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Artificial Intelligence as a Decision Layer in Brain-Computer Interface-Controlled Exoskeletons for Rehabilitation and Human Augmentation

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Abstract. A brain-computer interface (BCI) can detect neural activity related to movement, while a powered exoskeleton can provide the force needed to assist that movement. Electroencephalography (EEG) is noisy, muscle activity changes with fatigue and recovery, and the correct amount of assistance depends heavily on the person and the task, so artificial intelligence is useful mainly because it can work with several of these changing signals at once rather than relying on one fixed input. This paper reviews how EEG, electromyography (EMG), and mechanical sensing can be combined in exoskeleton control and considers two applications with very different goals. In stroke rehabilitation, robotic assistance should remain connected to the patient's own movement attempt and should decrease as voluntary control improves. In healthy users, assistance is useful when it reduces the energetic or muscular cost of a task. Recent studies have applied deep learning, transfer learning, hybrid EEG-EMG control, and human-in-the-loop optimization to these problems. The results are promising, but they also show that improving classification accuracy alone is not enough. Latency, calibration, fatigue, uncertainty, and physical safety all affect whether a system is actually useful. A practical design would therefore use AI mainly to interpret the user and choose a high-level assistance strategy, while conventional controllers continue to enforce torque, joint, velocity, and other mechanical limits.

Keywords: brain-computer interface, exoskeleton, artificial intelligence, stroke rehabilitation, human augmentation

1. Introduction

For most people, reaching for an object feels like one action. A person decides to move and the movement follows. Physiologically, much more is happening. The nervous system has to form a motor plan, send signals through descending pathways, recruit the correct muscles, and generate forces at several joints in the correct sequence.

After a stroke, parts of this pathway may stop working normally. A patient can still understand the movement they want to make, and may even be actively trying to make it, while the arm or hand produces little useful motion. This gap between intention and physical movement is one reason brain-computer interfaces (BCIs) have been studied for rehabilitation. A BCI records neural activity

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and translates selected signal patterns into commands for an external device [1]. An exoskeleton addresses another part of the problem by applying mechanical force around the body.

Putting them together creates a direct link between attempted movement and assistance. For example, a patient can imagine or attempt opening the hand while electroencephalography (EEG) is recorded. If the system detects a motor-related pattern, a hand exoskeleton opens the fingers. What makes this different from ordinary robotic therapy is not that the hand moved. A robot could do that without reading brain activity. The important difference is that the movement occurred in response to the patient's own attempt.

Clinical studies suggest that this relationship may be useful. Frolov et al. tested a motor-imagery BCI connected to a hand exoskeleton in patients with severe upper-limb paralysis after stroke [2]. Both groups in the study improved, but the BCI group showed significant gains in several grasp and pinch measurements. A later randomized trial by Wang et al. included 296 patients with ischemic stroke and found greater improvement in upper-extremity Fugl-Meyer scores when BCI training was added to conventional rehabilitation [3].

Powered exoskeletons have also been developed for people with no neurological injury. In that case, there is no damaged motor pathway to restore. Researchers are instead asking whether a wearable robot can reduce the physical cost of walking, carrying loads, or performing repetitive work. Several studies have reported meaningful reductions in metabolic cost, particularly when assistance is personalized or optimized [4-6]. These two uses may involve similar hardware, but they create almost opposite control goals. A rehabilitation device should not simply perform the movement for the patient. Some active effort needs to remain. For a healthy person carrying a heavy load, however, removing effort may be exactly why the device is useful.

This difference is what makes the software side of exoskeleton control interesting. Recognizing that someone wants to flex an elbow is only the beginning. The system still has to determine how much assistance is appropriate at that moment. That decision can depend on EEG, muscle activation, fatigue, joint motion, previous performance, and the task itself. Recent studies have started using artificial intelligence (AI) for this broader problem: deep-learning models have been used for intention recognition, transfer learning has been used to reduce calibration, and hybrid EEG-electromyography (EMG) systems have adjusted their behavior as muscle fatigue increases [7-9].

Building on these developments, this paper reviews how EEG, EMG, and mechanical sensing can be combined in exoskeleton control, and compares two applications with very different goals: stroke rehabilitation, where assistance should remain connected to the patient's own movement attempt, and augmentation for healthy users, where assistance is useful when it reduces the energetic or muscular cost of a task. The significance of this comparison is that it clarifies what AI can realistically contribute to these systems: not simply replacing an older classifier with a more complicated model, but giving the controller a way to interpret a user whose signals and abilities are constantly changing.

2. The workflow of a BCI-exoskeleton control loop

EEG is attractive for movement control because useful neural activity can appear before a large physical movement occurs. Both motor imagery and actual movement change oscillatory activity over the sensorimotor cortex. In particular, changes in mu and beta rhythms, including event-related desynchronization and synchronization, have been used in motor BCI research for decades [10].

