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Article

Can Digital Behavioral Phenotypes Predict Long-Term Community Participation After Stroke? Evidence from Wearable Data and Smartphone-Based Behavioral Research

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Abstract: Long-term stroke rehabilitation requires attention to the situation of patients' participation in social and community activities. Traditional follow-up assessments can only provide clinical information, but they are difficult to comprehensively reflect the daily behaviors of patients outside the medical setting. This study conducted a longitudinal secondary analysis to explore whether digital behavioral phenotypes obtained through wearable devices can predict the community participation of elderly individuals with a history of stroke one year later. The study used the publicly available registered data from the National Health and Aging Trends Study, with the 11th round wrist acceleration data as the baseline, and the 12th round data was used to assess subsequent community participation. Digital behavioral phenotypes included activity level, inactivity behavior, behavior fragmentation, time rhythm, and daily volatility. Community participation was measured using a breadth score, which combined indicators such as social visits, religious activities, organizational activities, and leisure outings. Regression analysis and prediction models were used to compare the predictive effects of demographic characteristics, health status, functional indicators, and behavioral characteristics obtained through wearable devices when used alone or in combination. The empirical analysis further evaluated the application value of digital behavioral phenotypes obtained through wearable devices as potential biomarkers for neurorehabilitation, and the results showed that they have the potential to complement clinical assessment and provide support for long-term community rehabilitation.

Keywords: digital behavioral phenotype; stroke rehabilitation; community participation; wearable accelerometry; digital biomarker

1. Introduction

Many stroke survivors still encounter difficulties in leaving their homes, participating in social activities, taking on family responsibilities, and re-adopting their previously valued social roles [1]. Therefore, community participation provides an important perspective for assessing daily rehabilitation progress, as it can reflect the interplay between functional limitations and personal habits, environmental conditions, and social opportunities [2]. Insufficient community participation may also be associated with lower health perception, social isolation, and decreased quality of life [3]. However, these situations are often difficult to fully reflect through the assessment results obtained from short-term clinical follow-ups.

Traditional rehabilitation assessment mainly relies on standardized scales, interviews, and regular follow-ups. These methods can only reflect the patient's situation at a certain point in time and are unable to continuously record their daily behaviors in the community environment [4]. During the assessment process, patients may be able to complete various tasks successfully, but when they return home, they rarely engage in activities and lack social participation [5]. At the same time, between planned assessments, the patients' daily activity ability and activity organization ability may have gradually improved, but these changes are often difficult to be recorded in a timely manner [6].

Wearable devices and smartphone sensors provide new supplementary means for traditional assessment [7]. These technologies can continuously record behavioral information such as activity volume, exercise intensity, sedentary time, activity transitions, and time patterns [8-9]. After aggregating these data, a digital behavioral phenotype reflecting the individual's behavioral characteristics can be formed. Such phenotypes are used to describe the way an individual organizes and conducts daily activities in real-life environments [10]. For example, reduced activity volume, prolonged sedentary time, irregular activity rhythm, and fewer behavioral state transitions, etc., may reflect an individual's activity ability, endurance, daily life stability, and interaction level with the surrounding environment. Currently, digital rehabilitation research after stroke mainly focuses on motor function, gait characteristics, activity recognition, and short-term monitoring [11-12], and there are still few studies on whether the behavioral characteristics collected outside the clinical environment can predict long-term community participation, social role recovery, and quality of life [13]. Moreover, the application value of these behavioral characteristics as candidate digital biomarkers for neurorehabilitation has not been fully verified. In particular, it is necessary to further clarify whether they can provide additional information beyond demographic characteristics, health status, and functional indicators [14-15].

This study investigated whether behavioral characteristics obtained through wearable devices could help predict the long-term community participation of individuals with a history of stroke. A set of numerically interpretable digital behavioral phenotypes was constructed, including activity level, inactive behaviors, daily rhythms, behavioral variability, and movement state transitions, among other indicators. These features were further analyzed in relation to community participation, social role function, and quality of life, among other outcomes. Based on publicly registered NHATS data, this study conducted a repeatable empirical assessment of the potential value of digital behavioral phenotypes in long-term stroke rehabilitation, and explored their application potential as supplementary biomarkers for remote monitoring and individualized rehabilitation support in neurorehabilitation.

