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A progressive prediction model towards home-based stroke rehabilitation programs

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ABSTRACT

More than 795,000 people suffer from stroke each year in the United States. Rehabilitation is crucial to help restore mobility function in activities of daily life. Many research works manifest that effective prediction of rehabilitation outcomes can significantly improve personalized rehabilitation strategies and maximize health outcomes. Existing studies on predicting stroke rehabilitation outcomes are primarily based on clinical or inpatient data, and there are few in-depth investigations in home-based rehabilitation prediction. In this work, we perform a retrospective study on mRehab (mobile rehabilitation), a six-week home-based rehabilitation program, where we investigated the in-program user data across 12 different rehabilitation activities performed by 16 stroke survivors. We proposed a new progressive prediction framework that constructs the multiple linear regression (MLR) and the random forest (RF) models, and found that combining the clinical and demographic data of stroke survivors with movement phenotyping data will significantly improve the prediction model's performance. Specifically, our proposed model can accurately predict the outcome only with the first two weeks' data with the root mean square error (RMSE) of 0.1050 in the MLR model and 0.0011 in the RF model. Moreover, we identify the features that significantly contribute to the prediction outcomes in home-based rehabilitation programs through feature correlation analyses. To the best of our knowledge, this work is the first study towards the rehabilitation outcome prediction in a home-based program.

1. Introduction

According to the Centers for Disease Control and Prevention (CDC) of the United States, stroke is the fifth cause of death in the US and is the leading cause of severe long-term disability. More than half of stroke survivors over 65 years of age have reduced mobility (National Center for Chronic Disease Prevention and Health Promotion, Division for Heart Disease and Stroke Prevention, 2021). Some stroke survivors need to participate in rehabilitation programs in hospitals, outpatient clinics, or nursing facilities where exsit restrictions include limited rehabilitation time and places, the need for professional guidance, limited equipment resources, and

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expensive costs (National Institute of Neurological Disorders and Stroke, National Institutes of Health, 2020). Most stroke survivors need to return to their homes for rehabilitation. They urgently need effective rehabilitation programs that can be self-managed to conduct sustainable rehabilitation.

Studies have shown that stroke survivors who participate in self-management projects can effectively improve self-efficacy, quality of life and physical mobility (Chaiyawat, Kulkantrakorn, & Sritipsukho, 2009; Fryer, Luker, McDonnell, & Hillier, 2016; Lin et al., 2019; Vu et al., 2018). Rehabilitation experts have shown great interest in predicting models of stroke rehabilitation outcomes (Lee et al., 2020). Accurate predictions of rehabilitation outcomes can provide patients with feasible feedback and help experts make timely adjustment to the rehabilitation plan (Harari, O'Brien, Lieber, & Jayaraman, 2020). Thus, accurate prediction of home-based rehabilitation outcomes is urgently needed but still under-explored.

Several studies have shown accurate prediction of stroke rehabilitation outcomes. Lee et al. predicted and evaluated the rehabilitation intervention based on the combination of rehabilitation and clinical data (Lee et al., 2020). Harari et al. used demographics, stroke characteristics, and scores of clinical tests at admission to predict discharge scores of each clinical outcome measure (Harari et al., 2020). The papers mentioned above only performed predictions based on clinical and inpatient/in-laboratory rehabilitation data, which cannot be directly applied to home-based rehabilitation outcomes prediction research. Some studies researched home-based stroke rehabilitation. Johnson et al. proposed a suite of robot/computer-assisted motivating systems to help stroke survivors perform home-based rehabilitation (Johnson, Feng, Johnson, & Winters, 2007). Sheehy et al. demonstrated that virtual reality training (VRT) is feasible for home-based stroke rehabilitation (Sheehy et al., 2019). However, these studies only aimed at the innovation of home-based rehabilitation, and there are few studies on the prediction of rehabilitation outcomes based on home-based rehabilitation data.

Our study aims to establish a new progressive framework for predicting rehabilitation outcomes based on the home-based mRehab program. It will provide a prospective insight for further mRehab research and a general solution for other home-based rehabilitation studies. Compared with clinical or inpatient rehabilitation research (Harari et al., 2020), home-based rehabilitation research presents different challenges. First, our home-based mRehab program will provide unique and unprecedented movement phenotyping data which is completely different from clinical and inpatient data. Analysis of these data will have the potential to provide some unique perspectives, such as the style of rehabilitation exercise. In addition, how to extract features effectively from this kind of data and integrate them into the prediction framework is also a new challenge. Finally, establishing an effective progressive prediction framework by using as little data as possible is another challenge in our study.

