Predicting Neuromuscular Engagement to Improve Gait Training With a Robotic Ankle Exoskeleton

Karl Harshe, Jack R. Williams, Toby D. Hocking, and Zachary F. Lerner

***Abstract*—The clinical efficacy of robotic rehabilitation interventions hinges on appropriate neuromuscular recruitment from the patient. The first purpose of this study was to evaluate the use of supervised machine learning techniques to predict neuromuscular recruitment of the ankle plantar flexors during walking with ankle exoskeleton resistance in individuals with cerebral palsy (CP). The second goal of this study was to utilize the predictive models of plantar flexor recruitment in the design of a personalized biofeedback framework intended to improve (i.e., increase) user engagement when walking with resistance. First, we developed and trained multilayer perceptrons (MLPs), a type of artificial neural network (ANN), utilizing features extracted exclusively from the exoskeleton's onboard sensors, and demonstrated 85–87% accuracy, on average, in predicting muscle recruitment from electromyography measurements. Next, our participants completed a gait training session while receiving audio-visual biofeedback of their personalized real-time planar flexor recruitment predictions from the online MLP. We found that adding biofeedback to resistance elevated plantar flexor recruitment by 24 $\pm$ 16% compared to resistance alone. This study highlights the potential for online machine learning frameworks to improve the effectiveness and delivery of robotic rehabilitation systems in clinical populations.**

***Index Terms*—Exoskeletons, deep learning methods, physical human-robot interaction, wearable robotics.**

I. Introduction

IMPROVING mobility for those with neuromuscular disorders such as cerebral palsy (CP) is an essential, yet largely unmet, rehabilitation goal. Left untreated, deficits in strength, balance, and coordination associated with CP and similar diseases can result in decreasing mobility across the lifespan [1]. Functional gait training is the predominate focus of routine physical therapy for children with CP. Current approaches however, do not provide effective tools necessary to target the coordination and recruitment of specific muscle groups, like the ankle plantar flexors, which play a critical role in efficient walking [2].

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This work involved human subjects or animals in its research. The Institutional Review Board of Northern Arizona University approved this study under protocol #986744.

Karl Harshe and Jack R. Williams are with the Mechanical Engineering Department, Northern Arizona University, Flagstaff, AZ 86011 USA (e-mail: kh2638@nau.edu; jack.williams@nau.edu).

Toby D. Hocking is with the School of Informatics, Computing, and Cyber Systems, Northern Arizona University, Flagstaff, AZ 86011 USA (e-mail: toby.hocking@nau.edu).

Zachary F. Lerner is with the Mechanical Engineering Department, Northern Arizona University, Flagstaff, AZ 86011 USA, and also with the Department of Orthopedics, The University of Arizona College of Medicine-Phoenix, Phoenix, AZ 85004 USA (e-mail: zachary.lerner@nau.edu).

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Wearable robotic systems, particularly those providing resistance targeting specific muscle groups and functions, have emerged as potential tools for more effectively targeting appropriate timing of specific muscle groups within a functional context [3]. Current implementations of rehabilitative exoskeletons range from tethered multi-joint devices with complex learning algorithms, to single joint systems that control video games [4], [5], [6], [7]. In the future, these systems could deliver gait training at an appropriate frequency to elicit long-term gains (e.g., daily training at home) [8]. Machine learning has been used to improve human interactions with the control of wearable devices for tasks including EMG based grasping as well as upper limb rehabilitation [9], [10]. However, we are not aware of any other study that has leveraged machine learning to predict neuromuscular engagement during robot-resisted gait training. The ability of robot-aided functional gait training to facilitate motor learning depends on whether a user is actively engaging appropriately with the system [11]. Left unmonitored, individuals can adapt to the constraints posed by the robotic system in such a way that minimizes the desired neuromuscular response.

Monitoring the neuromuscular response (i.e., muscle recruitment) during gait training with robotic resistance is therefore necessary for optimizing rehabilitation outcomes as it would allow for appropriate intervention in the form of physical therapist instruction or automated performance biofeedback which appears most effective when both audio and visual feedback are used together [12]. Real-time visual and audio biofeedback based on electromyography (EMG) signals has been shown to have positive effects on rehabilitation outcomes [13], [14]. However, due to time, cost, reliability, and complexity constraints, real-time measurements of muscle activity via EMG is often not feasible nor desirable when monitoring gait training in clinical and home environments. Therefore, there is a need for the ability to predict muscle activity responses during gait training directly from the robot's integrated sensors. Machine learning techniques hold potential to predict human-robot interaction [15].