The difficulty is that scalp EEG is noisy. Brain-generated electrical activity is small compared with many other signals that reach the electrodes. Blinking, eye movement, facial muscles, electrode

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displacement, and electrical interference can all affect the recording. A moving exoskeleton creates an additional problem because the user and the hardware are both producing motion artifacts.

For this reason, EEG normally has to be processed before classification. The signal may be filtered, segmented, cleaned of obvious artifacts, and transformed into features. Earlier BCI systems often used methods such as common spatial patterns followed by a linear classifier or support vector machine. More recent work uses convolutional networks, transformers, and other neural-network architectures that learn relationships in the signal directly.

None of these methods completely solves the fact that EEG varies. Signals are different between users and can also shift between two sessions from the same person. Even small differences in electrode position can affect the recorded pattern. That leads to one of the practical limitations of BCI systems: calibration. A decoder often needs examples from the current user before it becomes reliable. This may be acceptable in a laboratory experiment, but rehabilitation time is limited. If a large part of every session is spent teaching the software how to recognize the patient again, there is less time left for therapy.

Kueper et al. investigated transfer learning as one way to reduce this problem [8]. Rather than training entirely from the new user's data, a model can begin from information learned previously. Their experiment involved healthy participants, so the same performance cannot automatically be assumed in stroke rehabilitation. Still, reducing calibration would make the technology much easier to use clinically.

EEG is also only one part of the available information. EMG measures electrical activity produced by muscle and can provide a much clearer signal when voluntary muscle control is preserved. A healthy person beginning elbow flexion, for example, may produce strong EMG before much joint movement occurs. Mechanical sensors describe another stage of the same action. Joint encoders measure angle, inertial measurement units estimate motion and orientation, and force or pressure sensors measure contact and loading. These measurements tell the controller what physically happened after the movement began.

It is useful to think of these signals as different observations of one process rather than competing technologies. EEG can provide information related to cortical intention. EMG shows whether the muscle is being recruited. Mechanical sensors show the resulting movement. Xia et al. similarly describe neural, muscular, and mechanical sensing as complementary parts of wearable robotic systems [7].

A simple example shows why this matters. Suppose a person tries to extend the knee. EEG indicates movement intention, but EMG remains weak and the joint barely moves. That combination means something different from a case where EEG, EMG, and the joint encoder all indicate successful movement. The disagreement between sensors can itself tell the controller that assistance may be needed.

Even then, the high-level decision has to be separated from the actuator. Recognizing knee extension does not determine the exact motor current required. Torque also depends on joint position, velocity, actuator behavior, the level of assistance requested, and physical safety constraints. This separation is especially important for machine learning. A classifier can be wrong while still producing a high confidence score. AI can help estimate what the user is doing, but the final physical limits should not depend on whether the model happened to be correct.

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3. The roles of artificial intelligence in exoskeleton control

3.1. Machine learning and multimodal signal fusion

One clear use of machine learning is movement recognition. Biological signals contain patterns across time and sensors that may not be captured well by a few manually selected features. Lee et al. demonstrated this using soft wearable EMG sensors and a deep-learning model [9]. The system classified four upper-limb joint movements with an average accuracy of about 96%, with a response time of roughly 500 to 550 ms. A pneumatic exoskeleton then assisted the detected movement.

This was an EMG system rather than a conventional EEG-based BCI, but the computational problem is similar: interpret a noisy biological signal quickly enough for a robot to respond appropriately. The study also raises an important design question. EEG should not automatically be added to every exoskeleton. If a healthy user already produces strong EMG and clear mechanical signals, EEG may add more electrodes, calibration, and motion artifacts without providing much useful information. The best sensor depends on what information the controller is missing.

The benefit of combining signals becomes clearer when one of them starts to change. Muscle fatigue is a good example because it affects EMG and can reduce the reliability of an EMG classifier over a long session. Ben Abdallah et al. studied a hybrid EEG-EMG interface for an elbow rehabilitation robot [11]. Instead of choosing only one signal, EEG and EMG were classified separately and combined through Bayesian fusion. As estimated muscle fatigue increased, the controller shifted more weight toward EEG.

The study only included five healthy participants, so it should be interpreted as an early proof of concept. Even so, the hybrid system reached 94.5% classification accuracy compared with 88.5% for EMG alone and maintained its advantage under higher-fatigue conditions [11]. The controller changed how much it trusted each sensor when the user's condition changed. This is closer to what a real wearable system needs to do. Electrodes can move, muscles become fatigued, and sensors do not remain equally reliable for an entire session.