2. Data Sources and Study Design

2.1. Data Source

The main data is sourced from NHATS, which is a longitudinal study conducted among Medicare beneficiaries aged 65 and above in the United States. NHATS provides publicly available post-registration data, covering information such as demographic characteristics, health status, physical function, daily activities, social participation, and subjective well-being. Before using the public data, researchers need to complete registration and abide by the data usage terms of NHATS.

This study utilized the NHATS survey rounds that simultaneously included interview data and wrist acceleration sensor data. According to the official acceleration sensor documentation, the physical activity data was collected by the ActiGraph CentrePoint Insight wristwatch, which is a research-grade three-axis accelerometer. Participants wore the device during the home interviews and were required to wear it continuously for 7 days. The publicly available acceleration sensor data includes both aggregated indicators and measurement data with time resolution, which can be used to describe behavioral characteristics such as activity intensity, duration, frequency of activities, and their temporal distribution.

Since NHATS was not specifically designed as a cohort for stroke rehabilitation, this study limited its research subjects to elderly individuals residing in the community and with a history of stroke. The study combined official questionnaires, variable coding manuals, cross-reference documents, and user guides to determine relevant variables such as stroke history, living conditions, community participation, health status, and accelerometer records. The data from the 11th round of interviews were matched with the 12th round of follow-up data, and finally, the analysis variables and sample were determined.

In addition, this study also referred to a published study on human activity recognition based on smartphones as a methodological reference. This study collected the smartphone accelerometer and gyroscope data of 44 participants during the completion of 41 mobile tasks. Due to the inability to independently obtain and verify the relevant data, it was not included in the empirical analysis of this study. It was only used as a methodological basis for explaining how smartphone sensors identify activity states.

2.2. Study Population

The research subjects were participants who resided in the community, self-reported a history of stroke, and completed the 11th round of the NHATS interview and wrist acceleration assessment. The 11th round data served as the baseline, and the 12th round data were used to evaluate the follow-up results one year later. The research sample mainly consisted of stroke patients living in the community.

The participants included in the study must have valid baseline accelerometer data, and the monitoring period should be no less than 4 days, with the device being worn for more than 90% of the time each day. Participants residing in nursing homes or other long-term care facilities were excluded. Additionally, those who did not complete the 12th round of follow-up, lacked community participation outcome indicators, or whose demographic and health covariate information was incomplete were not included in the final analysis.

The outcome indicators related to community participation were selected from the validated survey items in the NHATS, including social visits, religious activities, club or group activities, leisure outings, paid work, and volunteer services, etc. The final analysis sample was entirely derived from the publicly available and registered NHATS data.

2.3. Study Design

This study utilized the data from the 11th round of the NHATS as the baseline and the data from the 12th round as the follow-up one year later for conducting longitudinal secondary data analysis. The behavioral characteristics obtained by wearable devices were extracted from the wrist acceleration sensor records at the baseline, and the relationship between these characteristics and subsequent community participation and health-related outcomes was analyzed. Correlation analysis was used to evaluate the correlation between digital behavioral phenotypes and follow-up outcomes, and the prediction model further examined whether adding these behavioral characteristics could improve the prediction effect beyond demographic characteristics, health status, and functional indicators.

The NHATS data were not linked or merged with the data from the smartphone activity recognition study at the participant level. The smartphone sensing study was only used as a methodological reference to provide insights for explaining the behavioral characteristics obtained by wearable devices and for future digital behavioral phenotype studies in the stroke-specific cohort.

2.4. Variable Groups

The research variables are classified into four categories. Demographic variables include age, gender, educational level and living conditions. Health variables include chronic disease status, degree of functional limitation and self-assessed health condition. Digital behavioral variables include activity level, sedentary time, fragmented activity, time distribution characteristics and daily variability. Outcome variables include social participation, community activity participation, performance of social role functions and subjective well-being.

