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Using a machine learning approach to predict the outcome of intervention programs in children with unilateral cerebral palsy

Author:

H.G. VAN DEN BOORN

Supervisors:

Dr. M.L.A. JONGSMA
Dr. J. FARQUHAR

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H.G. van den Boorn [a,d] C.M. Baas [a] P.B.M. Aarts [b] B. Steenbergen [a,c]
J. Farquhar [d] M.L.A. Jongsma [a]

[a] *Behavioural Science Institute, Radboud University, Nijmegen, The Netherlands*
[b] *Department of Pediatric Rehabilitation, Sint Maartenskliniek, Nijmegen, The Netherlands*
[c] *Australian Catholic University, School of Psychology, Melbourne, Australia*
[d] *Donders Institute of Brain, Cognition and Behaviour, Radboud University, Nijmegen, The Netherlands*

Abstract

In order to improve upper limb function in unilateral cerebral palsy (uCP), two different approaches have been developed over the past years. One approach is modified Constraint-Induced Movement Therapy (mCIMT), which involves constraining the less-affected upper limb and intensively training the affected arm and hand. The other approach is Bimanual Training (BiT), which focuses on the use of both hands. While both therapies have proven to be effective on a group level, there are large inter-individual differences.

To detect these differences beforehand, machine learning models were trained to predict the outcome of intervention in 45 children by using predictors obtained prior to intervention. These include several demographic features as well as hand-capacity and manual ability scores and EEG features. In the end, intervention outcomes were predicted on ABILHand-Kids scores, CHEQ scores, reaction times and Box and Blocks scores. The explained variance on the predictions exceeded 0.5 for ABILHand-Kids and CHEQ scores, 0.6 for the reaction times and 0.7 on the Box and Blocks task. Prediction errors were below standard deviation for the CHEQ and Box and Blocks scores. Addition of EEG features did not change the prediction error.

This approach shows promising results in predicting the outcome of intervention in individual children. It can be used in future to create optimal tailored interventions for individual children with uCP.

1 Introduction

Cerebral Palsy (CP) is caused by non-progressive brain injury to parts of the brain involved in movement processes. It occurs before, during, or shortly after birth and predominantly affects the childs motor functioning (having a motor impairment is obligatory for the diagnosis of CP). Even though non-progressive, it still is associated with lifelong motor impairments and disabilities [25]. It has an incidence of approximately 2.4 per 1000 live births [15]. About 1/3 of children with CP consist of those with hemiparesis, which constitutes a substantially greater motor deficit in one upper extremity compared to the other [31]. This type of CP is commonly referred to as unilateral CP (uCP) and is often due to a lesion in one of the cerebral hemispheres.

1.1 Unilateral Cerebral Palsy rehabilitation

Although uCP is not curable, there are some treatments which lessen symptoms and teach children more independence and motor control. For example, rehabilitation therapy is offered to children with uCP in order to improve their hand capacity. Two training programs that are commonly offered are bimanual therapy (BiT) and modified Constraint Induced Movement Therapy (mCIMT).
As the name suggests, BiT [13] aims to improve bimanual coordination by having children engage in specific bimanual tasks. Children with uCP often have adapted their motor control to account for the motor disabilities in the affected hand; this may result in the children mainly using their less-affected hand in daily life [13]. BiT is not necessarily aimed at improving the capacity of the affected hand, but aims at improving the childs bimanual skills, by engaging the child in tasks which also need the use of the affected hand.
mCIMT is a type of intervention which is based on "forced-use intervention". With mCIMT, the less-affected hand is physically restrained by using a sling during therapy sessions. Thus, children are encouraged the train the affected hand during unimanual tasks [8]. The idea behind mCIMT is that the children will develop and increase the hand capacity of the affected hand, which in turn will lead to enhanced bimanual performance even after training [12].

Although both BiT and mCIMT interventions have proven to be successful in numerous studies [13, 8, 7, 1], the question remains which intervention is more effective. At group level it seems that there is little to no difference between intervention effectiveness [26]. However, large inter-individual differences exist. It is still unclear if children that respond minimally to either one of the intervention programs would respond better to the alternative intervention. Till now, placement in either intervention program is mainly based on preference of the child, parent, and/or therapist, and not on objective criteria supported by evidence based research.