Our contributions are four-fold: First, to the best of our knowledge, this work is the first study towards the rehabilitation outcome prediction in a home-based program without inpatient/in-laboratory intervention, and it is completely a self-management rehabilitation program. Second, the multiple linear regression (MLR) and the random forest (RF) models were constructed to predict rehabilitation outcomes, and by combining the clinical and demographic data of stroke survivors with movement phenotyping data, more accurate predictions were obtained. Third, the data obtained from the mRehab system were divided into different time dimensions. And in each time dimension, the clinical and demographic data were incorporated and four data dimensions were constructed to investigate the impact of increasing rehabilitation data on predictions. Our progressive prediction models could obtain accurate predictions only using 2-week data, which is significantly ahead of the prediction time. Finally, the influence of features with different complexity and types on rehabilitation outcomes was studied. Our mRehab dataset is generated by stroke survivors in a real 6-week fully home-based rehabilitation program, and our model is validated using this real-world mhealth-based (mobile technology to manage health) rehabilitation dataset.

Trial Registration: ClinicalTrials.gov NCT04363944; https://clinicaltrials.gov/ct2/show/NCT04363944

2. Home-based study and dataset

2.1. mRehab program introduction

mRehab is a portable smartphone-based system for home-based rehabilitation, which can provide real-time feedback on rehabilitation activities of the upper-limb function of stroke survivors (Cavuoto et al., 2018). mRehab is integrated with 12 rehabilitation activities designed by experts into a smartphone application (Langan et al., 2020), and embeds the smartphone into home functional objects generated by 3D printing technology (Bhattacharjya et al., 2019). When stroke survivors use this application and 3D printed objects to practice the activities of daily living (ADL), the software app program will use the sensors built in the smartphone to perform motion analysis and provide users with real-time feedback (Zhang et al., 2020). Our previous clinical research studies have also obtained satisfactory evaluations from stroke survivors on the usability, perceived usefulness, and acceptance of the mRehab system (Bhattacharjya et al., 2021). Stroke survivors using mRehab also showed a high degree of compliance and clinical efficacy (Zhang et al., 2020). Fig. 1 shows the overall mRehab system diagram. Fig. 2 shows the list of 12 rehabilitation activities.

The movement phenotyping data is automatically recorded by the mRehab program based on participants' rehabilitation. This kind of user driven data is much more complicated than other one-shot data, such as age and gender, because of the uniqueness and uncertainty of human behaviors. Also in the self-management mode it becomes much easier to introduce noise than in-laboratory programs. A 6-week program could also bring more unpredictable unforeseen issues, such as issues related to participants' behavior or physical condition. The challenge and significance of a home rehab program are that it can know the user's performance/status moment by moment, enabling just-in-time intervention or changes. Considering the challenges above and what we mentioned in the introduction, we constructed our datasets and feature space to address them.

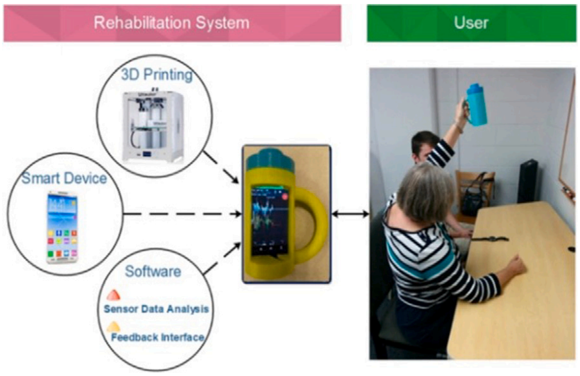

Fig. 1. The overall mRehab system diagram and user case.

In-Home mRehab Tasks

Object Transportation
Horizontal mug transfer
Vertical mug transfer
Horizontal bowl transfer
Vertical bowl transfer

Fractionated Finger Movement
Enter phone number
Quick tap

Prehensile Grip with Supination/Pronation
Sip from mug
Slow pour from mug
Quick twist mug
Turn key
Turn door knob

Walking with Object
Walk with mug

Fig. 2. The list of mRehab rehabilitation activities.

