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EXOSKELETONS

AI in therapeutic and assistive exoskeletons and exosuits: Influences on performance and autonomy

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Therapeutic and assistive exoskeletons and exosuits show promise in both clinical and real-world settings. Improving their autonomy can enhance usability, effectiveness, and cost efficiency. This Review presents a generic control framework for autonomous operation of upper and lower limb devices and reviews current advancements and future directions. We highlight how data-driven machine learning aids in intention recognition, synchronization, patient assessment, and task-agnostic control. In addition, we discuss how reinforcement learning optimizes control policies through digital human twins and how generative AI supports therapy planning and patient engagement. Richer patient-specific data and more accurate digital twins are needed for clinical validation and widespread deployment.

INTRODUCTION

Exoskeletons have been developed and used as therapeutic and assistive devices. Therapeutic devices are operated by therapists and used in a clinical setting for movement rehabilitation. These exoskeletons should provide as much support as needed, but not more, to avoid patient reliance on the device in lieu of recovery. Depending on the functional level of the patient, this could range from full to partial support. Assistive exoskeletons are used to support daily activities of individuals with physical disabilities. In most cases, partial support of the affected limb(s) is sufficient, except for the case of complete paralysis, in which full support is needed. Both types of exoskeletons are usually not autonomous because they rely on therapists to operate or on the conscious involvement of users or helpers. Machine learning (ML) as a subfield of artificial intelligence (AI) has the potential to improve the autonomy and performance of therapeutic and assistive exoskeletons. In this Review, we will use AI when referring to (modern) ML methods. With our focus on AI, this Review complements the large body of existing review papers [for example, (*1*–*5*)] of hardware and control developments for these types of exoskeletons. The following paragraph gives a global overview of developments in the field focusing on devices that have reached the market.

From the beginning of this century, stationary mechatronic devices such as the Lokomat (*6*) and Gait Trainer (*7*) for lower limb rehabilitation and devices such as the MIT-Manus (*8*), Armeo Spring (*9*), and Armeo Power (*10*) for upper limb rehabilitation have been developed and introduced to the market (see Fig. 1). These therapeutic devices were designed to physically unload the therapists, to facilitate more intensive movement rehabilitation programs promoting faster and better recovery, and to allow for more objective and quantitative assessment of (impaired) sensorimotor functions (*11*). Such devices were targeted for both stroke survivors (upper and lower limb) and individuals with spinal cord injury (SCI) (lower limb) and have been optimized and clinically validated in numerous randomized clinical trials (RCTs). A Cochrane systematic review concluded that people who received robot-assisted gait training in combination with physiotherapy after stroke are probably more likely to achieve independent walking than people who received gait training without these devices (*12*). A similar review for the upper limb concluded that patients who received robot-assisted arm training after stroke might improve their activities of daily living, arm function, and arm muscle strength (*13*). Although these studies showed that robotic therapy was effective, they did not prove that robots outperform human therapists when the intensity of therapy was matched.

After this first generation of stationary exoskeletons, advancements in sensors, actuation, electronics, and microprocessors facilitated the development of wearable exoskeletons that are potentially suited not only for therapeutic training but also for carrying out daily life activities at home and in the community. Using these technologies more extensively during everyday life may improve mobility and independence of patients and prevent secondary complications (*14*). Devices such as the Hal (*15*), ReWalk (*16*), eLegs (*17*), and Vanderbilt exoskeleton (*18*) were designed as assistive (personal) devices to allow paralyzed individuals to walk again outdoors and in their homes. Other devices [for example, EksoNR and Ekso Indego Therapy (Ekso Bionics, USA)] have been marketed as devices for movement rehabilitation in the clinic, as alternatives for stationary exoskeletons. A systematic review concluded that the use of these technologies still requires supervision and the use of walking aids (*14*). Evidence supporting their benefits is still limited to short-intervention trials with a limited number of heterogeneous participants, and RCTs are still needed to demonstrate their clinical efficacy (*14*).

All of these exoskeletons are rigid, but more recently, soft exosuits for therapeutic and (personal) assistive use have been developed (see Fig. 1) (*19*–*22*). Compared with rigid exoskeletons, soft exosuit are lighter, less bulky, and more comfortable for the user (*2*). Soft exosuits cannot generate the same level of support as rigid exoskeletons but are suited for patients with some remaining motor function who can benefit from partial support, such as individuals with an incomplete SCI, stroke, multiple sclerosis, Parkinson's disease, or muscle dystrophy. Notably, rigid exoskeletons that are lightweight and have good torque-tracking capacities are also suited for partial

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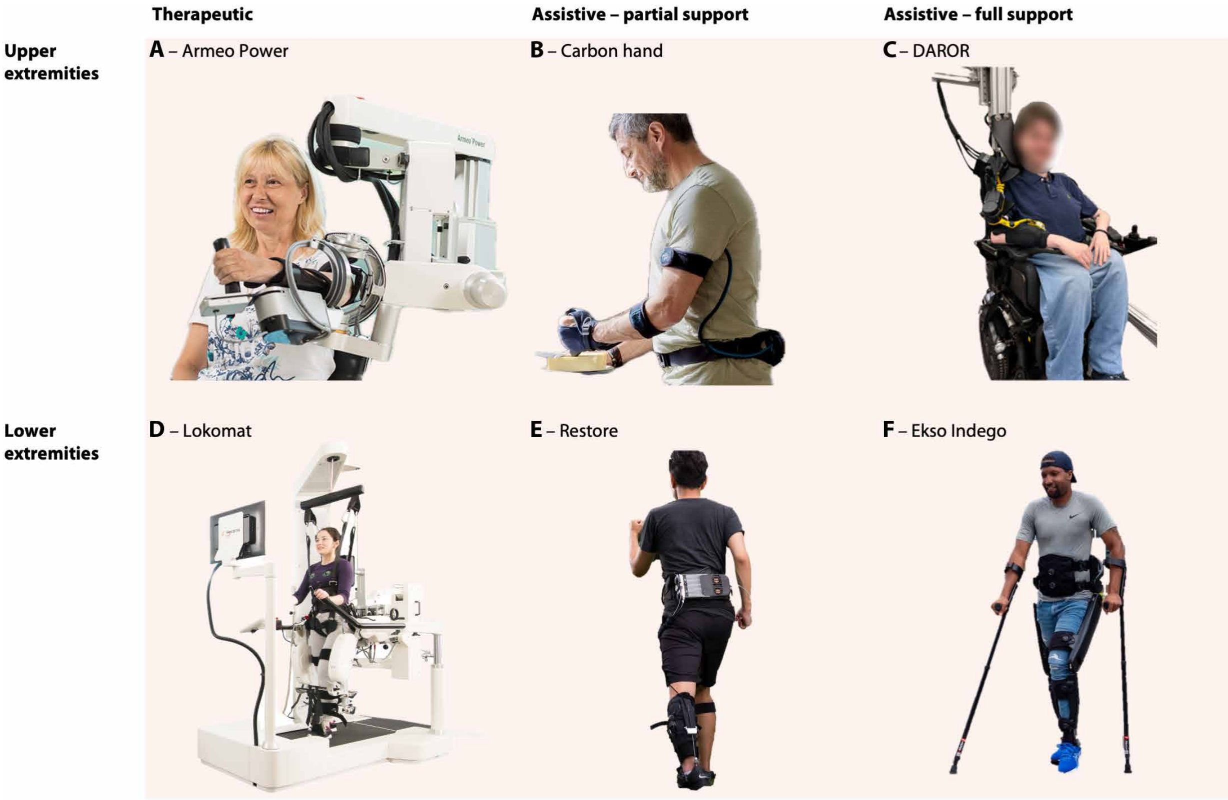

Fig. 1. Examples of therapeutic and assistive exoskeletons and exosuits. Upper extremity exoskeletons and exosuits: (**A**) Armeo Power, (**B**) Carbonhand, and (**C**) DAROR (*159*). Lower extremity exoskeletons and exosuits: (**D**) Lokomat Pro, (**E**) Restore, and (**F**) Ekso Indego Therapy.

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support (*23*–*25*), and some of them are commercially available, such as ExoBoot (Dephy, USA) for the ankle, MO/GO (Skip, USA) for the knee, and Gait Enhancing & Motivating System (GEMS) (Samsung, South Korea) for the hip. A systematic review revealed that wearing soft assistive exosuits improved both walking speed and distance in stroke survivors after training (*26*), implying that these devices could potentially be used for rehabilitation out of the clinic in real-world conditions.

Despite the reported benefits and potential of stationary and wearable exoskeletons and exosuits for therapeutic and assistive purposes, there remains a major drawback in that they cannot be operated independently by the user. For example, therapeutic exoskeletons rely on therapists to operate them, and wearable exoskeletons for personal use by individuals with SCI generally require the presence of another person to watch over the patient and act if needed to guarantee safety. Exoskeletons and exosuits that provide partial assistance are more autonomous, but it remains a challenge to provide effective or optimal support in all possible real-world scenarios. To be used more often in daily life, these assistive exoskeletons and exosuits should become more intuitive and easier to use independently; indeed, one of the main reported limiting factors of exoskeleton use is dependence on other people (*20*).