1.2 Main aim

If accurate individual predictions of the effectiveness of intervention can be made, then the more effective intervention program could be advised to individual children with uCP in the future. Such an approach would not only increase the net effect of intervention for an individual child, but could also reduce the amount of intervention needed. The main aim of this pilot study is therefore to develop an initial approach that allows individualised rehabilitation programs for children with uCP. This was done by, in retrospect, predicting the outcome of a given intervention program at the individual level with the application of machine learning. Thus, we investigated the prognostic value of a set of data obtained prior to intervention with respect to the effect size of intervention. This effect size is captured by several hand capacity measures as determined before and after intervention. In particular, Electroencephalography (EEG) data, and the Event-Related Potentials derived from the EEG recordings prior to treatment were included as to determine whether certain neuro-markers might be predictive with respect to the outcome of intervention.

2 Methods

2.1 Subjects

In total data from 45 children diagnosed with uCP were acquired from an existing database. Children were enlisted for participation in a combined intervention programme. The intervention program consisted of a mix of BiT and mCIMT, although there was a clear focus on bimanual therapy. For each child, age, gender, affected hand, MACS classification [10] and amount of BiT/mCIMT hours were documented. An overview of the participants can be seen in Table 1. Data were derived within an ongoing collaboration from an existing database of the Radboud University Nijmegen the Netherlands, in collaboration with the Sint Maartens clinic for rehabilitation, Nijmegen, The Netherlands and the Roessingh Clinic for rehabilitation, Enschede, The Netherlands. Approval of the initial study was obtained from the local Ethical Committee (Registration number: 2013/237; NL nr.: 44687.000.13). All parents of participating children signed an informed consent form as well as all children over the age of twelve.

number of children	45
mean age	11 years, 6 months
age range	8-17
gender	23 male, 22 female
affected hand	22 left, 23 right
mean BiT hours ($\pm$ standard deviation)	26.8 $\pm$ 4.8
mean mCIMT hours ($\pm$ standard deviation)	12.2 $\pm$ 5.0

Table 1: Overview of the uCP participants

2.2 EEG task and set-up

Prior to intervention, all children completed an EEG cue-target paradigm experiment involving effective motor responses from both the affected and less-affected hand. A schematic overview of the trials can be seen in Figure 1. At the start of a trial, a visual cue stimulus (a blue smiley) was presented on one side of a computer screen for 1000 milliseconds. This was followed by a blank screen for 500 ms and finally followed by a visual target stimulus (a yellow smiley) at the same side of the screen as the cue. Children were instructed to press as quickly as possible on one of two response buttons corresponding to the side of the screen on which the cue and target stimuli were presented (left or right). For both the affected and less-affected hand seventy trials were presented, across three blocks with breaks in-between. This paradigm makes it possible to extract visual evoked potentials [9] which are time-locked to the presentation of the cue and target stimuli. Also motor evoked potentials [27] can be determined which are time-locked to button presses.

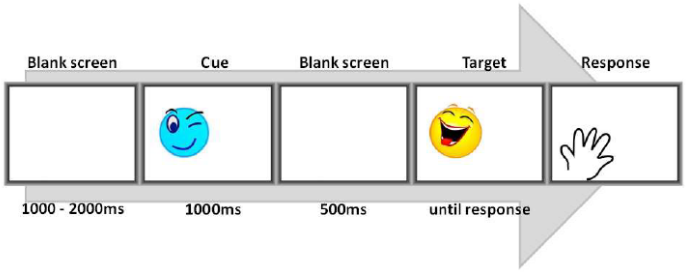

Figure 1: *A single trial for the cue-target paradigm. This image shows a trial for the left hand; for the right hand, both cue and target are presented on the right side of the screen.*

EEG was recorded on-site at the revalidation clinics. During measurements for the younger children, a parent or therapist was present. EEG recordings were performed with a 32-channel active electrode system (actiCap MedCaT B.V. Netherlands) and subsequently amplified with a 32-channel BrainAmp EEG amplifier. Electrode placement follows the international 10-20 system [16] with electrodes placed at Fz, FCz, Cz, Pz, Oz, Fp1/2, F3/4/7/8, FC1/2/5/6, C3/4, T7/8, CP1/2/5/6, P3/4/7/8, O1/2. The ground electrode was placed over AFz. Two electrodes were used to capture vertical and horizontal eye movements; they were placed below the right eye and at the outer canthus of the right eye respectively. Electrode impedance was kept below 25 kΩ. All signals were digitized at 1000 Hz.