The first goal of this study was to predict neuromuscular recruitment of the ankle plantar flexors without the need for EMG electrodes during exoskeleton resisted gait training in CP. In addressing this goal, we compared the relative accuracies of generic and custom model architectures. We also leveraged

TABLE I
PARTICIPANT DETAILS

Participant	Age [years]	Sex	GMFC level	Leg length [m]	Walking speed [m/s]	Mass [kg]	Resistance [Nm]
P1	13	M	I	0.86	1.01	56.8	7.8
P2	12	M	I	0.85	1.01	44.5	6.1
P3	35	M	II	0.92	1.05	63.6	8.8
P4	36	M	I	0.93	1.06	71.4	9.8
P5	18	F	II	0.80	0.60*	53.0	7.0
P6	18	F	II	0.76	0.96	62.5	8.6
P7	14	M	I	0.81	0.99	44.3	6.1

* Participant did not feel comfortable walking above this speed

the interpretability of linear regression models to evaluate the relative importance of each exoskeleton sensor feature in predicting recruitment. We hypothesized that ankle angle, ankle angular velocity, device torque, and plantar pressure measurement inputs into data-driven models would result in accurate predictions of plantar flexor muscle recruitment in this clinical population. We focused on predicting and incentivizing plantarflexor muscle activity due its clinical relevance in the management of CP [16], [17]. The second goal of this study was to utilize the predictive model of plantar flexor recruitment in the design of a personalized biofeedback framework intended to improve (i.e., increase) user engagement when walking with resistance. We hypothesized that biofeedback based on the real-time prediction of plantar flexor recruitment would improve muscle recruitment during resisted walking vs resisted walking without muscle recruitment biofeedback.

II. METHODS

A. Overview

We developed and trained multilayer perceptrons (MLPs), a type of data-driven supervised artificial neural network (ANN), to create subject-specific predictions of neuromuscular responses. We used features extracted exclusively from the exoskeleton's onboard sensors to predict synchronized label data generated from surface EMG activity of the plantar flexor muscles. To assess the importance of custom MLP architectures on predictive accuracy, we assessed both generic and subject-specific layer structures. Next, to demonstrate the clinical relevance of the framework, we used the subject-specific predictive models to provide real-time recruitment biofeedback during a gait training session.

We received approval for this study by the Institutional Review Board of Northern Arizona University (#986744). Participants over the age of 18 years provided written consent; those under the age of 18 provided verbal assent, with written consent provided by a parent. Our protocol and hypotheses were registered with the Open Science Framework prior to enrolling the first participant [18].

B. Participants

Seven individuals diagnosed with CP were recruited for participation (Table I). Inclusion criteria were an age between 10-65 years old; a body mass between 40 and 85 kg; a confirmed CP diagnosis with Gross Motor Functionality Classification System (GMFCS) level I-III; the ability to walk continuously on a treadmill for at least three minutes; the ability to follow both verbal and simple visual instructions; finally, the absence of any known medical condition that could cause harm or injury during participation.

C. Robotic Ankle Exoskeleton

We used a custom untethered ankle exoskeleton to deliver plantar flexor resistance, record feature data for predictive model building, and stream real-time sensor data for neuromuscular recruitment biofeedback (Fig. 1). Device characterization and sensor validation was reported previously [19], [20]. The exoskeleton was a lightweight, bilateral, battery-powered system that could assist or resist both plantar flexion and dorsiflexion of the ankle. In a centrally located waist assembly, two 24 V brushless DC motors (Maxon EC-4pole, 120 watt), one for each limb, were powered by a 910 mAh LiPo battery. Mechanical work from the motors were transmitted to an ankle assembly on each limb via steel cables inside Bowden sheaths. These cables rotated a pulley at the ankle, which drove a carbon fiber footplate to resist plantarflexion (Fig. 2).

For this study, a potentiometer-based angle sensor was mounted in-line with the ankle joint to provide onboard measurement of ankle angle and angular velocity. Force sensitive resistors (FSR), located in the footplate, recorded plantar pressure and were used to provide stance and swing state information. A custom low-profile torque sensor located at each ankle joint recorded real-time applied torque and was used by a closed-loop proportional-derivative controller, operating at 500 Hz, to ensure proper torque tracking. The exoskeleton was monitored and controlled with a MATLAB Graphical User Interface wirelessly over Bluetooth. System state data were displayed to researchers and recorded at 100 Hz.

