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Original Article

Contribution of physical impairment or imaging findings in the prediction of ADL outcome in stroke patients with middle cerebral artery infarction

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ABSTRACT

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Objective: Effective rehabilitation can be realized through improved prediction accuracy of activities of daily living (ADL) outcomes in stroke patients after cerebral infarction. We investigated whether physical impairment and imaging findings contributed to improved prediction accuracy of ADL outcomes in stroke patients with a first time unilateral infarction in the middle cerebral artery.

Methods: The study included a total of 331 patients with diffusion-weighted magnetic resonance images from an acute-care hospital, who were admitted to our Kaifukuki Rehabilitation Wards. Admission Functional Independence Measure (FIM) motor (FIM-M) score, admission FIM cognitive score, age, days until admission to our hospital, Stroke Impairment Assessment Set (SIAS) (motor function, trunk function, unilateral spatial neglect, and lower limb position), type of cerebral infarction, and presence of lesions were set as independent variables. Discharge FIM-M score and FIM-M gain were designated as dependent variables. Multiple regression analysis, logistic regression analysis, and decision tree analysis were performed. In addition, independent variables that significantly contributed to improved prediction accuracy of ADL outcomes were clarified by stratifying patients and inserting/deleting independent variables.

Results: Trunk function and presence of lesions contributed to improved accuracy in predicting FIM-M gain in patients with low admission FIM-M scores.

Conclusion: Using physical impairment and image findings in addition to the admission ADL in patients with first time unilateral infarctions in the middle cerebral artery after stratification was useful in predicting the discharge ADL.

Key words: functional outcome, FIM (functional independence measure), ADL (activities of daily living), cerebral lesion, cerebrovascular disorders

Introduction

It is necessary to predict the outcome of activities of daily living (ADL) after cerebral infarction to design effective rehabilitation strategies, instruct patients on their future life style, and provide assistance to patients and their families [1]. Their patient's age [2], degree of motor paralysis on admission [3], incontinence [4], and ADL level on admission [5] are among the factors considered important for the ADL outcome.

A number of studies have reported improved prediction accuracy of ADL outcome by adding the presence of lesions or type of cerebral infarction [6−9], while others noted no improvements [10−12]. As the reason for this discrepancy, Hand et al. [11] considered the differences in the severity of diseases, items of ADL outcome, timing of evaluation, co-existence of first-time and recurrent infarction, and differences in cerebral infarction location.

The Functional Independence Measure (FIM) [13, 14], modified Rankin scale (mRS) [15], or Barthel Index (BI) [16] is often used as the evaluation tool for ADL outcome prediction in patients with cerebral infarction. The discharge FIM score, discharge FIM motor score or FIM motor gain is also often used [3].

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The discharge FIM score was most frequently used as a variable of ADL outcome, and the admission FIM score or admission FIM motor score is believed to have the greatest influence on the discharge FIM score [3, 17–19]. On the other hand, variables that influence FIM motor gain have not been revealed [3]. Furthermore, to our knowledge, only a few studies have investigated what the conditions under which variables other than the FIM contribute to improved prediction accuracy of the discharge FIM motor score or FIM motor gain.

Therefore, we considered that the prediction accuracy of ADL outcome could be improved by limiting the targeted patients and lesions and by adding a variable other than ADL.

In this study, we examined the admission FIM, impairments, and imaging findings, limiting the patients only to those with first-time unilateral infarctions in the middle cerebral artery (MCA), and investigated their degree of contribution to the discharge FIM motor score and FIM motor gain.

Methods

1. Patients

The study included a total of 331 stroke patients with first-time unilateral infarctions in the MCA territory who were admitted to our Kaifukuki Rehabilitation Wards, Fujita Health University Nanakuri Sanatorium (the present Nanakuri Memorial Hospital) during the period from January 2010 to March 2015 and who had previous diffusion-weighted magnetic resonance (MR) images from an acute-care hospital.

2. Variables used for prediction (independent variables)

We examined the admission FIM motor (FIM-M) score, admission FIM cognitive (FIM-C) score, age, days until admission to our hospital, sum of motor function items in the Stroke Impairment Assessment Set (SIAS) [14, 20] (SIAS-M score) on admission, admission trunk function (verticality score), admission unilateral spatial neglect (visuospatial score), and lower limb position as clinical data.

SIAS scores the worst state as 0 in all items, and the best state as 5 in motor function and 3 in other items [20] (Table 1). Its validity has been verified [21].