2.3 Hand capacity and manual ability

Hand capacity and manual ability were assessed by several tests before and shortly after intervention. All scores were compared before and after rehabilitation to determine the percentage of improvement.
Unimanual hand capacity was determined with the use of the Box and Blocks Test [20]. Participants were asked to transport as many blocks as possible from one compartment to another within 60 seconds. The task was performed once for each hand. The less affected hand was always tested first. The raw score consists of the number of blocks transported with the affected hand.
Manual ability was determined with the use of the ABILHAND-Kids Questionnaire [2], in which 21 daily life activities that require upper limb use have to be rated on a three-level scale (i.e. impossible, difficult, and easy).
Bimanual performance was determined with the use of the Childrens Hand-use Experience Questionnaire [28]. Within this questionnaire, participants can indicate whether they use their affected hand on 29 bimanual activities, and how they experience their executive skills regarding the Effectiveness, Time Needed to perform the activity, and amount of Hindrance.

2.4 EEG processing and feature extraction

In addition to hand capacity and manual ability scores, several features were extracted from each child's EEG signal. Following earlier research, we focused on features that have been associated with activation of the motor cortex.

2.4.1 Background

It has previously been reported that different patterns of hemispheric dominance occur with respect to controlling the affected hand in children with uCP. Due to a lesion early in life,

the functional properties of lesioned areas are relocated to either surrounding cortical areas or the corresponding cortical areas from the undamaged hemisphere. In typically developing children, movements of the limbs are controlled by the contralateral hemispheres. Thus, the typical pattern is a contralateral dominance of hand control. In line, a fair amount of children with uCP show this typical contralateral dominance when controlling movements of their affected hand. However, in some children an ipsilateral dominance in controlling the affected hand has been observed [30, 17]. In addition, bilateral activation of the motor cortices has also been observed in some children with uCP when moving the affected hand.
In typically developing children, interhemispheric inhibition will occur when one hand performs a goal-directed movement [11]. This is a general inhibitory effect from one hemisphere to the other to suppress mirror movements (the synchronous and contralateral movement of two extremities). However, within children with uCP, the inhibitory effect from the non-lesioned to the lesioned hemisphere tends to be much larger than the other way around [21]. This suggests that movements of the less-affected hand inhibits the cortical areas involved in controlling the affected hand in children with contralateral corticospinal projections. Thus, children with uCP with contralateral motor control would benefit more from mCIMT intervention [19]. Since the less-affected hand is restricted by the sling during mCIMT intervention, the primary motor areas controlling movements of the less-affected hand will become less active and exert less inhibition of the corresponding areas in the damaged hemisphere. Since the lesioned hemisphere is less inhibited during mCIMT, the affected hand can be controlled more effectively. This concept is illustrated in Figure 2.