2.2. Dataset and feature space

Experimental Procedure: In this work, we performed a six-week home-based rehabilitation program, where we investigated the in-program user data across 12 different rehabilitation activities performed by 16 stroke survivors (age: 57.5 ±20.50, 5 females, 7 right hemiplegias, the occurrence of stroke > 24 months). The sample size (including training set and testing set) of 6-week is 4212, 4-week is 3193, and 2-week is 1759.

Our experiment process is divided into three phases. In the pre-testing phase, two baseline measurements were performed. At the first laboratory visit, the participants completed the questionnaire and in-laboratory clinical assessment, which includes the Wolf Motor Function Test (WMFT) (Wolf, Lecraw, Barton, & Jann, 1989), the Fugl–Meyer Assessment (FMA) (Gladstone, Danells, & Black, 2002), and the Mattis Dementia Rating Scale (MDRS) (Mattis, 1988). The second laboratory visit involves the same clinical assessment. During the home-based mRehab phase, the mRehab application records participants' rehabilitation performance data. In the post-testing phase, participants completed the same clinical assessment as the baseline.

Feature Space in mRehab Data: As shown in Table 1, demographic, clinical, and mRehab datasets were obtained during the whole program. And the feature space is divided into four categories: clinical features, demographic features, movement phenotyping features, and compliance features.

The clinical dataset contains pre-clinical and post-clinical features, such as WM_Before, Stroke_history and WM_After. It is worth noting that the mean value of the clinical data in the first and second laboratory visits was used as the value of pre-clinical features to obtain a more stable baseline level. The demographic dataset contains features Age and Gender. The mRehab dataset contains all movement phenotyping features, such as Avg_time, Avg_smoothness, etc.

The compliance features extracted from movement phenotyping data summarize the effects of rehabilitation in a satisfying generalization of compliance. In each time dimension, the movement phenotyping data were divided into three different compliance levels according to the total number of exercise days/sessions in that specific time dimension to derive the features Compliance_day and Compliance_session. It seems challenging to divide the movement phenotyping data equally, so that the combination with the smallest total difference was chosen to ensure the data of the three levels are as balanced as possible to avoid bias. The details of compliance features are shown in Table 2. For example, the sample size of our 4-week dataset is 3193. We calculated and sorted the total number of exercise days and the total number of sessions of each participant for each activity in these four weeks. For the first third of the sorted outcome, we defined the compliance level as Level I, the middle third is Level II, and the last third is Level III. In this example, if the participant's total exercise days of each activity in these four weeks is less than or equal to 12, then his Compliance_day will be defined as Level I. If the total number of exercise sessions is less than or equal to 17, then the level

Table 1
Feature space.

Features	Descriptions
mRehab dataset — Movement phenotyping features	
Hand	Affected hand by stroke
Exercise_day	Each participant's total exercise days for each activity
Exercise_session	Each participant's total exercise sessions for each activity per day
Activity	12 different activity types
Reps	Each participant's total repetitions for each activity counted per session
Total_Reps_In_Day	Each participant's total repetitions for each activity per day
Avg_time	Each participant's average time to complete each activity in each session
Avg_smoothness	Each participant's average smoothness to complete each activity in each session
mRehab dataset — Compliance features	
Compliance_day	Compliance level according to the total exercise days in the specific time dimension
Compliance_session	Compliance level according to the total exercise sessions in the specific time dimension
Clinical dataset — Clinical features	
WM_Before	The mean WMFT score of the first and second clinical assessment in the pre-testing phase
FMA	Fugl–Meyer Assessment (FMA) score
MDRS	Mattis Dementia Rating Scale (MDRS) score
Stroke_history	Total month the participant had stroke
Demographic dataset — Demographic features	
Age	Participants' age
Gender	Participants' gender

Table 2
Compliance feature.

Features	Compliance levels	2-week	4-week	6-week
Compliance_day	Level I[a]	TED[b] <= 7	TED <= 12	TED <= 19
	Level II[a]	8 <= TED <= 12	13 <= TED <= 21	20 <= TED <= 29
	Level III[a]	13 <= TED	22 <= TED	30 <=TED
Compliance_session	Level I	TES[c] <= 10	TES <=17	TES <= 24
	Level II	11 <= TES <= 14	18 <= TES <= 25	25 <= TES <= 30
	Level III	15 <= TES	26 <= TES	31 <= TES

[a]Compliance levels. Level I = low user. Level II = selectively committed. Level III = committed to program.
[b]TED — total exercise days.
[c]TES — total exercise sessions.

of his Compliance_session will be defined as Level I. The threshold of Compliance_session is greater than Compliance_day because participants can exercise multiple sessions for some or all activities.