Yang *et al.* (*27*) introduced a scale defining increasing levels of autonomy for medical robotics: 0, no autonomy; 1, robot assistance; 2, task autonomy; 3, conditional autonomy; 4, high autonomy; and 5, full autonomy. In this scale, full autonomy indicates that no external human operator needs to be in the loop for proper control and functioning. For regulatory, ethical, and legal reasons, an exoskeleton that achieves full autonomy is neither necessary nor desirable. For therapeutic exoskeletons, the maximum desired level would be high autonomy: a device that can make decisions under the supervision of a qualified doctor (*27*). For assistive exoskeletons, conditional autonomy is desired: a system that generates task strategies but relies on humans to select from among different strategies or to approve an autonomously selected strategy (*27*). Because these exoskeletons work symbiotically with their wearer, higher levels of autonomy are not desired and do not make sense. Ideally, the selection or approval is done without delaying the intended motion of the wearer and at a subconscious level.

Increasing the level of autonomy could make exoskeletons more versatile, effective, user friendly, and/or cost effective. The exponential increase of computational power following Moore's law has unleashed the unprecedented power and possibilities of deep learning (DL), generative AI (GenAI), and reinforcement learning (RL) (*28*, *29*). Given the recent impressive advances, AI might play a decisive role in enhancing the performance of exoskeleton technology toward greater autonomy.

This work aims to define the key functionalities that therapeutic and assistive exoskeletons must have to achieve greater autonomy, with a focus on device intelligence (software) rather than hardware considerations. To access the state of the art, we reviewed existing literature to determine how AI and related algorithms have been or could be applied to enhance both the performance and autonomy of these systems in relation to the defined functionalities. Performance

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is considered at both the algorithmic level, such as prediction accuracy and classification performance, and the use-case level, including improvements in outcomes such as walking speed. However, our primary emphasis is on algorithm-level metrics, under the assumption that advancements in this area will ultimately lead to better user-relevant outcomes. Last, we analyzed the gap between the required functionalities and the current state of the art and propose directions for future research and development to bridge this divide.

This literature review concentrates on the role of AI in enhancing the autonomy and performance of exoskeletons and exosuits. We were particularly interested in studies that used patient data to train, test, and preferably validate the results that these methods produced.

To improve the autonomy of exoskeletons and exosuits, the operations that are currently handled by the wearer or a therapist need to be automated. We broke down the software of therapeutic and assistive exoskeletons and exosuits into different functional blocks (see Fig. 2).

Blocks that are associated with therapy planning and the creation of appropriate serious games and exercises are only applicable for therapeutic exoskeletons. The presented scheme uses the taxonomy presented in Baud *et al.* (*30*). This comprises the categorization of low-, medium-, and high-level control; the differentiation in intention and terrain and scene recognition; timing and synchronization of the support; and determination of desired joint angles or torques. Although Baud *et al.* mainly reviewed non-AI methods to accomplish these steps, this Review focuses on AI techniques. In addition, we included therapeutic, assessment, serious games, and prediction of (mal)adaptation, which were not considered in the review of Baud *et al.* These functions pertain to diagnoses, prognoses, and clinical decision-making, which are currently managed by humans. However, exoskeletons collect data that, when combined with other clinical information, can be stored and subsequently used to enhance these functions using AI. AI can be used to establish end-to-end controllers, which directly map sensor data to desired joint angles or torques, without explicitly recognizing the (intended) human activity or environment; hence, they are also known as activity or task-agnostic controllers. AI can also be used to present this vast amount of data to patients or health professionals in an easily comprehensible manner. However, given that data visualization is a topic of its own, it will not be covered in this Review.

In the following sections, we describe for each functional block (Fig. 2) what is needed to become autonomous, followed by an analysis of the literature to determine the state of the art in that respect, with a focus on AI-based methods. Each section ends with a discussion on

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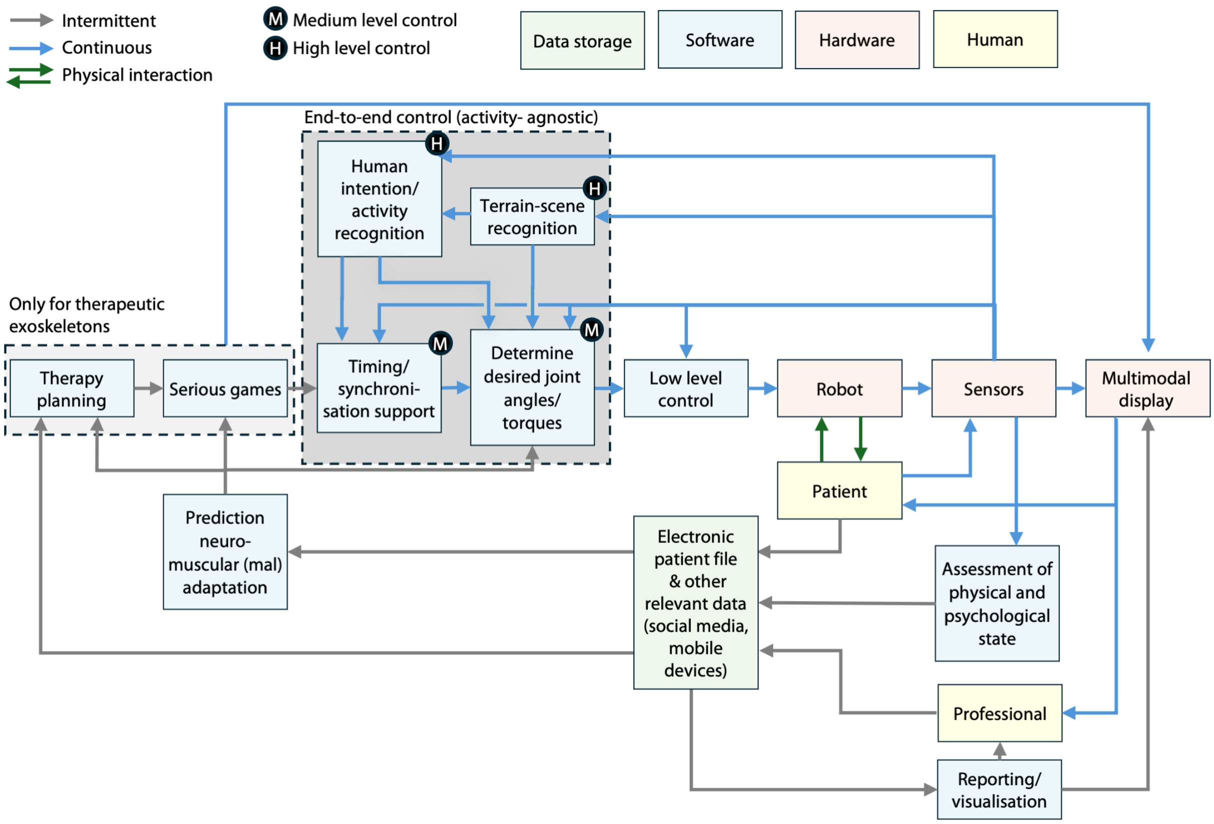

Fig. 2. Generic framework for the operation of autonomous upper- and lower-limb therapeutic and assistive exoskeletons and exosuits. The (control) software required to achieve autonomy is divided into several functional (blue) blocks. End-to-end controllers, which continuously map sensor data into desired joint angles or torques, can be identified. Alternatively, finite state machines are often used, in which high-level control determines state transitions and midlevel control governs actions within each state. Hardware blocks include the device's mechatronics, input interfaces, and additional wearable sensors. Blue and gray lines represent continuous and intermittent information flow, respectively, whereas green lines indicate interactive forces between patient and robot. Note that for some use cases, software blocks may be optional. Therefore, blocks that do not process data can still pass information from their input to their output. A health care professional oversees or supervises the operation of the device and may interact with it directly or indirectly.

what is currently missing and needed to make the associated functionality more autonomous. Whether AI methods are advantageous or needed compared with other state-of-the-art methods is still under investigation. In Discussion, we critically reflect on the added value of AI methods and their inherent challenges.

THERAPY PLANNING

Therapy planning is inherently a highly complex, multidimensional problem involving various health care professionals. Therapists must not only cooperate with patients and caretakers to understand and define long-term therapeutic goals at a high level but also make short-term, session-level decisions regarding exercises and movements to be performed, number of repetitions, and training intensity (*31*). Traditionally, therapists make these decisions on the basis of their clinical experience (*32*). Including therapeutic exoskeletons in this planning further complicates the workflow because the technology inherently adds more decisions regarding controller modalities and support parameters. Despite the potential benefits of these technologies, research still shows that therapists are mostly overwhelmed by their complexity, and time limitations prevent therapists from fully exploring the various possibilities (*33*) and gaining insight into how to optimize outcomes.

AI techniques, including large language models (LLMs), have shown promise in personalizing therapy planning by translating high-level treatment goals into actionable interventions, for example, converting patient goals into structured exercise plans. These personalized, evidence-based exercise plans have been positively evaluated by expert planners (*34*). In addition, several recent developments in other medical fields, such as dialysis care (*35*) and cardiac care (*35*), have also demonstrated notable potential in personalizing treatment planning.