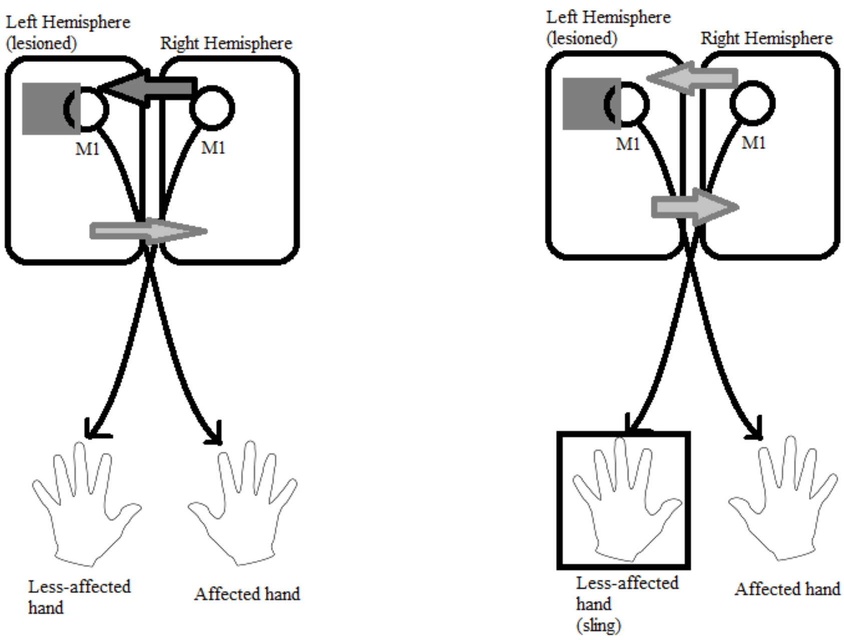

Figure 2: *Contralateral motor control with in a child with uCP. The unaffected hemisphere inhibits the lesioned hemisphere (marked with a rectangle) heavily the left image. In the right image, the less affected hand is constrained which cancels the strong inhibition to the affected hand. Image based on [19].*

Based on this functional anatomical model, it was decided to included EEG data obtained prior to intervention in this study. The reasoning is that EEG recordings during movement will produce event-related potentials which are more pronounced around the motor areas. This can give an indication of whether the motor areas are lateralized or not which in turn could be predictive for treatment outcome [19].

2.4.2 EEG pre-processing

All EEG processing was performed with the Python MNE package [14]. First of all, bad channels were identified, removed and interpolated. Next a band-pass filter was applied between 1Hz and 30Hz (except for Lateralized Readiness Potentials where the band pass filter was set between 0.2 and 24 Hz). This was followed by setting a common-average reference.

2.4.3 Feature Extraction

A variety of features were extracted from the EEG signal: The averaged Lateralized Readiness Potential (LRP) is a slow negative shift that is time-locked to - and occurs before - the onset of a movement and is more pronounced when recorded from electrodes overlying the hemisphere that controls the acting hand [27]. This can therefore indicate the location of the motor cortices as the LRPs are expected to be more negative in areas controlling the acting hand. Since the LRP is a low frequency negative shift, a 0.2Hz-24Hz band-pass filter was applied to the data during pre-processing. LRPs were obtained by selecting all epochs time-locked to the motor responses with a baseline from 0 to 500 ms relative to the onset of response. LRPs were determined to occur in the -100 ms to 0 ms latency window relative to the motor response.
For each electrode, three metrics were computed: the average amplitude (μV) within the fixed -100 ms to 0 ms latency window, the inter-trial coherence (ITC), and average mu (8-12 Hz) power (μV^2).

In line, Motor Evoked Potentials (MEPs) were extracted. Since MEP amplitudes areas are more pronounced at electrode sites overlying the the involved cortical motor areas, MEPs can be used to determine the hemispheric dominance in controlling the affected hand. Epochs (-500 ms to 500 ms) that were time-locked to the motor responses were selected, with a baseline from -500 ms to 0 ms. The rectified amplitude in the 0-500 ms window was calculated as well as the ITC and mu power.

In addition, mu rebound was determined. In general, during movement, mu activity (8-12 Hz) is decreased. However, around 500 ms after movement has ceased, the mu amplitude will show a marked increase or rebound effect. This so-called mu rebound [22] is more marked at electrodes overlying the dominant cortical motor areas. To calculate mu-rebound, epochs time-locked to the response onset were selected from -250 ms to 1000 ms (baseline from -250 ms to 250 ms). Next the average mu power was calculated associated with the onset of movement (from -250 ms to 250 ms) and the average mu amplitude associated with the mu-rebound (from 500 ms to 1000 ms). The onset mu was subsequently subtracted from the mu-rebound resulting in a net mu rebound value.