3. The proposed framework

Fig. 3 is the overview of our progressive prediction framework. The clinical and demographic datasets are obtained by clinical assessment and questionnaire. The mRehab dataset is obtained by built-in smartphone sensors through the mRehab phone. We defined the feature space and the predicted outcome, conducted normalization and categorization, and extracted progressive data with different time and data dimensions during data pre-processing. We then used MLR and RF models to generate our final estimation.

The reason why we adopted these two kinds of prediction models is that the MLR model could intuitively express the degree of correlation between each feature and predicted outcome, which can be well understood and explained (Marill, 2004). Considering it cannot fit nonlinear data well, the RF model, which has few assumptions and limitations, was adopted. And the relative importance of each feature can also be obtained in the RF model (Horning, 2013). These two kinds of models could complement each other for more comprehensive results.

3.1. Basic data pre-processing

(1) Define Predicted Outcome: The percentage difference of WMFT score was defined as our target variable:

$$Delta\_WM = -\frac{WM\_After - WM\_Before}{WM\_Before}. \tag{1}$$

In Eq. (1), WM_Before is the mean WMFT score of the first and second clinical assessment in the pre-testing phase. WM_After is the WMFT clinical assessment score in the post-testing phase. Defining Delta_WM in this way is easy to understand and explain; for example, the higher Delta_WM value means the better rehabilitation outcomes by using mRehab.

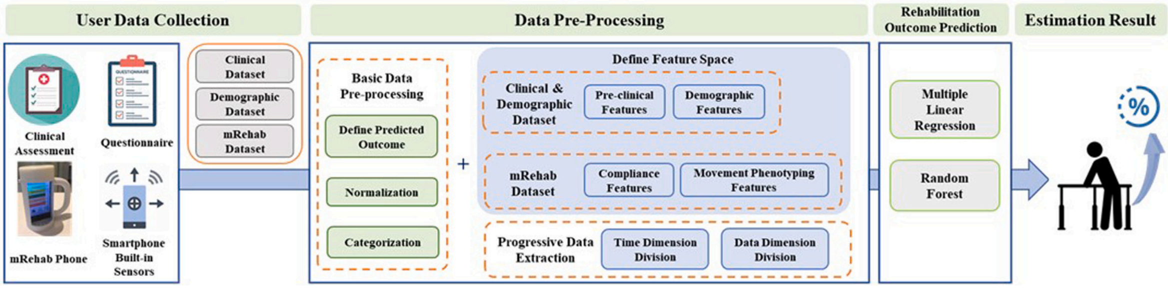

Fig. 3. The overall mRehab system diagram and user case.

Table 3
Time and data dimension division.

Time dimension	Data dimension	
	Model	*Features in model*
1–2 weeks' data 1–4 weeks' data 1–6 weeks' data	Model I	WM_Before + age + gender + stroke_history + FMA + MDRS
	Model II	Features in Model I + Hand + Exercise_day + Exercise_session +Activity + Reps + Total_Reps_In_Day
	Model III	Features in Model II + Avg_time + Avg_smoothness
	Model IV	Features in Model III + compliance_day + compliance_session

(2) Normalization & Categorization: All numerical features were normalized to ensure they are on a similar scale to compare the coefficients of each feature in MLR models. Compliance features were defined as ordinal categorical features where the larger number means the higher compliance. And one-hot encoding method was applied to categorical features with no ordinal relationship, such as Hand, Gender, and Activity.

3.2. Progressive data extraction

Existing studies on predicting stroke rehabilitation outcomes mainly depend on clinical data (Lin, Hsieh, Lo, Hsiao, & Huang, 2003) or using all rehabilitation data (Lee et al., 2020). Although they obtained accurate prediction models, the practical predictive application of the model was ignored. Also, to address the third challenge mentioned before, we constructed our models based on time and data dimension to get sufficiently accurate prediction results with limited data to realize timely and effective predictions.