Techniques similar to this have the potential to facilitate and enhance therapy planning, from the high-level design of therapy plans to selection and adaptation of exoskeleton parameters during individual therapy sessions, by providing intelligent decision-making agents to support therapists in planning. Despite this potential benefit, this area has been scarcely explored by the research community because, to this date, no well-defined universal framework exists that can relate the actions and decisions of the therapists to measurable and meaningful patient outcome metrics. This requires quantitatively characterizing the actions and decisions of the therapists on all temporal levels of therapy planning, along with identifying which patient-related metrics truly reflect their recovery status and preferences during the therapy process. Furthermore, relevant therapist and patient data associated with this framework need to be gathered in real-life scenarios before any AI-based model can be trained and tested. Such a system may eventually serve to bridge the gap between therapists and therapeutic exoskeletons by providing a translational module that can convert the medical terminology used by therapists into commands understood by automated robotic systems.

SERIOUS GAMES

Serious games are systems built with game technology and design principles for purposes other than pure entertainment. Serious games have been advocated and developed for years to enhance patient engagement in movement rehabilitation (*36*). Key overarching design characteristics of these games are meaningful play by clear and consistent feedback from the system that is directly relevant to the action carried out by the player, handling of failures without discouraging patients, and careful selection of difficulty to engage patients while matching players' sensorimotor and cognitive abilities (*37*). Serious games have been interfaced with a variety of platforms, including exoskeletons for robot-aided rehabilitation (*37*). A meta-analysis showed that serious games for upper limb rehabilitation after a stroke resulted in better improvements compared with conventional treatments (*38*).

AI has been used in serious games in several ways, including for adaptation of game difficulty (*39*). An AI agent has been used to play a game and cooperatively control an electromyography (EMG)–controlled exoskeleton in an assist-as-needed manner (*40*), resulting in more engaged and motivated participants compared with those using EMG control alone. AI has also been used to provide instructions to patients; trained with data from 58 survivors of stroke, an AI therapist provided verbal cues on the basis of the recorded state of the survivor during robot-aided gait training (*41*). In summary, AI-powered games enhance the autonomy of the therapy by motivating patients, adapting game play to their level, and providing verbal cues from an AI agent.

The development of serious games is time consuming. GenAI has been proposed to (semi) automatically generate game assets (*42*), such as general pretrained transformers for scenario development or latent diffusion models for text-to-image generation of characters and backgrounds. Although these techniques are not used commonly in serious game design yet, they have been pi;loted to ease the authoring of these games (*42*).

Although the use of AI has great potential to facilitate serious game design, enhance interaction of the patient with exoskeleton-powered serious games, and increase exoskeleton autonomy, its use is still in its infancy. Furthermore, AI can be used for generating virtual physical therapists. Given the rapid recent advances in chatbots powered by GenAI, it is likely only a matter of time before a virtual therapist can be as knowledgeable, engaging, and motivating as a physical therapist.

HIGH-LEVEL CONTROL

The high-level control determines the general behavior of an exoskeleton that can usually switch between several operating modes depending on the desired type of activity and the environment (*30*). Switching between operating modes is usually done by the users, for example, by pressing a button on a user interface to change ambulation modalities for an exoskeleton. AI techniques have the potential to further automate the involved high-level recognition and decision-making processes.

Terrain and scene recognition

Most gait exoskeletons require controller adjustments based on environmental conditions, such as walking on flat ground or climbing stairs. Similarly, upper-limb exoskeletons require controller adaptation for properties of the object being manipulated, for the desired task, and for collision avoidance. Traditionally, users or therapists manage this requirement via a graphical or physical interface, for example, buttons, touch screens, and joysticks. Automation is possible through AI using sensors to identify the environment and select appropriate controllers.

For lower limb exoskeletons, Weigand *et al.* (*43*) achieved accuracies higher than 98% in classifying locomotion mode and stair

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slopes using a single inertial measurement unit (IMU) mounted at the shank and an artificial neural network (ANN). Several studies, such as that of Chen *et al.* (*44*), proposed a convolutional neural network (CNN) and long short-term memory network (LSTM) on data retrieved from multisource sensors, including IMUs and plantar pressure sensors for slope prediction, achieving a root mean square error (RMSE) of 0.25°. Ramanathan *et al.* (*45*) used line-fitting features and active sensor fusion (IMUs and camera and exoskeleton joint encoders) to enhance recognition performance, including obstacles and gaps to step over (Fig. 3). Wang and colleagues (*46*) used RGB (red, green, blue) cameras and IMUs to generate continuous terrain maps such that an indoor environment could be identified and modeled. Tricomi *et al.* (*47*) equipped a hip exosuit with an RGB camera and successfully distinguished between three different walking terrains using a CNN. They adapted the gain that modulated the amplitude of walking assistance accordingly. Notably, locomotion mode classification can also be performed without explicit awareness of the surrounding scene or terrain (see next section).

For upper limb exoskeletons, Tyron *et al.* (*48*) created a CNN classification model able to determine the weight of an object manipulated by the participant by decoding information from both electroencephalogram and EMG signals during elbow flexion-extension. The results showed a mean accuracy of 80.51 ± 8.07%. In addition, RGB camera sensors have also been used to estimate the weight of lifted objects to adapt the level of provided support, achieving a mean classification accuracy above 86% (*49*). Real-time object stiffness classification has been achieved using a nonlinear logistic regression classifier (*50*). ML has also been applied to a camera and piezoelectric sensory glove equipped with an IMU using a three-step extreme learning machine–based approach for gesture and object recognition (*51*).

Terrain and scene recognition play a fundamental role in making the use of exoskeletons more intuitive. AI techniques have made substantial improvements in performance and autonomy, but there remain considerations for future research. Across the literature, a broad range between simple and complex sensor setups can be found, yet it is unclear whether the more complex sensor setups lead to better accuracies and are worth the higher level of system complexity at the cost of reduced robustness and higher chances of failures. Laschowski *et al.* (*52*) concluded that DL outperformed other AI techniques in image-based environment recognition but

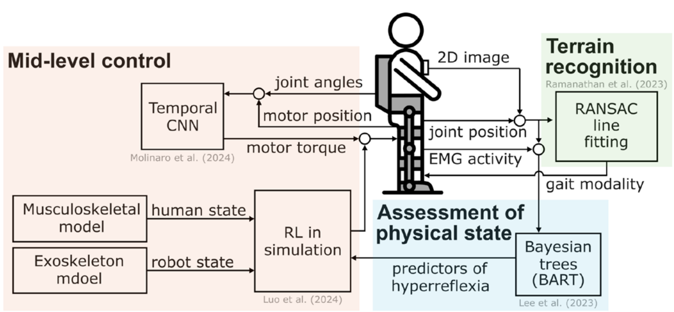

Fig. 3. Illustrative example of a control framework for lower-limb exoskeletons. In this example, multiple types of sensor data (such as 2D images, joint positions and angles, and EMG activity) are fused to identify the scene around the user [according to (*45*), green] and the user's physical state [according to (*107*), blue] and to determine the required motor torque [according to (*72*), orange]. The torque profile can be refined using simulation frameworks and data-driven RL [according to (*101*), orange].

suggested that DL methods should become more efficient because of the limited computational resources onboard the devices. In short, with novel AI algorithms, exoskeletons can reduce cognitive burden and allow users to better focus on the task at hand, rather than being preoccupied with controller mode changes. Vision-based systems are not as widely adopted in exoskeletons as they are in other areas of robotics. However, they hold notable potential to enhance both performance and autonomy. For instance, in current lower limb exoskeletons, paraplegic users often need to manually select preprogrammed motion profiles. In the future, these motions could be dynamically planned on the basis of the device's real-time environmental awareness.

Human intention or activity recognition

Just as scenes and terrains can change dynamically when using an exoskeleton, the user's movement intentions may also vary. For lower limb support, users may want to change gait speed or perform different activities such as turning, standing up, sitting down, and switching between walking and resting (*53*). Similarly, upper limb devices should accommodate motions in different planes, support various hand positions and orientations, and allow manipulation of objects with different grasp patterns. To ensure natural movement, exoskeleton systems should automatically interpret the user's movement intentions and adjust the controller without user input. Ideally, the user's intent would be identified before the activity begins; however, if this is not always possible, the activity should be identified as quickly as possible.

The current literature shows that a multitude of sensing modalities has been combined with many different AI methods to automatically recognize the user's intention. Focusing on lower limb exoskeletons, Lonini *et al.* (*54*) used motion sensors paired with random forest (RF) classification to classify a set of functional activities that able-bodied individuals and patients with diverse neurological and neuromuscular disabilities performed with a passive knee-ankle-foot orthosis (KAFO) or a computer-controlled adaptive KAFO (Ottobock C-Brace). Device-specific models trained on individual data outperformed general models trained solely with data from able-bodied individuals. This highlights the poor transferability of results from studies solely trained on able-bodied individuals. In Cheng *et al.* (*55*), a single IMU at the thigh and a force-sensitive resistor at the foot were fused to create a one-dimensional (1D) feature space, and these data were fed to heuristic feature-based AI algorithms. The system could classify transitions between sitting, walking, and ascending and descending stairs, with error rates lower than 1%. Because of the simplicity of the hardware and software, real-time results could match offline performance, showing the potential for the design to be applied in practice. In Benabid *et al.* (*56*), a tetraplegic patient with a C4-C5 SCI was able to move all four of his paralyzed limbs by decoding epidural electrocorticography data. These data were recorded by two fully implanted wireless devices placed above the functionally located sensorimotor cortices.