In an attempt to capture the trans-colossal inhibition, we determined to which extent EEG activity in the left hemisphere preceded the activity in the right hemisphere and vice versa. This was determined for -200 ms to 200 epochs time-locked to the response. The cross-correlation was computed for each pair of electrodes on opposing sides of the scalp. The average correlation and maximum correlation were extracted from the measurements. Cross-correlations were always calculated from electrodes on the side ipsilateral to the affected hand, to electrodes contralateral to the affected hand.

With respect to the visual cue and target stimuli, averaged visual ERPs were constructed from averaged -300 ms to 600 ms epochs with respect to the stimulus onset. Since these ERPs are maximal over midline sites, a linked mastoid reference was used instead of a common average reference. The N200 component amplitude was determined by finding the largest negative peak within the window of 330 to 370 ms, while the P300 component amplitude was determined by the largest positive peak in the window between 530 and 570 ms. Both time windows were established by finding where the components were largest in a grand average ERP across all participants.

2.4.4 Feature post-processing

Several steps of post-processing were applied to the ERP data. This was done in order to capture the differences between left and right hemisphere activity, and differences in EEG signals between the affected and less-affected hand. Post-processing was applied in all combinations to the processed EEG features and consisted of the following steps:

Channel selection: only a subset of channels is used as peripheral electrodes will not have a high signal-to-noise ratio. Three options were used for each EEG feature:

1. C3/4
2. F3/4, C3/4, FC1/2
3. F3/4, C3/4, FC1/2/5/6, CP5/6, CP1/2, P3/4

Hemispheric average: Feature averages were calculated in three regions of interest; in the hemisphere either ipsilateral or contralateral to the affected hand or by simply averaging all feature values of all selected electrodes.
Feature differences: either the data was left intact or values generated for the affected hand were subtracted from the values generated for the least-affected hand.
Common spatial pattern (CSP): a Common spatial pattern (CSP) procedure was applied to the EEG signal in the LRP and MEP conditions. CSPs use eigen-value decomposition in binary class problems to find vectors which differ maximally between classes but minimally within classes [24]. In this study, a CSP with a Ledoit−Wolf Estimator was applied with respect to features related to the responses in the affected and less-affected hand in order to detect the electrodes that differentiated maximally between the affected and less-affected hand. The number of selected components was determined to explain at least 95% of the variance. After processing the CSP map with the best discriminance was used for feature extraction.

For each child the aforementioned EEG features were calculated and subsequently post-processed. By using all possible post-processing options this yields a grand total of 220 EEG features per child, all of which were based on pre-treatment measurements.

2.5 Machine learning

In order to make predictions about the effect size of intervention, various machine learning regressors were trained and optimized. The input data of the models consisted of data obtained prior to intervention. These were demographic features (such as age, gender etc.), hand-capacity and manual ability test scores and the previously mentioned EEG features. All features were standardized before model fitting, by transforming the features to variables with

zero mean and unit variance. Machine learning regressors were trained to transform the predictive features to the continuous hand-capacity and manual ability scores. Four outcome scores are predicted: the CHEQ score (which is an average of hindering, effectivity and time-efficiency), Box and Blocks score (for the affected hand), reaction times in the EEG task (for the affected hand) and ABILHand-Kids scores. Models were evaluated using leave-one-out cross-validation where at each iteration a participant is selected for validation, while all other participants are used for model training. This is then iterated for every participant. This process increases generalizability by ensuring that each participant is used once for model validation, while not being simultaneously present in the model training set. Model validation is done with the Root Mean Squared Error (RMSE) metric where the observed hand-capacity and manual ability outcome scores and predicted scores were compared. For each predicted outcome variable, participants with incomplete data were excluded from analysis. Each outcome score was predicted independently from the others as the relatively small size of the data-set would not allow for a single complex model to predict all scores at once.
Since the outcome scores have different underlying distributions, a total of five different regressors were modeled for each outcome: the Support Vector Regressor [3], ADABoost regressor [4], Random Forest regressor [6], linear regression and Bayesian regression [5, 4]. These regressors cover a wide range of machine learning techniques and have been known to produce accurate predictions even in the absence of large amounts of data. All regressors are implemented in the Python SciKit-learn package [23]. Each regressor has certain hyper-parameters which are not data driven. A grid-search was performed on all hyper-parameter combinations to yield the combination with the best prediction scores. An overview of the grid-search and pre-processing can be found in Table 2.