All the comprehensive indicators are constructed based on the verified survey items in the NHATS, and the coding method of the indicators, the rules for handling missing data, and the scoring process have been clearly described.

3. Digital Behavioral Phenotype Construction

3.1. Wearable-Derived Behavioral Phenotypes

The digital behavioral phenotype was constructed based on the aggregated data from the accelerometers in the 11th round of the NHATS and the detailed record files (Table 1). Participants wore the ActiGraph CentrePoint Insight device on their non-dominant wrist for continuous monitoring. The three-axis acceleration data was converted into minute-level activity counts. Participants whose device was worn for less than 90% of the time on valid monitoring days were excluded, and those with less than 4 valid monitoring days were also excluded.

The constructed digital behavioral phenotype encompasses features such as activity level, sedentary behavior, time rhythm, and diurnal variability. Activity-related indicators include total vector amplitude activity count, log-transformed activity count, daily active minutes, number of active periods, average duration of active periods, and the maximum cumulative activity volume within 10-minute, 30-minute, and 60-minute windows. Since the NHATS accelerometer data files do not provide daily step information, steps were not included in the analysis. Additionally, the duration of mild to moderate-intensity activities and high-intensity activities was not used as the relevant standardized intensity classification indicators did not directly provide this information.

The inactive and fragmented activity indicators include the number of inactive minutes per day, the number of inactive periods, and the average duration, as well as the probability of transitioning between active and inactive states. These transition indicators are used to describe the frequency of changes in behavioral states. Due to the continuous wearing scheme of the device and the fact that the data does not directly distinguish between sleep and wakeful periods, the inactive time is not directly interpreted as sedentary behavior. The sedentary-related indicators are estimated only after excluding the preset nighttime period.

The time rhythm-related indicators are calculated based on minute-level activity records and are used to describe the distribution characteristics of daily activities in different time periods, including the start time of morning activities, the concentration of activities during the day, the concentration of activities in the evening, and the stability of the daily rhythm. Among them, the start time of morning activities is defined as the first continuous activity period within the preset morning period; the concentration of activities reflects the proportion of awake activities within a specific time period; and the stability of the rhythm is used to measure the consistency of daily activity patterns between different valid monitoring days.

The daytime variability indicators include the mean, standard deviation, coefficient of variation and range of the total daily activity count, which are used to describe the fluctuation of an individual's activity level during the monitoring period and the stability of their daily behavioral patterns.

Table 1. Digital behavioral phenotype domains

Domain	Measures
Activity volume	Total counts, active minutes, active bouts, maximum 10-/30-/60-minute activity
Non-active behavior	Non-active minutes, bout frequency and duration
Behavioral fragmentation	Active-to-non-active and non-active-to-active probabilities
Temporal pattern and variability	Activity onset, time-window concentration, rhythm stability, daily variation

3.2. Smartphone-Based Behavioral States

The research on smartphone sensing is used only as a methodological reference. The activity recognition studies cited utilize the accelerometer and gyroscope signals from smartphones to identify sitting, standing, lying down, large-scale movement, going up and down stairs, daily minor actions, and transitions between different activity states.

These activity categories indicate that the information obtained by smartphone sensors may reflect the activity level and can also provide characteristics related to specific behavioral contexts. For instance, information such as walking, going up and down stairs, changes in posture, and transitions in activity states, can help further understand an individual's daily activity capabilities and task performance. However, since this study did not provide reusable individual-level raw data and could not be independently verified, no data variables based on smartphones were included in the statistical model of this study.

3.3. Rehabilitation Interpretation and Biomarker Position

The constructed features are regarded as proxy indicators reflecting daily behavioral patterns. A lower activity level may suggest limited activity ability. Longer inactivity or fewer behavioral changes might mean a decline in endurance or insufficient participation in daily tasks. Irregular time distribution patterns and large differences in daytime activity levels may prove unstable life rhythms, which can also be influenced by factors such as concurrent diseases, environmental conditions, and personal living habits.