For arm and hand exoskeletons, Van Ommeren *et al.* (*57*) classified reach (five different locations on a table, performed in pronation and supination) and grasp movements of 10 survivors of stroke, recording data from IMUs at the wrist, hand, and fingers and feeding them into a support vector machine (SVM) classifier. Accuracies of up to 96% were achieved. Earlier detection (50 to 80% of movement completion) was also possible at the cost of slightly reduced accuracy (up to 90%). They also demonstrated that individualization of the algorithms allowed better accuracy (96% instead of 83%

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for multiuser classification). The algorithm was run offline. Where IMUs may not be used, Wahid and colleagues (*58*) showed that a RF algorithm reached 77.5% accuracy in classifying six hand gestures (supination, pronation, wrist flexion, wrist extension, radial deviation, and ulnar deviation) using EMG signals. Furthermore, the overall classification accuracy could be substantially improved up to 80% by increasing the window size and up to 90% when increasing the number of votes in the majority voting strategy, but the strategy had to be run offline.

Trigili and colleagues (*59*) developed an algorithm that identifies the onset of a reaching movement from a resting position and back to a resting position. A set of participant-independent time-domain EMG features was selected, and their probability distributions were modeled by a two-component Gaussian mixture model (GMM). Sensitivity was 89.3% and 60.9% for transitioning from resting to moving and from moving to resting, respectively, but for both events, the algorithm was able to detect the onset before the actual movement, and computational load was compatible with real-time applications.

Many algorithms have been developed for motion intention detection using a variety of sensors, but there is still no clear indication of a superior AI technique or sensing modality. Few studies trained their models with patient data despite the demonstrated poor transferability of data collected from able-bodied individuals (*54*). Therefore, to ensure that algorithms function effectively for the intended (patient) population, these models must be retrained and retested with patient-specific data.

MIDLEVEL CONTROL

The midlevel control computes the desired joint torque or positions at each time step of the main control loop (Fig. 2). Timing and amplitude of these desired values are critical in shaping the interaction of the exoskeleton with the user. Several non-AI methods exist that automate the corresponding functions (*30*). However, AI could enhance their performance by improving timing accuracy, predictive capabilities, and robustness across varying conditions.

Timing and synchronization support to determine the continuous phase or discrete state of gait or hand-arm movement

For effective and safe support of movements, it is key that the exoskeleton and its user work in synchrony, meaning that the provided robotic support is well timed with respect to the activity generated by the user and the phase of the movement. This is key not only for assistive purposes but also for therapeutic ones when assist-as-needed (*60*) approaches are being used. For walking movement, appropriate timing is mostly achieved by estimating the current percentage of the gait cycle and providing support as a function of this percentage. For upper limb movements, many algorithms depend on the current state (position and velocity) of wearable devices, which inherently ensure appropriate timing for tasks such as weight compensation, movement along a haptic tunnel, or interaction with force fields (*61*). Developments have mainly been in detection of the gait phase, so we focus on the lower limbs in the rest of this section.

Appropriate timing for lower limb devices is already achieved in well-controlled conditions and/or environments, such as walking on a treadmill or over ground, using sensors integrated in the robotic devices (*30*) and non–AI-based algorithms such as time interpolated gait phase and adaptive frequency oscillators (*62*). The latter study showed errors in the estimated gait cycle percentage of about 5% during free overground walking. In their systematic review, Kolaghassi and colleagues (*63*) examined AI methods for estimating gait phase, reporting accuracies between 70 and 98% using various AI-based models, whereas DL models generally outperformed conventional models. These reported accuracies were high already but were still achieved under controlled laboratory conditions.

Recent research has shifted toward demonstrating the effectiveness of AI methods, especially DL, using fewer sensors under various (out of the laboratory) conditions (*64*) and real-time applications. Studies focusing on fewer sensors generally used IMUs on one or two body segments, showed robust models across different conditions, and achieved errors of 2% across various gait speeds (*65*) and 5% error across various locomotion modes such as overground, stair or ramp ascent and descent, and transitions (*66*). Recent studies have demonstrated that AI-based models can effectively generalize from laboratory-based walking to real-life conditions (*43*). Proof of successful real-time application was achieved by Kang and colleagues (*66*, *67*), who integrated their neural network–based and CNN-based gait phase estimation in the control of their exoskeleton. They showed a better and more robust synchronization and a resulting decrease in torque tracking error of 40% compared with that in conventional time-based methods when walking with varying speeds and of 63% during different locomotion modes (stairs and slopes).

In short, DL models can improve the accuracy and robustness of gait phase estimation in a wide variety of conditions and environments, which allows for appropriate timing of robotic support (note that the support magnitude and dose is covered in the next section). Future developments are needed to enable real-world application, including the ability to handle perturbed walking and to allow fast and easy personalization of trained networks for new users, particularly those with heterogeneous pathological gait patterns. All aforementioned studies used only data from able-bodied participants, so applicability for those with gait abnormalities is uncertain. Initial attempts show promise; an LSTM and CNN model achieved a 0.95 correlation with actual gait phases in a child with cerebral palsy and a typically developing child (*68*). Furthermore, these models were more robust to changes in gait speed and abrupt movements compared with adaptive frequency oscillators.

Determine desired joint torques or joint angles

Midlevel controllers use information measured from human-worn or exoskeleton-embedded sensors—such as EMG, joint angle encoders, and interaction force transducers—to determine reference profiles for torque-based or kinematic-based low-level controllers. Autonomy is required to translate sensor signals into device commands that automatically adapt on the basis of human states—including factors such as fatigue level, residual strength, and user intention—and environmental conditions derived from scene recognition, such as ground morphology or contextual factors (see Fig. 2). The automatic tuning of control parameters or trajectories based on the user's performance is a major challenge in exoskeleton-based gait therapy.

Sensing human kinematics variables to tune exoskeleton assistive force and moment profiles

IMU data collected from the lower limbs in patients with stroke were used to train neural networks to model the relationship between IMU-estimated metrics and an exoskeleton control parameter associated with peak knee flexion torque (*69*). Results indicated the ability to predict peak knee flexion torque for a subset of recruited

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patients who have moderate gait impairments. A soft hip exosuit was proposed that actuates Bowden cable displacement on the basis of commands derived from hip angular velocity information to reduce the metabolic costs of walking in outdoor settings (*70*). An end-to-end control framework (see Fig. 2) was developed for a hip exoskeleton using actuator-mounted encoders along with pelvis- and thigh-mounted IMUs to inform a temporal convolutional network (TCN) for predicting biological joint moments across 35 ambulatory cyclic conditions (*71*). In a follow-up study, this approach was extended to a hip-knee exoskeleton with additional shank-mounted IMUs, foot IMUs, and force-sensitive insoles (*72*). In this latter study, the TCN was trained and evaluated not only under cyclic but also under noncyclic conditions, thereby covering a broader spectrum of human movement. In both studies, the TCN made better predictions of biological moments for cyclic activities compared with the user- and stride-averaged moments from the same dataset used to train the TCN. This result demonstrates the TCN's capability to capture both inter- and intra-user variability, variability that is lost when simply averaging moments across users or repetitions of a given activity. Last, scaling and delaying the TCN-predicted moments before applying them to the exoskeleton led to reduced metabolic costs during level ground and inclined walking (*71*, *72*) and during load lifting and running (*72*) when compared with zero-torque control.

Sensing human kinematics variables to tune exoskeleton joint kinematics profiles

Gait data collected from children with neurological disorders were used with DL to forecast future joint trajectories (*73*), which could be used as feedforward input to control lower-limb robotic exoskeleton trajectories. Joint trajectories were predicted up to 200 ms in the future, with mean absolute errors ranging from 0.095° to 2.531° when an LSTM network was used and with errors from 0.129° to 2.840° when a CNN network was used.

EMG-based

EMG-based controllers were proposed to create exoskeleton reference control signals that automatically scale with human effort. CNNs were used to achieve robust prediction of joint torques in able-bodied individuals from lower-limb EMGs despite artifacts in EMGs due to exoskeleton assistance (*74*). ANNs were used to classify EMGs acquired from patients with poststroke hand impairments to characterize three muscular levels and define exoskeleton assistance (*75*). Results indicated that the proposed control system generated exoskeleton motions with a reference tracking error < 5%. Deep RL was proposed to learn optimal assistance gains for EMG-based controllers to support movement via arm exoskeletons (*76*). However, the superiority of AI methods with respect to non-AI methods in determining EMG-dependent reference control profiles for exoskeletons remains unclear. EMG-driven neuromechanical model–based controllers were proposed to estimate joint torques from EMGs for real-time control of wearable trunk, leg, and arm exoskeletons in able-bodied individuals (*77*–*79*) and in those after stroke, with SCI, or with muscular dystrophy (*80*, *81*). These models enabled the task-agnostic control of exoskeleton torques, dynamically adapting across diverse movement conditions, such as varying locomotion speeds, ground inclinations, and even transitions between walking modes (*82*). RL could be used in the future to train neural network–based policies to personalize EMG-driven musculoskeletal models more efficiently than current optimization-based model calibration techniques (*83*). Recent studies have already shown that a generic upper limb musculoskeletal model can serve as a baseline to train an artificial neural network–based policy to fine-tune the model parameters (*84*).