Table 2: *Overview of regressors and settings*

Regressor name	Pre-processing	Hyper-parameters
Support Vector Regressor	normalize data, feature selection	number of features, feature selection method, kernel shape
ADABoost	normalize data	number of trees, learning rate, max depth
Random Forest	normalize data	number of trees, max depth
Linear Regression	normalize data, feature selection	number of features, feature selection method
Bayesian Regression	normalize data, feature selection	number of features, feature selection method, number of iterations

3 Results

3.1 Improvement of scores

For each hand-capacity and manual ability test, the correlation between test scores prior to and after intervention was calculated as well as an improvement rate. This improvement rate is the median percentage increase for a hand-capacity and manual ability test between pre- and post-intervention. For the Box&Blocks task, a large positive correlation was found between test scores before and after intervention (Pearson's $r = 0.90$, $p < 0.001$, $n = 45$). The amount of blocks which participants could transport within a minute increased after intervention with

16%. There was also a large positive correlation between reaction times in the EEG task before and after intervention (Pearsons's $r = 0.78$, $p < 0.001$, $n = 40$), with an median improvement of reaction time of 6.6%. With the CHEQ scores, a large positive correlation was found between pre- and post-intervention scores (Spearman $\rho = 0.71$, $p < 0.001$, $n = 41$) with an median improvement rate of 10.9%. Finally, there was a large positive correlation between scores before and after intervention on the ABILHand-Kids test (Spearman $\rho = 0.67$, $p < 0.001$, $n = 43$). The median improvement rate on the ABILHand-Kids test was 21.4%.

3.2 Individual improvement

To assess individual differences in therapy outcome, individual improvement rates are established. For each subject, an improvement rate score was determined as the median improvement of outcome on CHEQ, Box and Blocks, reaction times and ABILHand-Kids. These individual score improvement rate are shown in Figure 3 as percentiles. It can be seen that children in the lower 30th percentile receive hardly any benefit from the intervention (average improvement rate is 0.0). Conversely, children in the upper 30th percentile increase their hand capacity and manual ability scores on average by an amount of 26%.

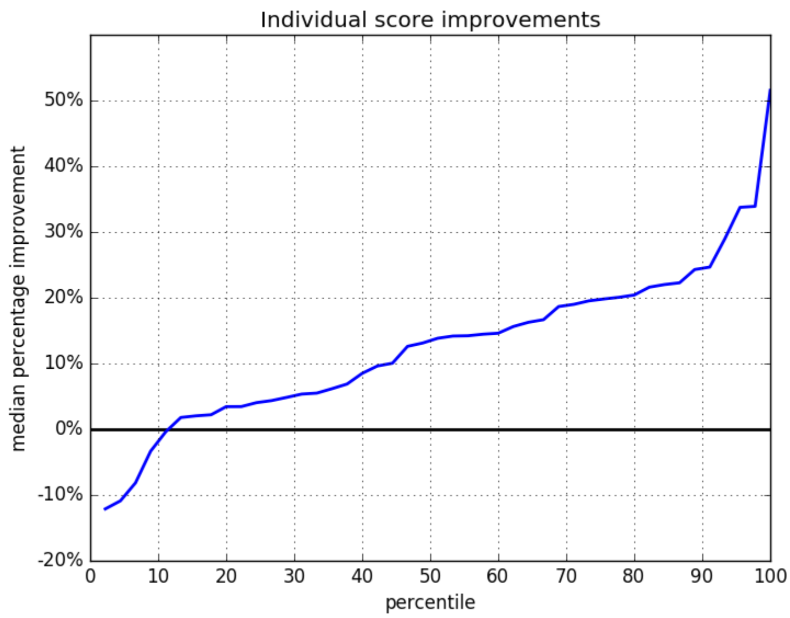

Figure 3: *Individual median improvement rates on CHEQ, Box and Blocks, reaction times and ABILHand-Kids tests.*