D. MLP to Predict Plantar Flexor Recruitment

We used Scikit-learn, a validated Python machine learning library, to implement our multilayer perceptron (MLP) [21]. We selected the MLP structure of an ANN primarily for its abilities to fit linear and non-linear functions, as well as predict continuous output values [22]. Two different multilayer perceptron regressions were used for each participant, a generic model, and a custom model. The generic model had a relatively simple three-layer architecture with six fully connected nodes in the first layer, four fully connected nodes in the second, and two fully connected nodes in the third, this generic architecture was selected on the basis of showing the most accurate learning across participants in pilot testing. There was also a bias term on each layer and hyperbolic tangent activation functions after

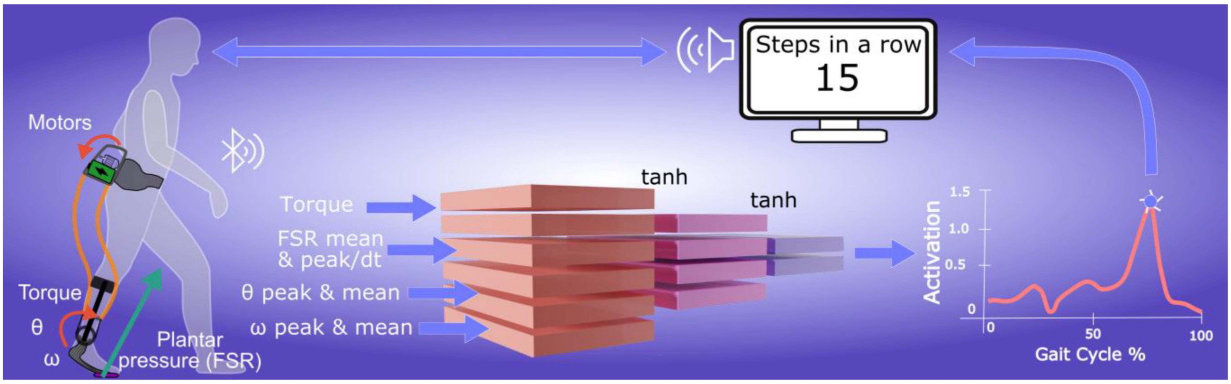

Fig. 1. Overview of our real-time plantar flexor recruitment biofeedback framework. Data from the exoskeleton were transmitted over Bluetooth and passed into a multilayer perceptron (MLP) used to predict a change in muscle recruitment. Predictions above the recruitment target incremented a visual display counter and provided an auditory "reward". Predictions below the target reset the counter to zero. Participants were instructed to maximize the number of steps counted in a row without the counter resetting.

TABLE II
MLP ARCHITECTURE AND ACCURACY INFORMATION

	Step count	Custom model architecture [Nodes per layer]	Mean absolute % Error		
			Custom	Generic	Linear
P1	381	[9, 5, 1, 1]	10.5%	11.1%	11.4%
P2	319	[10, 2, 4, 4]	18.1%	22.2%	20.3%
P3	659	[10, 3, 2, 2]	14.6%	15.5%	15.4%
P4	454	[9, 3, 9, 9]	11.9%	14.5%	14.7%
P5	139	[10, 6, 3, 10]	15.9%	18.7%	17.0%
P6	480	[9, 9, 3, 5]	11.9%	15.9%	16.3%
P7	390	[10, 3, 3, 3]	6.8%	8.1%	7.8%

Fig. 2. Motors, controllers and power were all contained in the motor control assembly that was worn around the waist of all participants. The ankle assemblies were augmented with bilateral brackets and angle sensors, which provided angle and angular velocity measurements.

non-terminal layers. The Limited-memory Broyden-Fletcher-Goldfarb-Shanno (LBFGS) solver was used for gradient updates. A custom MLP was also generated for each participant based on minimum mean squared error (MSE) of the validation set. To create each custom model, we evaluated all architectures where the total layer number was between two and five with node numbers ranging from one to ten in each layer, test set data were never used to train models, only the train set. The custom MLP architectures are shown in Table II. Identical to the generic model, the custom architecture also contained bias terms, hyperbolic tangent activation functions and used LBFGS for gradient updates.