Human-in-the-loop

Human-in-the-loop optimization (HILO) using metabolic cost feedback was proposed to determine optimal torque references for reducing walking effort with leg exoskeletons (*85*–*87*). Originally, these methodologies relied on optimization techniques to determine assistive torque profiles that minimized the measured metabolic cost of walking. More recently, they have been combined with ML methods, such as logistic regression, to accelerate the generation of optimal assistive torques (*88*). Assistance optimized during 1 hour of out-of-the-laboratory walking increased self-selected speed by 9 ± 4% and reduced the energy used to travel a given distance by 17 ± 5% compared with that used with normal shoes (*88*). HILO has also been used to improve several other physiological measurements or clinical outcome metrics (*89*). For example, HILO has been performed on a user's preference in exoskeleton assistance (*90*), which may be more relevant than reduction in metabolic cost. In this context, new methodologies have emerged to optimize exoskeleton assistance to an individual that account for factors that are difficult to measure but equally important to the user. A study on ankle exoskeletons demonstrated that users could reliably self-tune assistance, with preferences influenced by walking speed, device exposure, and technical background (*91*). Similarly, the region of interest active learning framework was shown to recover exoskeleton users' utility landscapes using preference-based feedback while maintaining safety and comfort (*92*). Utility landscapes refer to probabilistic models of a user's preferences over assistive behaviors, such as desired speed, trajectory smoothness, or level of autonomy, which are inferred from user interactions and used to guide personalized assistance (*92*).

Learning by demonstration

AI was proposed to create motion-planning policies that enabled exoskeletons to learn to reproduce human arm and leg trajectories demonstrated by human operators. A motion planning system was presented that used dynamic motion primitives to construct task-specific and patient-specific joint trajectories on the basis of human-learned trajectories (*93*). This approach was demonstrated on a four-degree-of-freedom (4-DoF) upper limb exoskeleton, a 5-DoF wrist-hand exoskeleton, and four patients with limb girdle muscular dystrophy. Other studies have demonstrated the feasibility of using recorded repetitions of therapist-guided movements with an upper limb exoskeleton to generate ready-to-use trajectories that reflect the therapist's intended motion patterns (*94*). DL has been used to teach robotic exoskeletons to learn patients' gait style and modify it into a new recovery gait pattern that more closely resembles able-bodied gait (*95*).

Reinforcement learning

RL has been proposed in combination with model-based simulations of the human musculoskeletal system with parallel exoskeletons to design exoskeleton controllers in silico (Fig. 3) (*96*). RL and adaptable central pattern generators have been proposed to learn individualized human-robot physical interaction behaviors and to refine exoskeleton walking trajectories in simulation environments (*97*). RL has also been integrated with musculoskeletal modeling to simulate lower limb exoskeleton controllers to support locomotion under conditions mimicking neuromuscular disorders, including passive muscles (as in quadriplegia), muscle weakness, and hemiplegia (*98*). In addition, deployment-efficient RL has been used to implement reactive balance strategies, such as stepping for standing

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push recovery on the Atalante exoskeleton (*99*). Results from simulation were successfully transferred to the exoskeleton with a test dummy. However, controllers learned in simulation have not yet been used for individuals with neuromuscular disorders. A deep RL controller for lower limb rehabilitation exoskeletons (LLREs), trained with randomized simulations to handle uncertain human-exoskeleton forces, was shown to assist users with neuromuscular disorders in real-world settings. It demonstrated robust joint tracking, gait symmetry, and stability across diverse patient conditions and exoskeleton dynamics (*98*). Purely data-driven RL-based frameworks have been used to personalize torque assistance for robotic exoskeletons without explicitly modeling human-robot dynamics (*100*). More recently, deployment-efficient RL was used to learn a real-world hip exoskeleton controller entirely in simulation (*101*). Although results showed that the control policy learned in simulation could be successfully transferred to a physical exoskeleton in the real world, these findings still require extensive validation and reproducibility.

Despite recent advances, several challenges remain. Although end-to-end controllers successfully estimated hip and knee joint moments across a diverse set of movements (*71*, *72*), additional operations, such as scaling and delaying, were required to achieve reductions in metabolic costs compared with zero-torque control. These operations were determined on the basis of prior work, physical insight, and pilot experiments. However, they were applied uniformly across conditions, which might be suboptimal for reducing metabolic costs. For instance, Molinari *et al.* (*71*) found reductions in metabolic costs of 5.4% for level ground walking, which is considerably lower than the 19.8% reduction achieved with an autonomous robotic hip exoskeleton (*25*) and lower than reductions reported for other devices (*102*). This difference in finding suggests that predicting and applying biological moments (with ML) may not be sufficient to maximize improvements in metabolic cost or other performance metrics, which was one of the main reasons why researchers started with HILO experiments. Combining TCN predictions with data-driven or user-driven RL methods might further enhance relevant metrics. Future work should be aimed at enabling task-agnostic prediction of biological joint moments that account for individual pathologies. Several open questions remain. For example, should TCNs for clinical applications be trained on data from able-bodied individuals or from specific patients? Another important question is whether applying scaled and delayed predicted biological moments, derived from impaired gait kinematics, will improve gait or potentially amplify gait abnormalities. It is likely that, depending on the severity of a movement disorder, TCN predictions will need to be combined with other control algorithms to ensure safe and effective assistance.

ASSESSMENT AND MONITORING OF PHYSICAL AND PSYCHOLOGICAL STATE

Assessment is crucial for tailoring therapy or support to the user in a single session, tracking progress over several sessions, and predicting the (mal)adaptation and outcome of rehabilitation (see next section). For these purposes, the assessment of underlying motor impairments, physical and mental state, and biomechanics is used. Conventional methods allow assessments in well-controlled environments (*11*), whereas AI methods extend the possibilities to more meaningful movements, such as those performed during therapy or daily activities, by extracting useful information from large streams of robotic sensor data (see Fig. 2) and relating it to other sources of information.

To target motor control issues with robotic training or assistive devices, it is crucial to assess and identify the underlying cause of impaired movement. Joint movement problems can result from muscle weakness or increased joint resistance caused by neural factors, such as hyperreflexia, or by non-neural mechanisms. Generally, these causes can be identified in well-controlled experiments (*103*–*105*). AI can enhance these approaches by deriving biomarkers of these different causes from the sensor data. Initial efforts include using an LTSM-based classifier to distinguish hyperreflexia-induced muscle activity from normal muscle activity, aiding in spasticity severity identification (*106*). In addition, Bayesian additive regression trees have been used to predict the occurrence of hyperreflexia in the rectus femoris from lower-limb kinematic variables (*107*) (Fig. 3). Monitoring and potentially controlling these variables can help manage hyperreflexia during walking with the aid of a wearable exoskeleton, for instance, by adjusting the movement planning.

Assessment of the user's cognitive and physical state can be used autonomously to adjust robotic support during therapy. Koenig and colleagues pioneered the use of AI to quantify cognitive load during robot-assisted gait training, estimating mental engagement from heart rate, respiration frequency, skin conductance, and temperature, with a 2.1% classification error (*108*). These estimates were later integrated into a closed-loop adaptive controller to ensure an appropriate level of active engagement during robot-assisted training in individuals with stroke (*109*). More recently, physical load was quantified during robot-resisted gait training in children with cerebral palsy using ANN (*110*). These estimates of cognitive and neuromuscular engagement have the potential to further improve the tailoring and effectiveness of the provided therapy.

For biomechanical assessment and its clinical validation, AI can be of crucial importance. Robotic device sensors provide a wealth of data to derive kinematic and kinetic variables [see (*111*) for a review of robot-aided motion analysis]. Although deriving metrics might be straightforward during structured rehabilitation sessions, it becomes challenging in daily life because of the need to identify and classify relevant motions from large data streams. Panwar and colleagues (*112*) showed that CNNs can classify arm movements in people with stroke at home. Another challenge is assigning clinical meaning to all of these data and distinguishing good from impaired movement. DL models also showed promise here. Rahman *et al.* (*113*) used the open KIMORE dataset (*114*), which includes measurements of both able-bodied and impaired movements, to demonstrate that DL models outperform classical methods, such as SVMs, in predicting clinical interpretations.

In short, robotic devices were already successfully used to perform assessments in laboratory environments (*11*, *105*, *115*). Future research directions include leveraging AI approaches to derive meaningful and clinically valid assessments from movements in more natural settings. These enhanced assessments could then be used to autonomously tailor support in real time, whether in single sessions or over multiple sessions, by predicting how humans adapt to assistance (see next section).

PREDICTING NEURAL AND MUSCULAR (MAL)ADAPTATION

Predicting how the neuromuscular system adapts after injuries or degenerative disorders is critical for effective rehabilitation robotic

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interventions. The neuromuscular system deteriorates throughout aging or in response to injuries (*116*, *117*). However, the neuromuscular system is plastic, meaning that it can develop new functional neural pathways or regenerate structurally healthy skeletal muscle (*118*, *119*). In this scenario, neuromuscular adaptation can be "steered" across days to weeks via physical training with an appropriate afferent input to the nervous system and mechanical loads to muscles (*120*–*122*).