3.3 Machine learning predictions

Outcome predictions were generated under two conditions: one where the training set included all features and one without EEG features. For each outcome score, the model with the lowest RMSE in leave-one-out cross-validation was selected. Next, the proportion of explained variance was calculated to evaluate the models. The results can be seen in Figure 4. A subsequent statistical testing with a two-tailed Mann-Whitney-U test was performed to examine the influence of the inclusion EEG features to the data set. It revealed that inclusion of the EEG features does not change the RMSE for the CHEQ (Mann-Whitney $U = 852$, $n_1 = 39$, $n_2 = 40$, $p > 0.05$ two-tailed), Box and Blocks (Mann-Whitney $U = 934$, $n_1 = 40$, $n_2 = 41$, $p > 0.05$

two-tailed), reaction times (Mann-Whitney $U = 723$, $n_1 = 36$, $n_2 = 36$, $p > 0.05$ two-tailed) nor for the ABILHand-Kids (Mann-Whitney $U = 869$, $n_1 = 40$, $n_2 = 41$, $p > 0.05$ two-tailed).

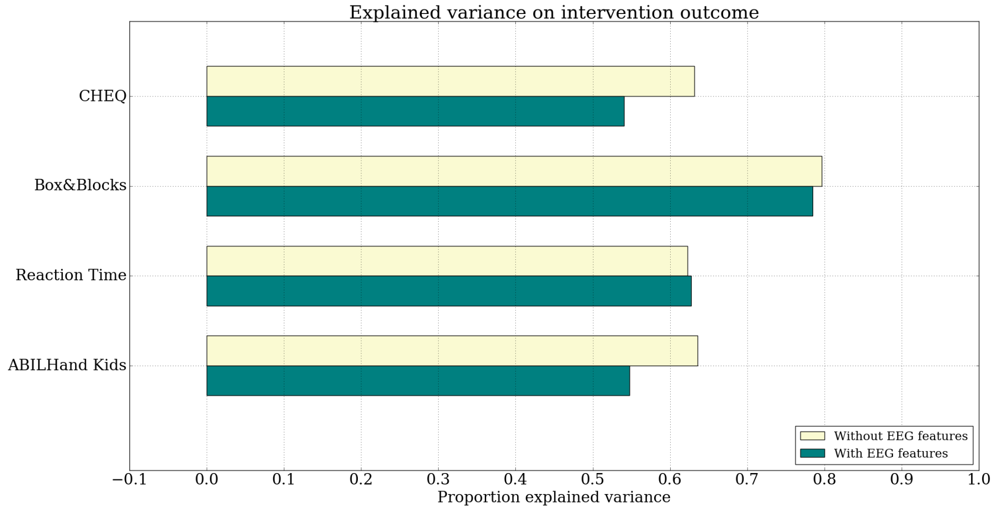

Figure 4: *Explained variance rates for HvH subjects with and without EEG features included.*

It was also tested whether the RMSE of the predictions were significantly below the standard error on the outcome scores. If this is the case, it means that the predictions are more accurate than the average of the outcome scores. For each test a one-tailed Mann-Whitney U test was performed. The test results are summarized in Table 3. It can be seen that although the prediction RMSE is in all cases below the standard error, this is only significant for CHEQ and Box and Blocks measures.

	prediction RMSE	outcome standard error	n	p-value
CHEQ	0.31	0.47	39	0.02*
Box&Blocks	3.39	6.88	40	0.001**
Reaction times	70.5	107.0	36	0.07
ABILHand-Kids	0.68	0.99	40	0.06

Table 3: Comparison of prediction RMSE with outcome standard deviation. The asterisks show significance levels (*$p < 0.05$,**$p < 0.01$,***$p < 0.001$) on one-tailed Mann-Whitney U tests.

4 Discussion

The current retrospective cohort study reveals that machine learning models can create accurate predictions on the outcome of uCP intervention. Post intervention scores of four hand capacity and manual ability scores were predicted based on baseline measurements. The explained variance on the predictions exceeded 0.5 for ABILHand-Kids and CHEQ scores, 0.6 for the reaction times and nearly reached 0.8 on the Box and Blocks tasks. In addition, for all hand capacity and manual ability test scores the prediction error was below the standard error and

for CHEQ and Box and Blocks measures this was even significantly so. This indicates that the machine learning models perform better than a model with a constant prediction of outcome scores.
We also found that although the intervention program was effective for the cohort, there were large inter-individual differences. In the lower 10th percentile of the group, manual ability even decreased on average and in the 30th percentile the average improvement rate is 0%. Conversely, children in the higher percentiles had a large amount of improvement of their outcome scores. This shows that there still is a great variety in therapy effectiveness.