(1) Time Dimension: As shown in Table 3, all mRehab data are separated into three groups by using every bi-weeks as time node: 1–2 weeks, 1–4 weeks, and 1–6 weeks. In each time dimension, the clinical and demographic data were incorporated, and all the data were modeled into four different data dimensions. The reason for using bi-weeks as time nodes here is that it is necessary to ensure there is enough data in the smallest time interval for analysis. The trade-off between the length of the time interval and the model performance also be considered.

(2) Data Dimension: To explore the effects of movement phenotyping and compliance features on the performance of predictive models, it is necessary to incorporate mRehab data progressively. The data dimension division details also are shown in Table 3. Four models were constructed in each time dimension to demonstrate the impacts of different features on rehabilitation outcomes' prediction. Only pre-clinical and demographic features were used to build the benchmark (Model I). These features are all one-shot data that are relatively uncomplicated. Then, the simple part of movement phenotyping features was incorporated to build Model II. Although these features are user-driven, they are either a simple count or an explicit categorical variable. Model III added Avg_time and Avg_smoothness, which reflect the participants' real-time rehabilitation performance. Compared to other features, they are more complicated, easier to introduce noise, and have more considerable variations. Model IV added two compliance features. By exploring the participants' compliance level to obtain the relationship between compliance and rehabilitation outcomes, it is possible to provide specific guidance on exercise style for stroke survivors.

4. Results

4.1. Experimental setup

The 2-week, 4-week, and 6-week (the whole program) progressive mRehab data were extracted, and four prediction models were constructed by combining the corresponding clinical and demographic data for each time dimension to predict the rehabilitation outcomes. The root mean square error (RMSE) (Chai & Draxler, 2014), a commonly used error metric, was employed to measure the difference between the predicted Delta_WM and the actual Delta_WM. The smaller RMSE value indicates better prediction performance of the model. It is worth noting that the actual Delta_WM ranges from −0.09898 to 0.55948 in our dataset, so that a slight change in our RMSE may mean a significant improvement in the model's performance. The whole dataset was randomly

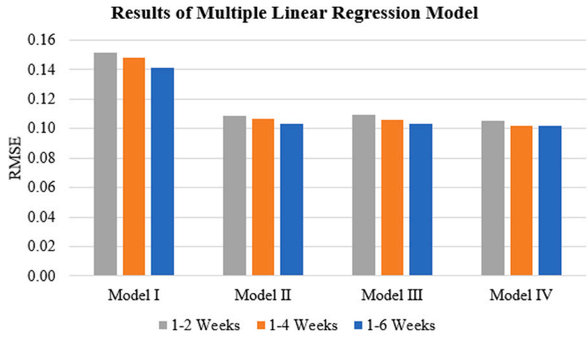

Fig. 4. The overall mRehab system diagram and user case.

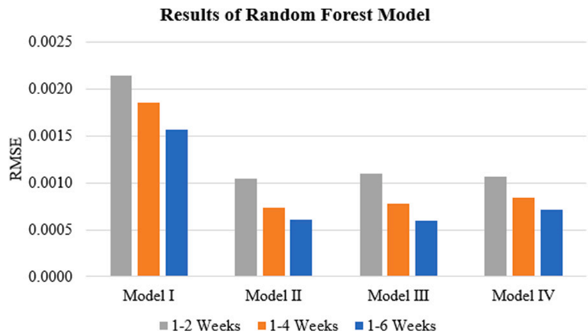

Fig. 5. mRehab rehabilitation activities.

split to 80%/20% for training and testing. Empirical research shows that such a split method can avoid overfitting and obtain great results (Gholamy, Kreinovich, & Kosheleva, 2018). Also the training data were divided into five-folds for cross-validation and the averaged RMSE was calculated to further avoid overfitting.

4.2. Prediction results

Impact of Models: Figs. 4 and 5 show the prediction results of the MLR and RF models, respectively. It is necessary to compare the performance of four different models using all the data (1–6 weeks) for exploring the impact of movement phenotyping data on the prediction results.

For the MLR models, the RMSE of Model I is 0.1416 with 6-week data, and it decreases to 0.1017–0.1033 in Model II, III, and IV. For the RF models, the RMSE of Model I is 0.0016 with 6-week data, and it decreases to 0.0006–0.0007 in Model II, III, and IV. Both results indicate that adding movement phenotyping and compliance features to the model, which only contains clinical and demographic features, can significantly improve the accuracy of the model's prediction. The results also show that the RF models significantly outperform MLR models because the RF models have much fewer limitations and assumptions than MLR.