3.2. Adaptation to the changing user

AI may also be useful because the user changes over a much longer time scale. This is particularly important in rehabilitation. A successful treatment is supposed to change the patient. Muscle recruitment can return, range of motion can improve, and the required amount of robotic assistance can decrease. Neural activity may also change during recovery. A decoder that worked well in the first week may therefore become less representative later.

Quiles et al. explored adaptation across multiple days in an asynchronous BCI for exoskeleton control [12]. Their work suggests that information accumulated from earlier sessions can improve later decoding instead of treating every session as completely independent. For a clinical system, this could eventually mean maintaining a history of the patient. Previous EEG, EMG, movement quality, and assistance levels could be used to update the model and follow how the person's ability changes.

3.3. From movement recognition to assistance decisions

This leads to a more important problem for AI: deciding assistance rather than simply recognizing movement. Consider a patient attempting elbow flexion early in rehabilitation. EEG indicates a strong attempt, EMG is very weak, and the joint moves only slightly. Additional robotic help is

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probably appropriate. Several weeks later, the same patient may show stronger EMG and complete most of the motion independently. The intention is still elbow flexion, but providing the same torque would now take away work that the patient is capable of doing. The movement class is identical. The correct response is not.

A higher-level AI controller could use EEG confidence, EMG strength, joint velocity, trajectory error, fatigue, and previous repetitions to estimate an assistance level. The output would not need to be a direct motor current. It could simply request more or less support, while conventional software handles the final mechanical limits.

The controller should also be allowed to reject a prediction. Most classifiers still return a best answer even when the input is unlike anything in the training data. That behavior is risky in a wearable robot. Lin et al. used evidential deep learning for myoelectric locomotion prediction to recognize unfamiliar inputs rather than forcing them into known categories [13]. A similar approach could be useful in exoskeleton control. If the sensor pattern is unfamiliar or contradictory, reducing assistance may be better than confidently performing the wrong action.

4. Rehabilitation and augmentation require different control

4.1. Adaptive assistance in stroke rehabilitation

In stroke rehabilitation, the value of the BCI comes mainly from connecting attempted movement with the assistance that follows. Frolov et al.'s study demonstrates this directly [2]. Patients performed motor imagery while EEG was monitored, and the hand exoskeleton opened when the relevant neural pattern was detected. Significant gains in grasp and pinch measures were reported in the BCI group, and decoding performance was also associated with improvement in upper-limb function.

Chen et al. examined EEG changes during repeated BCI-exoskeleton rehabilitation sessions [14]. Changes in sensorimotor rhythms were related to motor recovery. This does not establish that the EEG changes caused recovery, but it supports the idea that the neural state of the patient is not constant throughout treatment. An adaptive controller therefore makes more sense than one fixed assistance strategy.

Early in rehabilitation, a severely impaired patient may produce almost no voluntary EMG. EEG may then be more important for recognizing that the patient is genuinely attempting the movement, and relatively strong robotic assistance may be required. If voluntary muscle activity starts returning, the control strategy should change. EMG and movement sensors become more informative, while the amount of help from the robot should begin to decrease.

The difficult part is choosing how much assistance is enough. If there is too little, the patient may repeatedly fail to complete the movement. If there is too much, the robot completes the task while the patient contributes very little. A reasonable objective is therefore not maximum assistance. It is the minimum assistance that still allows a successful movement while preserving active effort.

The 296-patient randomized trial provides encouraging evidence that BCI training can contribute to rehabilitation, but the size of the effect should remain in perspective. Wang et al. reported a between-group mean difference of 3.35 points in one-month upper-extremity Fugl-Meyer improvement [3]. This is a meaningful result, but it does not imply that a more complicated AI model automatically gives a better clinical outcome. For example, increasing offline classification accuracy may not help if it also increases latency or requires a long calibration procedure. A rehabilitation system should ultimately be judged by what happens to the patient's function.

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4.2. Personalized augmentation for healthy users

Healthy users create a different problem. One of the strongest approaches in this area has been human-in-the-loop optimization. Instead of choosing an assistance pattern entirely in advance, researchers change the exoskeleton parameters while measuring how the person responds. Zhang et al. used this method with an ankle exoskeleton and reduced the metabolic cost of walking by 24.2 ± 7.4% relative to wearing the device unpowered [15]. The important idea is that the assistance pattern was optimized from the response of the person using the system.

Bryan et al. extended this approach to hip, knee, and ankle assistance and reported metabolic reductions of 48%, 41%, and 43% under no-load, light-load, and heavy-load walking conditions [4]. Only three participants were included, so these values should not be treated as general population averages. They do, however, show how strongly assistance timing and distribution can affect the outcome. Kim et al. used optimized hip-flexion assistance from a soft exosuit and reported about a 15% reduction in metabolic cost with the tethered system, along with a smaller benefit in the portable version [5]. These studies make one point very clear: more torque is not automatically better. Assistance has to be delivered at the correct time and in a way that matches the person.