In this scenario, the schematic block associated with this section (Fig. 2) should enable closing the loop between therapeutic and assistive exoskeletons and human neuromuscular adaptation. This re-quires exoskeletons that can steer neuromuscular adaptation rather than supporting movement function (*121*, *122*). Steering exoskeletons are intended to deliver mechanical stimuli that modulate neuromuscular tissue form and function in a controlled manner across timescales ranging from seconds, such as during a single movement cycle, to months, as seen during recovery after neuromuscular injuries (*121*, *122*). Here, we provide an outlook on existing work and future developments and challenges that must be addressed to achieve this vision.

Previous research has shown that wearable ankle exoskeletons can alter normative patterns of muscle coactivation, leading to changes in muscle synergies and potentially inducing long-term adaptations in neuromuscular structure (*123*). Moreover, long-term use of high-heeled shoes has been shown to structurally alter the neuromechanics of human walking (*124*). Although high-heeled shoes are not robotic exoskeletons, these studies provide indirect evidence that wearable exoskeletons may be capable of inducing long-term changes in the biological structure of human muscles.

Despite existing studies, current closed-loop control frameworks for current exoskeletons do not consider how biological targets, such as neurons, tendons, and muscles, adapt to robotic interventions, especially at extreme ends of the spatiotemporal scale, namely, over weeks to months (*121*, *122*). In this context, a key challenge is collecting large-scale data from the human neuromuscular system to enable the development of predictive models of neuromuscular adaptation. Achieving this requires the development of new noninvasive, stretchable, and wearable sensors, such as high-density electromyogram electrodes and thin-film ultrasound transducers (*122*, *125*, *126*). These sensors could be seamlessly integrated in breathable garments designed for daily wear, allowing continuous monitoring of neuromuscular activity (*127*).

Once large datasets of neuromuscular data are available, AI-based methods, such as transformer neural networks, could be used to process temporal series of neuromuscular data to learn the most likely adaptation to take place in the future (*128*). In this context, AI has already been used in predicting recovery outcomes after neurological injuries, such as stroke (*129*), traumatic brain injury (*130*), and SCI (*131*). Various AI methods—such as RL, logistic regression, decision trees, and deep neural networks (DNNs)—were used (*132*). These models were trained using patients' demographic and clinical data to predict exercise outcomes and noninvasive diffusion tensor imaging to forecast recovery in acute and hyperacute stroke (*133*) or to map to changes in the human connectome (*134*). Alternative approaches relied on explicit models of human sensorimotor activity driven by limb forces and motion data measured from stationary arm exoskeletons during therapy (*135*). These models could predict patients' plastic changes in response to robotic therapies, where plasticity mechanisms were modeled on the basis of activity-dependent changes in the motor system caused by sensorimotor activity (*136*). Generalist foundation models (large-scale generative models) were also proposed to predict various outcomes in neurology, such as treatment responses, progression, and outcomes (*132*, *137*). Other studies showed that, using a neural network–based discrepancy modeling framework, individual response to ankle exoskeleton could be quantified and predicted longitudinally (*138*). Predicted recovery estimates could be used, in the future, to adjust exoskeleton control parameters to ensure that the robotic therapy induced desired adaptations in the patient's neuromuscular system.

A key challenge lies in integrating AI-based predictive models into robotic control frameworks. Recent developments in LLMs show promise for the development of computationally efficient models that use optimized layers and attention mechanisms to reduce the number of calculations needed while maintaining performance (*139*). By using these AI-powered predictive models, future intelligent robots could autonomously identify the optimal electromechanical stimuli required to remodel the human musculoskeletal system, potentially surpassing the outcomes of conventional rehabilitation approaches (*122*). In this paradigm, the controlled process is the slow, nonlinear structural adaptation of the musculoskeletal system, such as muscle strengthening or lengthening, which necessitates predictive models operating at low frequencies, typically updating once per day. These models do not need to be embedded in wearable systems; instead, they can be hosted on cloud platforms running lightweight LLMs (*139*), enabling scalable, data-driven personalization of robotic therapy (*121*).

Although AI algorithms have also shown promise in prognostic assessment, challenges remain in achieving a higher prediction accuracy for practical clinical use (*140*). Accumulating more diverse data, such as medical imaging and bioelectrical signals, along with fostering collaboration among hospitals, could enhance the ability of AI to predict how neural and skeletal tissues remodel over months or years in response to prolonged exoskeleton assistance.

DISCUSSION

AI can substantially enhance the performance and autonomy of therapeutic exoskeletons, particularly of stationary ones, in several ways. It can facilitate developers of serious games (*40*), support therapists in operating these exoskeletons, assess physical and psychological states of patients (*109*), and predict recovery outcomes after neurological injuries (*131*) (Fig. 4). Moreover, the potential of AI to improve the autonomy and performance of wearable assistive exoskeletons and exosuits is increasingly evident (Fig. 5). For example, AI can detect the intent of the user (*54*, *57*) or recognize terrain conditions (*43*), enabling the system to automatically trigger appropriate control actions. It can also estimate desired assistive joint torques from limited sensory data across a wide range of walking tasks (*71*).

Therapeutic exoskeletons

AI applications for therapeutic scenarios include learning movement patterns from a therapist's demonstrations (*93*), learning to avoid movements that elicit spastic activity in patient limbs (*107*), and quantifying patients' cognitive load and mental engagement (*108*, *109*). AI has been used in adapting the difficulty level of serious games patients can play using exoskeletons (*39*). AI agents can also provide instructions,

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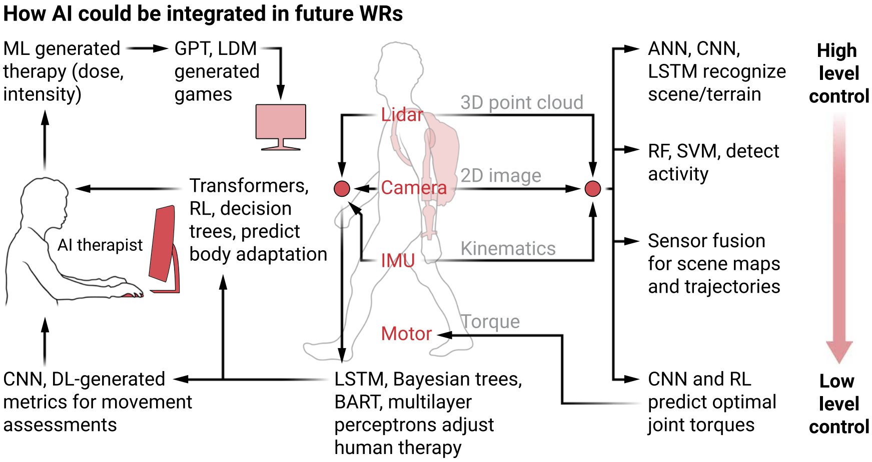

Fig. 4. Possible future use case that integrates AI-based technologies into a wearable robotic (WR) system. The methods are arranged according to the general framework outlined in Fig. 2. High-level control exploits neural networks, traditional classifiers, and multisensor fusion for scene and terrain recognition, as well as user activity detection. Midlevel control uses neural networks and RL for optimal torque prediction. User-facing modules leverage generative models to create personalized exercise routines and interactive game content. Recurrent neural networks and DL models are used to tailor assistance exoskeletons or exosuits.

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clues, and feedback to the patient or act as a player that the patient can compete with. Despite the potential for AI applications to support or relieve therapist load and increase device autonomy and performance, they have not been widely adopted.

Human therapists are still needed for therapy planning and for operating devices. This need arises from the lack of a predictive framework and related database, which relates therapists' decisions—such as type, frequency, number, and duration of exercises—and their instructions and actions to patient outcomes (*32*). This endeavor would require AI methods that can forecast future therapies on the basis of a description of the patient's current state (*31*) and prediction of future adaptation of the neuromuscular system (*122*). A limiting problem with applying AI for "therapy forecasting" is the absence of data from specific populations. Therapeutic exoskeletons could be instrumental in the assessment of sensorimotor functions before, during, and after exoskeleton-aided therapy to build the required database to come to a framework that relates therapeutic interventions to clinical outcome measures. Combining AI-powered assessment using improved exoskeleton sensors with predictive AI-based models of neuromuscular adaptation could lead to exoskeletons that steer the recovery of neural and muscular structures and functions (*121*, *122*) (Fig. 6). This could ultimately lead to more autonomous therapeutic exoskeletons that can make decisions and take actions under the supervision of a qualified clinician.

Assistive exoskeletons

AI has been more successfully applied in assistive exoskeletons designed to operate in real-life (out-of-the-clinic) conditions compared with therapeutic exoskeletons used in the clinic (Fig. 5). DL can classify more types of terrain (*141*); more accurately and robustly estimate gait phase in real-life conditions (*64*, *66*, *67*, *142*); and enhance human intention detection, high-level (motion) planning, and desired joint torque or joint angle prediction (*71*, *73*). The prediction of desired joint torques can use inputs from estimating the gait phase (*66*), motion planning (*73*), and human intention and terrain recognition (*142*) (see Fig. 2), but the advantages of AI were especially shown by end-to-end learning (*71*, *72*) by directly mapping sensor states to appropriate joint exoskeleton torques, skipping the need to estimate intermediate states. Effective joint torques could be learned not only from experimental data but also from simulations where RL found control policies for both the human and the exoskeleton controller using model simulations of exoskeleton-human interaction (*96*, *101*). However, this direct mapping will only work when the user initiates the motion, and the exoskeleton must give only partial support. For patients who need to be fully supported, the initiation and mode selection will depend on (AI-powered) human intention detection. Here, AI-enhanced scene and terrain recognition can be combined with AI-powered motion planning to dynamically generate appropriate movement patterns (Fig. 6) instead of manually selecting profiles from a motion library.