Thus, these characteristics were selected as candidate digital behavioral biomarkers for assessment in this study, aiming to provide objective and repeatable measurement information regarding an individual's daily activity organization, behavioral stability, and mobility capabilities. Their potential value was evaluated through the analysis of associations with community participation-related outcomes, as well as the assessment of additional predictive contributions in the predictive models for existing demographic, health, and functional indicators.

4. Outcomes and Analytical Methods

4.1. Primary Outcome

The main outcome indicator was the community participation status at the one-year follow-up of the 12th round of the NHATS (Table 2). Due to the lack of relevant data in the NHATS, this study constructed a comprehensive index based on the four types of activities participated in within the past month, including visiting relatives and friends, attending religious activities, participating in club or organization activities, and going out for leisure. One point was given for each activity participated, and 0 points for those who did not participate. The final community participation score ranged from 0 to 4. Responses that were refused or uncertain were regarded as missing values, and only participants who completed answering all four activities were included.

The consecutive community participation scores were used for regression analysis to assess the relationship between the digital behavioral phenotype and the level of community participation. At the same time, based on the distribution of the community participation scores, the group with lower scores was defined as the low participation group for further binary classification analysis. The low participation group was set as the participants in the weighted sample whose scores were in the lowest 20%. Since the community participation scores only range from 0 to 4, some participants may have the same score, so the actual proportion of low participation may be slightly higher than 20%. In addition, the study also conducted sensitivity analyses using the lowest 25% and 30% score ranges to test whether the results remained consistent under different low participation standards.

The items such as paid work, volunteer services, shopping, meal preparation, and activity restrictions are not included in the main community participation index, as these indicators more reflect the capacity to undertake social roles or the situation of activity restrictions.

Table 2. Outcome definitions

Outcome domain	NHATS measures	Analytical form
Community participation	Visiting family or friends, religious services, organized activities, outings for enjoyment	Continuous score, 0–4
Low participation	Community participation score at or below the selected percentile	Binary outcome
Social-role functioning	Paid work, volunteering, independent shopping, meal preparation	Individual indicators
Health and well-being	Self-rated health, depressive and anxiety symptoms, positive and negative affect	Ordinal or continuous outcomes
Functional independence	Available self-care, mobility, and household activity limitations	Individual items or verified summary measures

4.2. Secondary Outcomes

The secondary outcomes are mainly used to further examine the performance of stroke survivors in terms of social role recovery, daily functioning, and health perception. Social function is mainly measured through activities such as paid work, volunteer services, independent shopping, and meal preparation. They are used to demonstrate individual's ability to maintain social participation and independently complete tasks in daily life.

In addition, the study also examined multiple aspects related to health, including self-assessed health status, symptoms of depression and anxiety, as well as emotional experiences such as happiness, energy, loneliness, boredom, and pain. Activity ability, self-care ability, and limitations in family activities were used to explain in functional changes. Each indicator was analyzed to avoid simply merging information from different dimensions without proper basis.

4.3. Association Analysis

Continuous variables are described based on the data distribution using the mean and standard deviation or the median and interquartile range. Categorical variables are described using frequency and percentage.

This study established three models respectively: Model 1 only included population, health and functional information, Model 2 only included digital behavioral phenotypes, and Model 3 incorporated both types of variables. Then, the predictive effects of these models were compared.

If there is corresponding community participation information in the baseline stage, the relevant variables in the model should be adjusted accordingly. Continuous predictor variables are standardized before analysis, and highly correlated behavioral indicators are screened out. The model results are presented with a 95% confidence interval, and multiple tests are controlled using false discovery rate correction.

4.4. Predictive Modelling

Linear regression and logistic regression serve as the primary explanatory benchmark models. Only when the sample size and the number of outcome events meet the requirements, will elastic net, random forest, and XGBoost models be further adopted. Model training and evaluation are accomplished through repeated five-fold cross-validation. All data preprocessing, feature selection, and parameter adjustments are conducted only within the training set.

Continuous results were evaluated using R^2, mean absolute error and root mean square error; binary classification results were assessed by using the area under the receiver operating characteristic curve, F1 score, sensitivity and specificity. The classification threshold was determined solely based on the training data. The incremental value of the model was evaluated by comparing the changes in R^2 or AUC between Model 3 and Model 1. The likelihood ratio test was only used for regression models with nested relationships.