The input features for both custom and generic MLP models were a processed subset of the exoskeleton's state variables from the stance phase of walking, including peak torque, peak angle (θ), mean θ, peak FSR, mean FSR, peak angular velocity (ω), mean ω, peak $F\dot{S}R$ peak positive θ, peak negative θ, and peak negative ω. The mean and max values from each step were used as model input features to contain the amount of data required to predict peak plantarflexor recruitment. All input features were scaled such that every feature had a mean of zero and a standard deviation of one prior to model input.

In a post-hoc analysis, Scikit-learn was also used for the implementation of a linear regression model used to evaluate the relative importance of each of the 11 features when predicting plantar flexor recruitment. Its accuracy was also checked against the custom MLP to assess the necessity of more complex models for prediction. Each linear model contained a single weight for each feature and a bias term, all of which were summed to generate predicted values.

E. Experimental Data Collection

The participants were instructed to engage with resistance to the best of their ability by plantarflexing during late stance during all resisted trials (with and without biofeedback) across both sessions. During the first session, participants underwent five one-minute walking trials with the exoskeleton, including one zero-torque trial followed by four bouts of plantar flexor resistance. The target non-dimensional walking speed [23] was 0.35, though one participant was not able to achieve this speed. The target walking speed was based on leg length and selected to be slightly challenging for participant population, but not difficult enough to cause fatigue. Each participant wore four wireless EMG sensors (Delsys, Trigno) located symmetrically on the lateral gastrocnemius and soleus. Resistance torque was set at 0.137 Nm/kg [24].

After each trial, each participant rested for between one and five minutes. Participants were prompted in the third bout of resistance to take larger steps so that the training data would include more varied walking. Exoskeleton and EMG data were synchronized with the exoskeleton by having key start and stop events in each trial that allowed researchers to accurately identify initial and terminal steps.

Between sessions, 11 features were extracted from the exoskeleton's sensor data. EMG data were scaled to the mean activation of the highest ten steps from the zero-torque trial to isolate changes in recruitment caused by the resistive torque separate from adding mass to the body. The EMG data from the gastrocnemius and soleus muscles on each leg were then summed to form the label for the step; this was done to create a single metric that reflected the response from both muscles. We trained the "generic" MLP architecture for each participant to predict plantar flexor recruitment for the biofeedback system used in the second session. Left and right legs were trained independently so that asymmetries related to CP did not impact the accuracy of the prediction for the target (more-affected) limb.

F. Model Validation and Assessment

We compared predictions from each custom and generic MLP to a linear model (this simplest version of an ANN) and a featureless model that predicted the mean of its label data. This was done to identify meaningful learning rather than relative learning [25]. Standard 3-fold cross-validation was used to validate our ANNs and linear models, with each dataset split into a training set (85%) and a test set (15%); test datasets were not used to train the models. Loss (MSE) was tracked over every epoch of learning for both sub-train and validation datasets [22]. Each fold of the data generated characteristic validation losses relative to training epoch. The folds were then averaged, and the final loss vector provided the epoch at which to stop training to avoid overfitting. This mean curve displayed the characteristic under-fitting at low epoch counts and over-fitting at large epoch counts. The minimum mean-validation loss was identified and set as the optimal number of epochs for learning (Fig. 3).

We analyzed the linear models to inform our understanding of the importance of each exoskeleton data feature. We ranked the absolute values of each linear model weight across the cohort to assess the features that had the largest impact on predicted recruitment.

We computed model accuracy as one minus the percent error between predicted and measured change in plantar flexor recruitment. Model prediction accuracies were confirmed to be normally distributed based on the Lilliefors test for normality with alpha set at 0.05. We then used paired two-tailed t-tests to determine statistically significant differences in accuracy between the models; statistical significance was defined as $\alpha < 0.05$. We did not adjust our alpha values for multiple comparisons due to the exploratory nature of this work.

