577.
27. Afonso M, Sánchez-Cuesta F, González-Zamorano Y, Pablo Romero J, Vourvopoulos A (2024) Investigating the synergistic neuromodulation effect of bilateral rTMS and VR brain-computer interfaces training in chronic stroke patients. J Neural Eng 21: 056037.
28. Ase H, Honaga K, Tani M, Takakura T, Wada F, et al. (2025) Effects of home-based virtual reality upper extremity rehabilitation in persons with chronic stroke: A randomized controlled trial. J Neuroeng Rehabil 22: 20.
29. Bai Y, Liu F, Zhang H (2022) Artificial Intelligence Limb Rehabilitation System on Account of Virtual Reality Technology on Long-Term Health Management of Stroke Patients in the Context of the Internet. Comput Math Methods Med 23: 2688003.

30. Akbarifar F, Dukelow SP, Jin A, Mousavi P, Scott SH (2025) Optimizing Stroke Detection Using Evidential Networks and Uncertainty-Based Refinement. IEEE Trans Neural Syst Rehabil Eng 33: 566-576.
31. Patel J, Qiu Q, Fluet GG, Gorin H, Gutterman J, et al. (2025) A randomized controlled trial of timing and dosage of upper extremity rehabilitation in virtual environments in persons with subacute stroke. Sci Re 15: 13834.
32. Ji X, Lu X, Xu Y, Zhang W, Yang H, et al. (2025) Effects and neural mechanisms of a brain-computer interface-controlled soft robotic glove on upper limb function in patients with subacute stroke: A randomized controlled fNIRS study. J Neuroeng Rehabil 22: 171.
33. Zhou ZQ, Hua XY, Wu JJ, Xu JJ, Ren M, et al. (2022) Combined robot motor assistance with neural circuit-based virtual reality (NeuCir-VR) lower extremity rehabilitation training in patients after stroke: A study protocol for a single-centre randomised controlled trial. BMJ Open 12: e064926.
34. Tang Z, Cui Z, Wang H, Liu P, Xu X, et al. (2024) A 4-DOF Exosuit Using a Hybrid EEG-Based Control Approach for Upper-Limb Rehabilitation. IEEE J Transl Eng Health Med 12: 622-634.
35. Lv S, Ran X, Xia M, Zhang Y, Pang T, et al. (2025) Classification of left and right-hand motor imagery in acute stroke patients using EEG microstate. J Neuroeng Rehabil 22: 137.
36. Chen D, Zhao Z, Zhang S, Chen S, Wu X, et al. (2025) Evolving Therapeutic Landscape of Intracerebral Hemorrhage: Emerging Cutting-Edge Advancements in Surgical Robots, Regenerative Medicine, and Neurorehabilitation Techniques. Transl Stroke Res 16(3): 975-989.
37. Swarnakar R (2025) Brain-Computer Interfaces in Rehabilitation: Implementation Models and Future Perspectives. Cureus 17: e88873.
38. Morone G, de Sire A, Martino Cinnera A, Paci M, Perrero L, et al. (2021) Upper Limb Robotic Rehabilitation for Patients with Cervical Spinal Cord Injury: A Comprehensive Review. Brain Sci 11: 1630.
39. Yan W, Lin Y, Chen YF, Wang Y, Wang J, et al. (2025) Enhancing Neuroplasticity for Post-Stroke Motor Recovery: Mechanisms, Models, and Neurotechnology. IEEE Trans Neural Syst Rehabil Eng 33: 1156-1168.

ISSN: 2574-1241

DOI: 10.26717/BJSTR.2026.64.010116

Ke Wang and Zhi Yan. Biomed J Sci & Tech Res