4.5. Sensitivity Analyses

To verify the stability of the results, the study further adjusted the criteria for determining low community participation, and conducted analyses using three different division methods of 20%, 25%, and 30%. At the same time, the requirement for the effective recording days of the accelerometer was raised to at least five days, and the influence of individual activity indicators and comprehensive digital behavioral characteristics on the results was compared. The study also examined whether these factors would affect the main results by changing the handling method of missing data and including different living conditions.

5. Results and Discussion

5.1. Behavioral Differences

The original accelerometer sample included 747 participants from the NHATS study. Among them, 696 individuals completed the 11th round of wrist accelerometer measurements. Of these 696 participants, 696 also entered the 12th round of follow-up stage. 24 individuals were unable to continue due to death, and 27 did not complete the individual interviews. The final analysis subjects were further limited to those who lived in the community, self-reported having a history of stroke, had sufficient and valid accelerometer records, completed the relevant assessment of community participation, and had complete demographic and health information.

Figure 1 shows the standardized differences in wearable device usage behavior characteristics between the low community participation group and the high community participation group. The low community participation group had a lower overall activity level, manifested as a decrease in daily activity volume, a reduction in active time, a decrease in the duration of continuous activity, and an increase in non-active periods. At the same time, this group had fewer activity state transitions, a later start time for morning activities, and lower stability of the daily activity rhythm. The difference in daytime activity variability between the two groups was relatively limited.

These results suggest that the level of community participation may be related to an individual's daily activity pattern. Simply observing the overall activity level does not fully reflect the characteristics of daily activities. There may also be differences in whether the activities are continuous, how the activity status changes, and whether the schedule is regular. Therefore, even if individuals have similar total activity levels, their daily activity patterns may still differ.

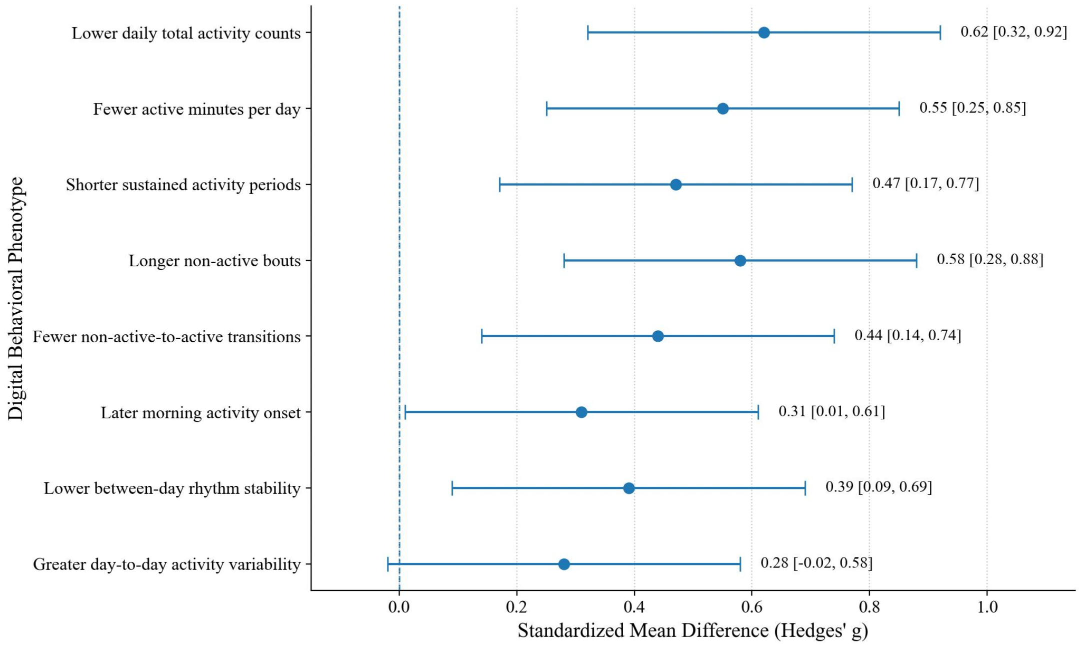

Figure 1. Standardized differences in wearable-derived digital behavioral phenotypes between participants with low and higher community participation.