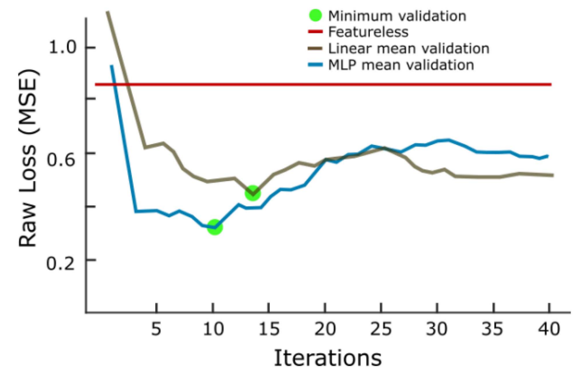

Fig. 3. Example mean loss curves for linear and generic MLPs. A different number of epochs was expected to produce the most accurate model. In this example, the generic model would be trained to 10 epochs, and the linear model would train to 14.

G. Real-Time Biofeedback From Online Predictions

Once the generic MLP model was trained for an individual, they returned for a second session in which they completed three additional one-minute walking trials. Listed in order of delivery, the walking trials included walking with (1) zero-torque, (2) resistance alone, and (3) resistance plus real-time biofeedback delivered to the more affected limb. The biofeedback target was set at the 60th percentile of predicted plantar flexor recruitment from the first session. When each participant succeeded in walking in such a way that resulted in a predicted recruitment above the target level, they received an auditory and visual reward in the form of a "chime" sound and a TV-displayed counter informing them how many consecutive steps they had achieved with elevated recruitment. The text changed at 5, 15 and 25 consecutive elevated recruitment steps and disappeared following a below-target prediction. One participant was unable to return for their second session within the study window.

III. Results

A. Model Prediction Accuracy

All three data-driven models designed to predict plantar flexor recruitment showed effective learning relative to baseline ($p < 0.049$ for all models, Fig. 4(b)). The generic MLP had an average accuracy of 84.9%, which was similar to the accuracy of the linear model at 85.3% ($p = 0.323$). With an average accuracy of 86.8%, custom MLP architectures were more accurate than the generic architecture and the linear model ($p < 0.004$, Fig. 4(a))

The linear model was evaluated for each participant and the absolute values of the weights were used to rank the impact that each variable had on predicted plantar flexor recruitment (Table III). The features varied in rank from person-to-person,

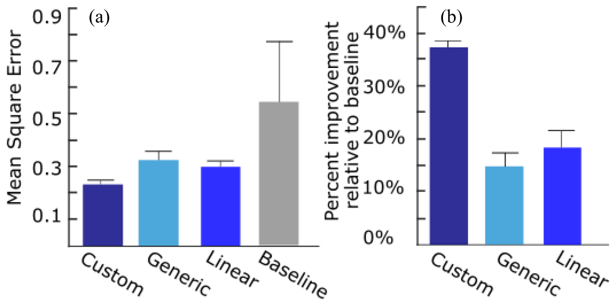

Fig. 4. (a) The mean Mean Squared (MS) Error across all participants and their observations. (b) The mean accuracy improvement relative to baseline across all participant. Error bars depict variance.

TABLE III
LINEAR REGRESSION FEATURE RANKINGS

Variable	Mean of Individual Ranks	Group Ranking
Peak FSR	3.1	1
Mean θ	3.9	2
Mean FSR	4.0	3
Mean ω	5.3	4
Peak torque	5.6	5
Peak θ	6.1	6
Peak - ω	6.6	7
Peak +θ	7.0	8
Peak -θ	7.6	9
Peak ω	7.9	10
Peak $\dot{FSR}$	8.3	11

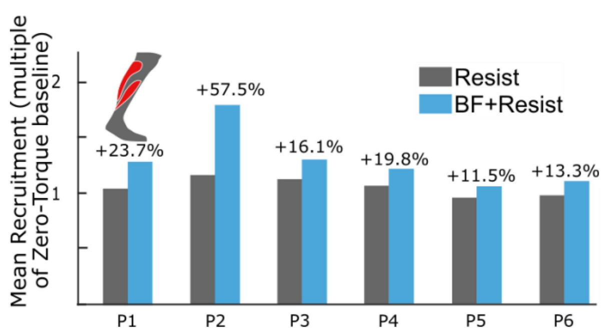

Fig. 5. Change in plantar flexor recruitment across participants during walking with resistance alone (Resist) vs resistance plus MLP-predicted recruitment biofeedback (BF+Resist).

where peak FSR, mean angle, and mean FSR during stance phase were the top three features. Only peak FSR was in the top five features for all participants.