AI could eventually allow some of this optimization to continue outside a laboratory. Real use involves stairs, changing speeds, crouching, load carriage, fatigue, and different terrain. A controller could first recognize the context from inertial measurement units, force sensors, EMG, and other measurements and then choose an assistance profile that has previously worked well for that user.

Military load carriage is one possible use, but the available evidence also shows why these results need cautious interpretation. Sefton et al. tested a commercial powered ankle exoskeleton while participants carried a rucksack equal to 30% of body weight [6]. Oxygen consumption and energy cost per minute decreased, but time to exhaustion did not clearly improve. The study also included only nine participants. Reducing metabolic cost, therefore, is not automatically the same as improving real-world performance. The exoskeleton itself adds mass, batteries, moving components, and another possible failure point.

The same tradeoff exists in civilian work. Firefighters, nurses, warehouse workers, construction workers, and rescue personnel may benefit from lower muscle demand or reduced joint loading, but only if the device remains practical enough to wear. For healthy users in particular, continuous EEG control may not always be necessary. EMG and mechanical sensors already provide strong information during ordinary movement. EEG becomes more interesting when the system needs earlier information about an upcoming action or when muscle and mechanical signals are ambiguous. A practical system may therefore be BCI-capable without being BCI-dependent for every step.

5. Safety and future development

Safety is where AI-controlled exoskeletons become very different from ordinary machine-learning applications. If an image classifier makes the wrong prediction, the result may be a wrong label. If an exoskeleton makes the wrong prediction, the result can be force applied to a person's body at the wrong time. A real system will eventually encounter conditions that were not represented in the training data: electrodes can loosen, communication can fail, sensors can disagree, and a person can stumble or move unexpectedly. Critical inference should therefore run locally, or fall back to a simpler local controller, so that losing communication reduces functionality in a predictable way. AI may estimate fatigue or suggest an assistance level, while torque, speed, power, and joint limits are still enforced separately by deterministic software.

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Latency matters for the same reason. Lee et al.'s system responded in approximately 500 to 550 ms [9], and the hybrid EEG-EMG system reported end-to-end latency below 500 ms [11]. This may be acceptable during slower rehabilitation exercises, but it becomes more problematic during running, jumping, or balance recovery. Classification accuracy alone is therefore not enough to evaluate an intelligent exoskeleton; false activations, missed movements, response time, and behavior after errors are also important.

Long-term personalization is another likely direction. A future controller might remember the user's EEG features, EMG recruitment, fatigue patterns, and previous assistance settings, an idea that resembles the myoelectric digital twin developed by Maksymenko et al. for generating realistic simulated data [16]. Prediction before movement is also an open area. Lu et al. used EEG and a Vision Transformer model to study jump-movement intention, where a prediction that arrives after the person has already left the ground has little practical value [17]. Whether EEG can provide reliable enough advance information to justify the extra sensors remains uncertain.

6. Conclusion

BCI-controlled exoskeletons are often described as a path from thought to movement, but the real engineering problem is much broader. Brain signals are noisy, muscle activity changes with fatigue and recovery, sensors fail, and the person wearing the system can change significantly over time. For stroke rehabilitation, the main contribution of the BCI is that mechanical assistance can be linked to the patient's own attempt to move, and randomized clinical studies support a benefit when BCI training is added to conventional rehabilitation. As voluntary control improves, the robotic contribution should decrease. For healthy users, the exoskeleton is useful when it reduces the physical cost of the task enough to justify wearing it: personalized assistance can substantially lower metabolic cost, although physiological improvement should not automatically be interpreted as better real-world performance.

These findings return to the question raised in the introduction: how much assistance is appropriate for a specific person at a specific moment. The strongest role for AI is not direct motor control. It is interpretation and decision making above a lower-level mechanical controller. This separation also explains why rehabilitation and augmentation should not use the same control objective. A rehabilitation exoskeleton should gradually become less necessary as the patient improves, while an augmentation exoskeleton remains useful only while the assistance continues to provide enough benefit. For future research, this suggests that progress should be measured not only by classification accuracy but by whether the controller chooses appropriate assistance for a specific person and task.

This review also has limitations. Much of the evidence discussed comes from small studies, often with three to nine participants, and many of the technical demonstrations involved healthy users rather than clinical populations, so the reported performance cannot automatically be assumed to transfer to patients.

Future systems will probably rely more heavily on dynamic sensor fusion, in which EEG, EMG, and mechanical measurements are weighted according to their current reliability, and on shared autonomy, in which the user provides a high-level intention such as stand, reach, or climb while the exoskeleton handles the detailed movement. The hardware for rehabilitation and augmentation may eventually become similar. The difficult part is building software that understands who is wearing it, what that person is trying to do, and how much help is actually appropriate at that moment.

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