5.2. Associations with Community Participation

The analysis results show that there is a certain correlation between the daily activity patterns and the community participation level one year later. Participants who have less activity, remain inactive for a long time, have less initiative in resuming activities, and have significant variations in their daily activity patterns tend to have a lower level of community participation. After considering factors such as age, gender, education level, health status, degree of functional limitation, and baseline participation, these correlations weaken, indicating that some of the differences may be related to the individual's original health and functional status.

However, the information recorded by wearable devices can still provide some details of daily behaviors that are difficult to observe through traditional assessments. For instance, although the total amount of activity for some individuals is similar throughout the day, there may be significant differences in whether the activities are continuous, whether they remain inactive for long periods, and whether the daily activity patterns are stable. These daily behavioral characteristics may help to further understand an individual's living conditions and participation capabilities.

These results merely indicate a connection between behavioral patterns and community participation, but do not prove a direct causal relationship between the two. The reduction in activities may be influenced by factors such as declining physical function, fatigue, pain, emotional problems, environmental constraints, or insufficient social opportunities; at the same time, less participation in community activities may further reduce the opportunities for daily activities.

5.3. Predictive Value

Figure 2 compares the three different models. For continuous community participation outcomes, the combined model performed the best, with a higher explanatory power than any of the models using only one type of information, and a relatively lower prediction error. Compared to the model that only uses digital behavior characteristics, the demographic and clinical information model performed better, indicating that health status, functional level, and living environment are still closely related to community participation.

After incorporating digital behavioral characteristics, the model's performance further improved, indicating that the daily activity information recorded by wearable devices can provide additional references. However, the improvement was limited, which is consistent with the fact that community participation is influenced by multiple factors. Social support, transportation conditions, community environment, and personal preferences cannot be directly measured by accelerometers.

Regarding the classification prediction of the low participation state, the model performance is evaluated through indicators such as AUC, F1 score, sensitivity, and specificity. Since a single indicator may not fully reflect the model's effectiveness, multiple indicators are compared in combination. The error bars represent the fluctuation range of the model's performance during the repeated cross-validation process.

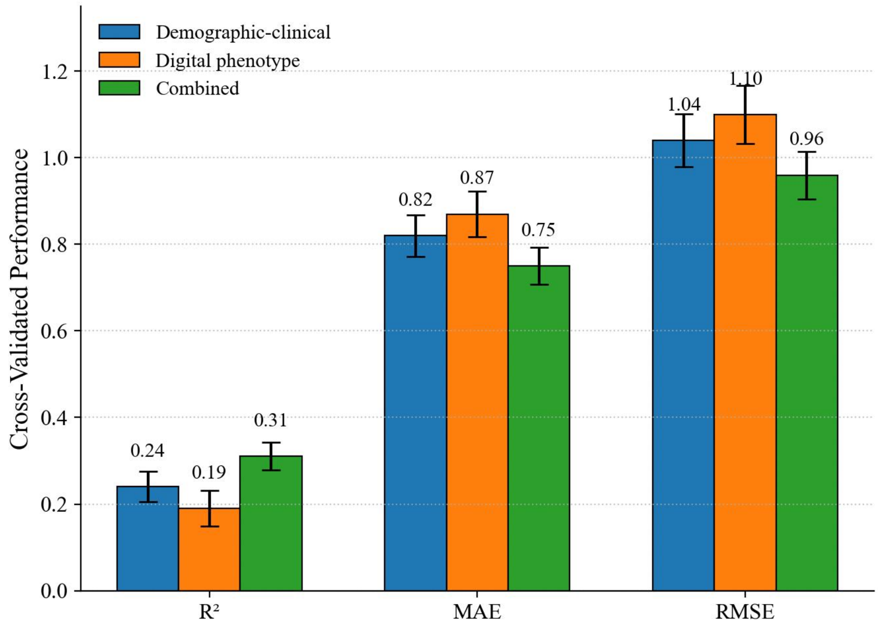

Figure 2. Cross-validated performance of demographic-clinical and digital behavioral phenotype models for predicting community participation.