Impact of Projection Duration: By comparing the four models in these three time dimensions, it is not difficult to find that MLR models do not show significant differences between the four models in each time dimension. For the RF models, although the more data contained in the time dimension, the more accurate the prediction results, but the improvement is not significant. It means our model could accurately predict the rehabilitation outcomes four weeks ahead of time.

Impact of Features: The feature correlation analyses was conducted in order to identify the features that greatly contribute to the home-based rehabilitation outcome's prediction. The 6-week dataset was used to calculate the correlation coefficient at the 95% significance level; this statistical measurement method could help us have prior insights about the correlations. The results are shown in Fig. 6. Then it is necessary to compare the coefficients of each feature in the MLR model and calculate the feature importance in the RF model. The higher coefficient or importance means the more considerable contribution. The results in our model interpret the coefficient of each feature, which describes how the feature is numerically correlated with the predicted outcome. It is helpful to get a comprehensive understanding of the importance and correlation of each feature by combining these two results.

The feature FM, WM_Before and Stroke_history usually have a higher value of the coefficient in the MLR model and higher value of importance in the RF model than other features, indicating that these three features have more significant influences on the prediction outcomes. Moreover, a more profound finding is that feature Reps is essential among the movement phenotyping features, and it positively correlated with our predicted outcome. Also, Compliance_day is more critical than Compliance_session. It means the number of exercise days and repetitions may affect the home-based rehabilitation outcomes significantly.

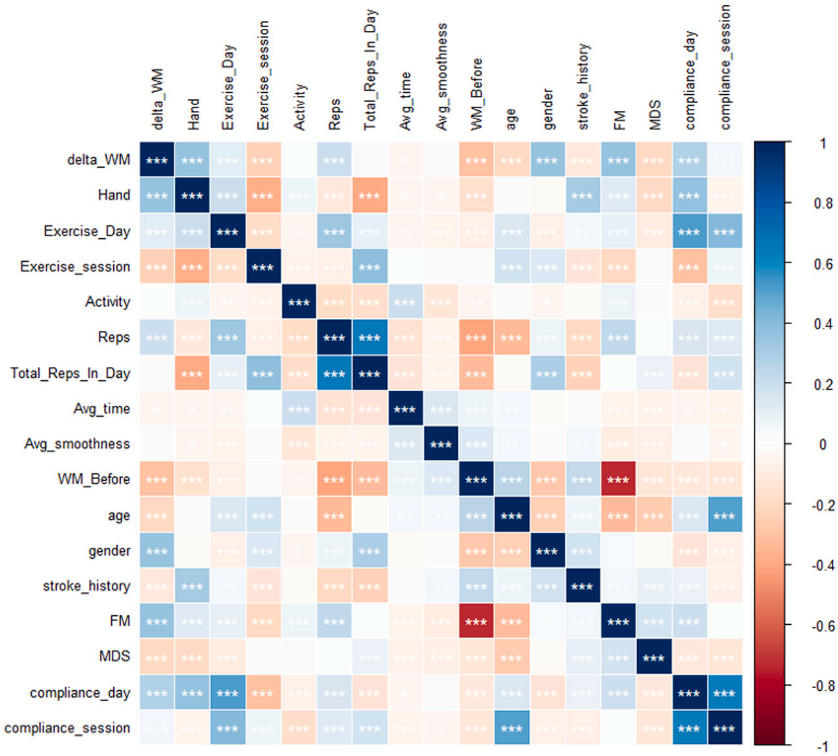

Fig. 6. Results of Correlation Coefficient of 6-week data.

5. Conclusion

In this paper, we proposed a new progressive prediction framework based on home-based mRehab in-program data and combines the clinical and demographic data to predict rehabilitation outcomes by using the multiple linear regression and random forest model. We divided the data into multiple time and data dimensions, and found that adding in-program movement phenotyping data to the benchmark model could significantly improve prediction accuracy. Also, our progressive prediction models could obtain accurate predictions only using 2-week data, which provide stroke survivors and rehabilitation experts with timely and effective feedback, and could help them to obtain the best rehabilitation results. The analysis of feature impact was conducted to study the importance of features. The results indicate that feature Reps has a relatively high and positive effect on the prediction of home-based rehabilitation outcomes than other features, and we may assume that if we increase exercise repetitions, the rehabilitation outcomes may also increase.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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