B. Biofeedback Improved Muscle Recruitment

Real-time plantar flexor recruitment biofeedback increased mean peak in plantar flexor recruitment by $23.6 \pm 15.7\%$ relative to resistance only ($p = 0.028$); the range of increased recruitment across individuals was 11.5–57.5% (Fig. 5). Plantar flexor recruitment for the less-affected leg, which was not receiving biofeedback, increased by $10.5 \pm 5.2\%$. Peak FSR voltage, mean angular velocity and peak angular velocity all increased relative to resistance only conditions.

IV. Discussion

In this letter, we sought to predict neuromuscular recruitment of the ankle plantar flexors during exoskeleton resisted gait training without the need for EMG electrodes. We found that custom and generic MLP s were able to predict changes in plantar flexor muscle activity to between 80–90% accuracy across a diverse group of individuals with CP. Our second goals was to develop and validate biofeedback delivery framework based on the MLP predictions to demonstrate clinical relevance. We found that predicted recruitment biofeedback significantly improved neuromuscular engagement during gait training with exoskeleton resistance in CP.

We compared accuracies between generic, custom MLP and linear architectures across our participants. We did not use conservative reporting which might have devalued the validity of other researchers elaborating on methods that we did not find optimal, but still showed promise. The custom architecture models were statistically more accurate than the generic models, as expected.

Our biofeedback results suggest that the observed prediction accuracy (85–87% on average) is adequate for the intended purpose of improving human-robot interaction. There was a potential ordering effect due to the fact that all participants received the same testing order. We purposefully implemented the resistance plus biofeedback trial after the resistance alone trial because once the biofeedback system taught the user to improve engagement through the incentivized scoring, it is unlikely that that skill would be unlearned for the remainder of the session. More rigorous evaluation of the testing order effects should be investigated in future work. The group-level increase in plantarflexor activity during the resistance plus biofeedback condition, while significantly improved over the resistance alone condition, was less than what was reported previously by Conner et al., [3]. This is likely because Connor et al., used a longer acclimation period (four 20-minute sessions). Participants walked for only four minutes with resistance in the present proof of concept study. Additional acclimation would likely result in greater increases in plantarflexor activity during resisted walking with automated biofeedback. For the resistance alone condition, it is possible that additional acclimation may not change engagement as people may elect to remain disengaged in the absence of external cueing. Comparing the neuromuscular response to our automated resistance plus biofeedback system following a longer acclimation period is something we plan to investigate in the future.

In a post-hoc analysis, we also developed linear regression models for each subject with the primary goal of understanding the strength of the relationships between our model features and plantar flexor muscle activity. On average across the cohort, the most predictive features were peak and mean plantar pressure measured from embedded FSRs, ankle angle and angular velocity, and exoskeleton torque. The similarity of the linear model accuracy compared to our MLP predictions was a surprising, but welcome outcome. There may be many benefits of utilizing linear regression vs MLP models in this and similar frameworks. Regression models are simpler, easier to interpret and communicate, and faster and less complicated to implement. Such a model would be less computationally expensive and easier to embed completely on board the robotic system.

This study lays the foundation for our long-term goal, which is to develop a single generalizable data-driven model that can accurately predict plantar flexor activity across individuals with wide ranges of neurological conditions and walking patterns. A generalizable model that would not require patient-specific modifications or additional training data is likely necessary for translation to clinical practice. We intend to meet this need in our future work, with a focus on increasing the reliability of sensor measurements across individuals, device fitting, and time-points.

Several limitations to this study exist and should be noted. First, data were time series but were summarized into event driven observations, so some context could have been lost during processing. Second, because we targeted plantarflexor activity as opposed to the plantarflexor joint moment, there was the possibility of increased plantarflexor activity not resulting in an increase in the plantarflexor moment due to co-contraction. This limitation is worthy of further consideration. Finally, we did not account for multiple comparisons due to the exploratory nature of this work. The level of evidence from each comparison in our study should be carefully interpreted from our reporting of the unadjusted p-values.

This letter showed that supervised machine learning techniques, such as MLPs, and even simple linear regression, can be used to estimate peak plantar flexor activity from exoskeleton features during gait training in individuals with neuromuscular impairment. We also demonstrated the relevance of these predictions through the application of a real-time biofeedback scheme that resulted in improved plantar flexor recruitment. These results highlight the potential for this framework to improve the effectiveness and delivery of robotic rehabilitation systems in clinical populations. Future work will evaluate the framework over longer training interventions, attempt to generalize a data-driven model across multiple individuals, and extend predictions to additional muscle groups.

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