4.1 EEG features

Another major aspect of this study was to investigate whether inclusion of EEG features could improve the prediction quality. Following the theory of Kuhnke [19] and Staudt [30], we would expect that identification of the motor area location could be a valuable predictor for the intervention outcome. In order to determine the hemispheric dominance for controlling the affected hand has thus far been based on TMS [19] and fMRI [30]. However, there are several drawbacks with respect to the application of TMS in pediatric groups. First of all, those studies were performed with transcranial magnetic stimulation (TMS) and fMRI respectively, which may not be suitable for all subjects. Although TMS is very useful, it is considered as an invasive tool and cannot be used on young children and neither in children who suffer from epilepsy (which is in around 35% of all CP patients [32]). fMRI scans can also aid in localizing the motor areas, however scans can be costly and many children find the process of undergoing an MRI scan stressful [29]. In the current study, we therefore determined hemispheric dominance based on several EEG features since EEG is non-invasive (as oposed to TMS) and more cost efficient than fMRI. We built on the theory of hemispheric dominance and applied it in a novel context by using it as predictor for therapy effectiveness.
Although direct source localization algorithms [18] such as LORETA and BESA were attempted, the results were fairly poor with a high variability and low predictivity. A major problem with source-localization algorithms is that they require signals from a sufficient set of EEG electrodes and a correct forward model (based on neuro-typical persons). In the current study, measurements from the more peripheral electrodes were often lost due to artifacts. In addition, children with uCP have cerebral lesions meaning that the forward modelling of source localization becomes invalid. It was therefore decided to extract the more dynamic EEG features that are known to reflect cortical activations associated with motor control. The inclusion of these EEG features however had no significant effects on prediction. In the current models, the pre-intervention scores appeared to be highly informative (since the baseline and post-intervention scores revealed a high correlation) and were thus selected as main features for the machine learning models. By increasing the size of the data-set in future projects, more complex prediction models can be created based on more features. These models could include EEG features which can further increase the prediction quality.

4.2 Clinical implications

We propose that machine learning can contribute to more personalized interventions for children with uCP. Within our study, there appeared to be a large variation in improvement scores meaning that more than 30% of the participants of the intervention programs had either stable or decreasing scores on the hand-capacity and manual ability tests. Thus, the intervention program for these children led to only minimal improvements. Possibly, these children would have gained a more marked improvement with a different intervention program, e.g., a program with the focus on mCIMT instead of a focus on BiT. However, future studies are needed to explore these possibilities. A greater data-set could also enhance the predictions even further as more participants would allow for more complex machine learning models, which we expect would to produce better predictions. In particular, a data-set with a large variation in BiT and mCIMT hours would be very informative as the influence of the duration of intervention w.r.t. the outcome could then be determined on an individual level. By knowing in advance which children will benefit greatly from a certain intervention and which children do not, we could make the intervention more effective for both the individual child as well as on a group level.

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Appendix A Justification

All data mentioned in this thesis (i.e. data concerning the 45 uCP participants) were gathered in an earlier stage by Marjolein Baas, Marijtje Jongsma and others from the Behavioural science institute in cooperation with Pauline Aarts and others from the Sint Maartenskliniek in Nijmegen, The Netherlands and the Roessingh Kliniek in Enschede, The Netherlands. Data used for this thesis were obtained from a database at the Behavioural science institute and include the demographic data, hand-capacity and manual ability scores and EEG recordings. All subsequent methods and analyes were developed and performed by the first author, Héctor van den Boorn, using the Python programming language with, including but not limited to, SciPy (for statistical analyses), SciKit-Learn (for machine learning) and MNE (for EEG processing) modules. This thesis is an original research and apart from data collection, carried out and written by the first author under guidance of subsequent authors.