For assistive devices, the goal is conditional autonomy, where a human selects or approves tasks or strategies generated by a machine (*27*). Although (AI-powered) solutions exist to achieve this level of autonomy for devices that provide full support, they have not yet been fully integrated and tested. To enhance the autonomy of fully supportive exoskeletons, additional (AI) techniques successfully used in autonomous legged robots can be adopted (Fig. 6). The required functionalities and corresponding algorithms for full supportive exoskeletons share many similarities with those of powered prostheses. For this reason, several of the papers we cited are also applicable to prosthetic technologies. For assistive devices that offer partial support, this approval/selection of tasks should be intuitive and quick without interfering with other mental or motor tasks. Several task-agnostic devices already achieve this level of autonomy with or without AI (Fig. 5) (*77*, *80*, *143*, *144*). However, there is still room for improvement in performance and robustness across different users and environmental conditions (Fig. 6).

In some cases, it is difficult to make a distinction between therapeutic and assistive exoskeletons because assistive devices can have therapeutic effects. Assistive devices have an unleashed potential for movement rehabilitation at home and in daily-life conditions. Assessing physical and psychological states outside of laboratory settings is more complex, but AI can play a crucial role. AI algorithms have been shown to excel in evaluating these functions in real-life conditions (*112*). Combining assessment with the predictive capacities of AI could close the high-level control loop and lead to steering (wearable) exoskeletons (Fig. 6) and exosuits that promote recovery and prevent maladaptation (*121*, *122*).

Generalizability

The advantage of DL over other AI approaches lies in its potential for accurate and robust performance across a wide range of environmental conditions, which makes it highly suitable for real-life applications. However, the performance of DL, like other AI algorithms, can be device-specific and patient-specific. Therefore, the data used for DL-based models must be sufficiently rich. To avoid the need for individual training of these algorithms for each specific device or patient

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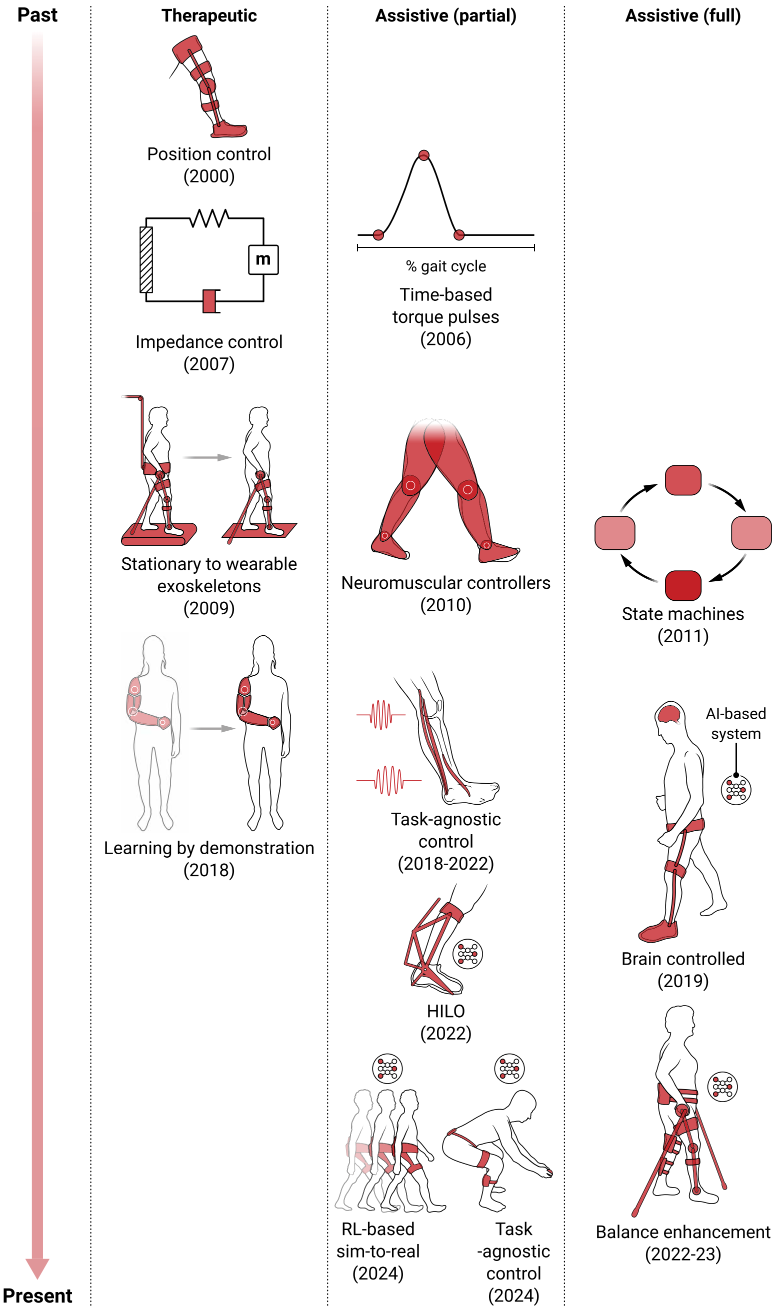

Fig. 5. Evolution of control strategies for therapeutic and assistive exoskeletons and exosuits. Therapeutic exoskeletons have evolved from basic position control strategies (*6*, *7*) to more advanced controllers using impedance control (*160*). Subsequently, nonstationary wearable exoskeletons began to be used for gait training, primarily for individuals with SCIs or post-stroke conditions, and were clinically evaluated as therapeutic devices (*14*). In addition, motion planning systems based on learning by demonstration emerged for upper limb exoskeletons, enabling assistance during activities of daily living in unstructured environments (*93*). Partial assistive exoskeletons and exosuits transitioned from time-based desired torque pulse trajectory controllers to non-AI, task-agnostic model-based controllers (*77*) and trajectory-free controllers (*23*). More recently, AI-based methodologies have emerged, including ML-based HILO strategies (*161*); experiment-free sim-to-real techniques (*101*); and AI-based, task-agnostic, end-to-end exoskeleton controllers (*72*). Fully assistive exoskeletons have progressed from finite state machines (*16*–*18*) to direct brain-exoskeleton interfaces (*56*). More recently, balance-enhancing controllers have emerged using RL in combination with human-exoskeleton models (*98*, *99*).

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group, device and patient characteristics should be captured by well-chosen hyperparameters and fed into the DL-based model. In addition, mapping sensor signals to device-invariant variables, for example, ankle and knee displacements (*145*), can be beneficial. The effect of disturbances should also be taken into consideration, particularly regarding joint- and whole-body stability, given that previous studies have shown that data-driven controllers, although effective during unperturbed walking, can amplify the impact of external disturbances (*146*, *147*). The advantages of DL come with the requirement for large, sufficiently rich, and reliable datasets, which usually take a huge effort to collect. Hence, open databases, such as those provided by Camargo (*148*) and the KIMORE dataset (*114*), are essential for training and validating DL-based models. Wearable exoskeletons and exosuits can also generate valuable data, which would enlarge available datasets, especially when these devices are aware of user characteristics and recognize the environmental context. Alternatively, generalizable, task-agnostic exoskeleton controllers can be achieved by merging RL, model-based simulations, and simulation-to-reality policy transfers (Figs. 4 and 6) (*99*, *101*).

Data-driven algorithms versus RL by digital twinning

DL and related approaches have been shown to be able to predict biomimetic joint kinematics and kinetics under a wide range of real-world conditions. However, this is often insufficient for developing effective or optimal control policies. RL, when combined with computationally efficient physical simulators of digital twins of real-world systems, can eliminate the need for collecting massive amounts of experimental data and has the added advantage of incorporating control objectives. In the field of autonomous legged robots, researchers have recently closed the simulation-to-reality gap for deployment-efficient RL: Agile navigation and locomotion skills learned in simulations were successfully transferred to a quadrupedal robot (*149*). The combination of RL and digital twinning has also been explored for exoskeletons (Fig. 5). Only recently, however, the simulation-to-reality gap has been claimed to be bridged, for example, for a hip exoskeleton that reduced metabolic costs of able-bodied users (*101*) and in the Atalante exoskeleton, with which a dummy learned standing push-recovery strategies (*99*). These results are promising, but given that there are limited reports on bridging this gap in exoskeleton research, many aspects need to be further investigated and validated. This approach exploits simulation to train exoskeleton controllers in more conditions than would be possible in the real world. In silico–trained controllers are then transferred to the real device. Despite this milestone, several challenges must be overcome to extend this result to more joints, metrics other than walking efficiency, and, most importantly, various patient groups. In general, accurately and reliably modeling the human neuromuscular system, as well as the physical interaction between the exoskeleton or exosuit and the human, is substantially more challenging than modeling the physics of a robot, especially when accounting for different patient groups (*77*, *96*). Data-driven RL has also proven beneficial for online learning of personalized