Sensitivity analysis examines whether the main results are stable by adjusting the classification method of low participation levels, the inclusion requirements for effective accelerometers data, and the combination method of behavioral characteristics. Under different analysis conditions, the model performance and main trends remain largely consistent, indicating that the research results are not significantly affected by a specific analysis scheme.

5.4. Digital Biomarker and Rehabilitation Implications

The behavioral characteristics recorded by wearable devices have the potential to serve as digital behavioral biomarkers, capable of continuously reflecting an individual's activity levels, activity patterns, and behavioral changes in their daily environment. Such information can complement traditional clinical assessments and help understand the real-life status of patients outside of the medical setting.

If it is observed that the duration of activities is continuously decreasing, the frequency of returning to activity from a non-active state is declining, or the daily activity pattern becomes unstable, it may indicate the need for further attention to the individual's functional changes. These pieces of information can be used to assist in formulating rehabilitation plans for mobility training, fatigue management, home activity scheduling, and promoting community participation. Long-term tracking of an individual's behavioral changes also helps to identify changes in their own activity patterns.

It is important to note that these measurement results are mainly used as a reference for clinical judgment and cannot alone determine the treatment plan. Smartphone sensors may also provide more information about posture changes, walking, stair activities, and movement transitions. However, this study did not use the smartphone data of the NHATS participants, nor did it incorporate this information into the prediction model.

5.5. Limitations

This study still has room for further improvement. NHATS is not a specialized cohort specifically designed for stroke rehabilitation. Therefore, the information about stroke mainly comes from the self-reports of the participants. The study lacks or cannot fully obtain relevant information such as the severity of the stroke, the location of the lesion, the time of onset, and previous rehabilitation experiences. The indicators related to community participation and social roles have not used assessment scales specifically designed for stroke patients.

The participation score constructed in this study mainly reflects the scope of activities participated in over the past month. It cannot further measure the frequency, duration, satisfaction level or quality of participation. Moreover, some activities can be completed online, so this score does not fully equate to the actual level of community activities.

Since the wearable device data and smartphone activity recognition data come from different research samples, this study is unable to conduct individual-level multimodal data integration analysis. Additionally, the research results may also be difficult to generalize to young stroke patients or institutional care populations. The accelerometer records mainly reflect physical activity conditions and cannot directly capture important factors that affect community participation, such as social support, transportation conditions, cognitive status, personal motivation, and environmental factors. Moreover, wrist devices may have limited activity recognition capabilities for arm movements that are less frequent, situations where individuals rely on assistive devices, or those using wheelchairs.

6. Conclusion

This study found that the daily activity data recorded by wearable devices are related to the level of community participation among elderly people with stroke. Individuals who have less activity, remain inactive for long periods, and have significant changes in their daily activity patterns tend to have lower community participation levels one year later. Compared to traditional assessment methods, wearable devices can record the actual activities of patients in their daily lives, providing additional information for understanding the post-rehabilitation living conditions.

It should be noted that these behavioral characteristics do not independently reflect the patient's recovery status. Reduced daily activities may be related to decreased physical function, fatigue, disease burden, living environment, or insufficient social support. Additionally, lower community participation may further affect an individual's activity opportunities. Therefore, wearable device data is more suitable as a supplement to clinical assessment, helping to observe long-term behavioral changes in patients, rather than replacing existing rehabilitation evaluation methods.

Smartphone sensing technology may further enrich the observation of daily behaviors in the future, such as providing more information about movement patterns and activity processes. However, the smartphone data involved in this study did not come from the participants of the NHATS and were not used for predictive analysis. Therefore, it is only used as a reference for the relevant methods.

Further studies can incorporate wearable device data, clinical information, and environmental factors in the same study population, and use more appropriate participation assessment methods for stroke patients to further clarify the application value of these behavioral characteristics in rehabilitation. Currently, such data are mainly used to supplement clinical assessment and help understand the long-term behavioral changes of patients.

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