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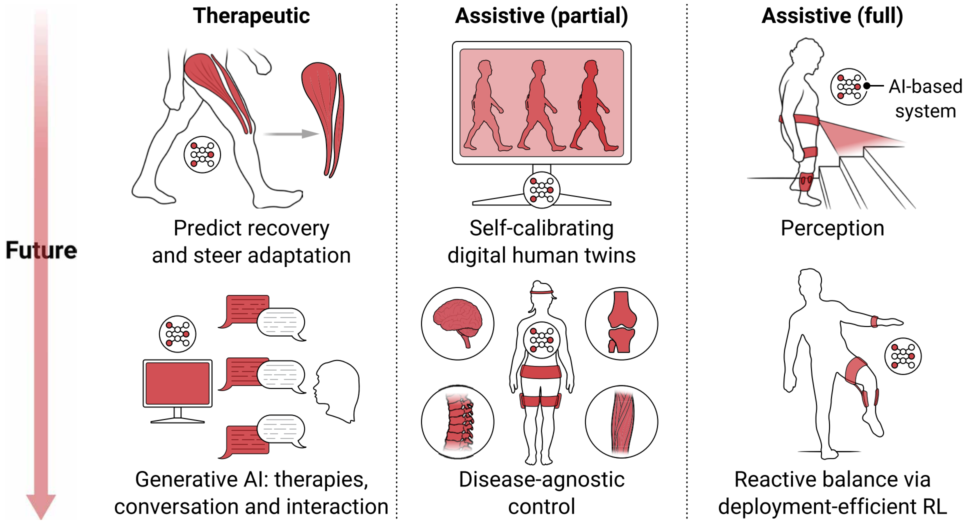

Fig. 6. Future directions for therapeutic and assistive exoskeletons and exosuits. Future technologies are expected to leverage AI to predict the effects of exoskeleton and exosuit support, optimizing both therapy planning and assistance levels. In addition, virtual AI therapists are anticipated to provide motivational feedback and longitudinal training instructions to patients. In this context, we envision GenAI-powered systems that enable and automate human therapy planning, including conversational interactions with virtual AI therapists or assistive devices. For such applications, explainable AI will be essential to ensure that AI-driven decisions are interpretable and transparent. Deployment-efficient and data-driven RL approaches are expected to play a key role in training exoskeleton controllers, supporting the development of disease-agnostic assistive technologies. Furthermore, AI techniques such as RL could be used to rapidly personalize EMG-driven musculoskeletal models for individual users, facilitating the creation of myoelectric model-based controllers for exoskeletons and exosuits. Using onboard sensors and cameras, DL can enable exoskeletons to perceive terrain and dynamically plan foot placement, eliminating the need for users to manually select preprogrammed joint trajectories.

optimal control policies from wearable sensors (*100*) or from time-consuming offline model calibrations (*84*). The latter could be expanded to learn optimal control policies from experimental data collected from HILO studies.

Comparison with non–AI-based methods

In this Review, we focused on AI methods designed to enhance the performance and autonomy of therapeutic and assistive exoskeletons (Fig. 2). However, several non-AI approaches also exist for these functions (Fig. 5), as discussed in other review papers that use similar functional terminology, such as Baude *et al.* (*30*). Although data-driven ML and RL methods are well suited for developing end-to-end controllers, task- or activity-agnostic controllers have also been developed and tested using non–AI-based methods, like those by Bishe *et al.* (*150*) and Lin *et al.* (*151*), or EMG-based approaches (*77*, *78*, *80*,*144*). In general, the strength of DL lies in its ability to handle a wide range of conditions and variations. However, its performance must be objectively compared with non–AI-based methods through rigorous and independent benchmarking. Several of the reviewed papers include comparisons between AI and non-AI approaches, but the non-AI methods used were not always state of the art. For instance, novel non–AI-based methods for gait phase estimation, such as those using extended Kalman filters (*152*) or HILO (*153*), have been developed. These methods outperformed conventional time-based approaches and achieved accuracies comparable to those of AI-based techniques, such as estimation errors as low as 2%, across diverse conditions, although they have not yet been directly compared against each other.

Benchmarking is not yet a common practice in the field of wearable robotics. However, it is strongly recommended, as it is in other disciplines, because benchmarking provides a means to assess the reproducibility of scientific studies. Algorithms for estimation, classification, recognition, and prediction of joint angles and torques can be relatively easily benchmarked, given that many open-source datasets are available for this purpose [see (*154*) for an overview and (*155*) for a more recent example]. Most databases contain data from nondisabled individuals. For clinical applications, however, databases including datasets from individuals with movement disorders are essential for training and validating algorithms. Benchmarking task- or activity-agnostic controllers, or overall control behavior, is more challenging. Accurately predicting nominal biological torques or kinematics does not necessarily translate to optimal or effective support. For instance, in efforts to reduce the metabolic cost of walking, the timing of peak torque is critical and often delayed relative to the biological peak torque (*87*). Accordingly, studies using DL to predict biological torques have incorporated delay operators (*71*, *72*). Optimal support depends on what metrics are deemed important, which may vary by individual and device. Therefore, comparing the effectiveness of different controllers is inherently difficult and typically requires costly experimental evaluation, especially when involving heterogeneous patient populations.

AI also comes with several inherent challenges. First, recent advancements in AI largely stem from the use of DNNs, which consist of many layers. This depth increases the complexity of the relationship between inputs and outputs, making these models less interpretable than traditional rule-based approaches. As a result, ensuring and demonstrating the safety of DNNs becomes more difficult, particularly considering the stringent regulatory requirements for medical devices. Therefore, it is crucial to rigorously evaluate the behavior of the network outside its training distribution to ensure the absence of unintended or potentially harmful outputs. Second, because of the complexity of DNNs, it is also not feasible for humans to manually tune these networks to meet individual patient needs. However, this limitation might be addressed indirectly by combining HILO with other model-free RL techniques, for example, by time-shifting and scaling the prediction of biological moments from TCNs as discussed in the section on how to determine desired joint torques or joint angles. In addition, advances in explainable AI (*156*) may help overcome this challenge, particularly as DNNs gain the ability to adapt their outputs through conversational interactions, as seen in GenAI-based chatbots. Last, power consumption increases with DNN complexity, which may present a major challenge for wearable devices. Therefore, when benchmarking different algorithms, power efficiency should also be considered as a

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critical evaluation metric. Our generic framework (Fig. 2) introduces clear boundaries for each control block, facilitating the integration of ML and non-ML methods—a strategy adopted in several of the referenced studies. Ultimately, the optimal combination of methods or algorithms will be highly dependent on the specific use case.

CONCLUSION

This Review of the state of the art of AI in therapeutic and assistive exoskeletons reveals several promising studies, many of which have led to (potential) improvements in performance and autonomy over non-AI methods (Fig. 5). However, achieving high autonomy remains a long-term goal for therapeutic exoskeletons. Also, conditional autonomy for fully assistive exoskeletons has not been realized, although the required technologies seem to be available to achieve this soon. For partially assisting exoskeletons, this level of autonomy has been realized. Nevertheless, there is still a need to improve performance by making the control even more intuitive and fluent across a broader range of environmental conditions. Most research in assistive exoskeletons has focused on improving walking efficiency in nonpatient groups. However, individuals with neurological disorders or older adults are likely to prioritize reducing falls and pain (*157*).

In summary, the full potential of AI-powered exoskeletons has not been fully realized, and much research and development lie ahead (Fig. 6). For data-driven AI methods, more data are needed to predict long-term effects of exoskeleton support. There is a strong need for clinical and patient data to train and validate AI because most studies so far only included data from able-bodied individuals, whereas AI-based models have the risk of not generalizing well when not properly trained. Collecting data over large timescales (weeks) of patient neuromuscular state and motor capacity is challenging because currently no infrastructure is available. Exoskeletons and exosuits could contribute to collecting the necessary data also in real-world conditions, given that they are and can be equipped with various sensors. Although some cited studies contrasted results from AI methods with non-AI methods, many other studies did not make such a comparison. Because researchers use various nonuniform methods, if any, to validate the results of their algorithms, comparisons are sometimes difficult to make. More standardized validation and comparison methods would make it easier to compare different methods and access advancements in exoskeleton technology. Deployment-efficient RL does not rely on data but on accurate digital twins because learning on the physical human-exoskeleton combination is often not possible and is much more time consuming. The simulation-to-reality gap has been claimed to be bridged for RL exoskeleton controllers in some promising studies. However, to achieve broader applicability, it is essential to develop accurate and reliable digital twins of human-exoskeleton interaction and adaptation for different patient groups. Data-driven RL can be, and has been, used to learn optimal control (tuning) policies online, either from wearable sensor data or from offline data collected from time-consuming HILO experiments or neuromuscular model optimizations. Last, for these technologies to become a viable product, the computational efficiency of AI algorithms, particularly those processing image data, must be improved. In this context, advancements in neuromorphic computing are promising (*158*).

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Correction (21 November 2025): In the first paragraph of the "Predicting neural and muscular (mal)adaptation" section of the published paper, the introductory sentence, "Predicting how the neuromuscular system adapts after injuries or degenerative disorders is critical for effective rehabilitation robotic interventions," was erroneously repeated at the end of the same paragraph. The duplicated sentence at the end of the paragraph has now been deleted. The conclusions are not affected.

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AI in therapeutic and assistive exoskeletons and exosuits: Influences on performance and autonomy

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