Hereafter, the admission FIM-M score and admission FIM-C score are referred to as the "FIM data," and all other data as "other clinical data."

We also investigated the presence of lesions and types of cerebral infarction. We used the Alberta Stroke Program Early CT Score + W (ASPECTS + W) with diffusion-weighted MR images to discriminate the lesions [7]. ASPECTS + W is proposed as a simple way to semi-quantify early ischemic changes. It divides the MCA territory into 11 areas with two slices. One slice is the cross section passing through the lentiform and the thalamus, and the other is the cross section passing through about 2 cm cranial to the first slice, making the lentiform no longer visible. The lesion size was scored by deducting one point from the 11 points when early ischemic changes were recognized in each area [7]. ASPECTS + W scores 11 points if there is no ischemic lesion, and scores 0 if the entire region is damaged. In this study, we determined the presence or absence of lesions in each area of ASPECTS + W and calculated the ASPECTS + W score (11 − foci number of areas).

Types of cerebral infarction were classified into

Table 1. Scoring of trunk function (verticality), unilateral spatial neglect (visuospatial), and lower limb position (L/E position) in SIAS (Stroke Impairment Assessment Set).

Verticality	
0	the patient can not maintain a sitting position
1	a sitting position can only be maintained while tilting to one side and the patient is unable to correct the posture to the erect position
2	the patient can sit vertically when reminded to do so
3	the patient can sit vertically in a normal manner
Visuospatial	
0	more than a 15 cm deviation from the central point
1	an error between 15 and 5 cm
2	an error between 5 and 2 cm
3	deviation from the mid-point by less than 2 cm
L/E position	
0	no position change is detected by the patient after the maximum possible motion
1	the patient recognizes movement of the digits but not the correct direction, even at maximal excursion
2	the patient can correctly perceive the direction of a moderate excursion
3	the patient can correctly identify the direction of a slight movement

This table was partially reproduced from "Chino N, et al. Jpn J Rehabil Med 1994; 31: 119–25."

lacunar infarcts (LACI), total anterior circulation infarcts (TACI), and partial anterior circulation infarcts (PACI) according to the Oxfordshire Community Stroke Project (OCSP) classification [22]. They were further classified into large-artery atherosclerosis, cardioembolism, small-artery occlusion, other determined etiology, and undetermined etiology according to the Trial of Org 10172 in Acute Stroke Treatment (TOAST) classification [23]. The former classification is based mainly on clinical symptoms [8], and the latter is based on examination data such as imaging findings [9].

Lesions, ASPECTS + W, and OCSP and TOAST classifications are referred to as "lesion data or stroke types."

3. Predicted (dependent) variables

Discharge FIM-M score and FIM-M gain were defined as dependent variables.

4. Data analysis

1) The relationship between the independent and dependent variables was studied using the scatter plot method. The difference in the dependent variables among the types of cerebral infarction was tested by analysis of variance.

2) We determined the cut-off point of the admission FIM-M score when the discharge FIM-M scores exceeded 70 points, which was considered to be a criterion of self-care independence [24, 25], by creating a receiver operating characteristic curve (ROC curve) and calculating the area under the ROC curve (area under the curve; AUC). Based on the cut-off point, we set a group with low admission FIM-M scores and a group with high admission FIM-M scores.

3) We performed an incremental stepwise multiple regression analysis to calculate multiple regression coefficients (R^2). First, we performed the multiple regression analysis using only the admission FIM data as independent variables. Thereafter, we performed the analysis using both the FIM data and other clinical data. In addition, we performed the analysis adding the lesion data or stroke types to the FIM data and other clinical data. We investigated the change in R^2 when performing these analyses. The statistical analyses were conducted for all patients, for patients with low admission FIM-M scores, and for patients with high admission FIM-M scores.

4) We divided the FIM-M gain results into two groups: (a) high recovery group (with FIM-M gains over the median value) and (b) low recovery group by referring to the method of Terasaka et al. [24]. We determined the significant independent variables by which the high recovery group could be discriminated by logistic regression analysis (backward method). Odds ratios were calculated for significant independent variables. A high recovery was predicted when the odds ratio was higher than 1, and a low recovery when it was lower than 1.

5) Furthermore, we calculated the sensitivity and specificity for predicting a high or low recovery. Sensitivity was defined as a ratio correctly identified as belonging to the high recovery group, and specificity was defined as a ratio correctly identified as belonging to the low recovery group.

6) Finally, we performed a decision tree analysis in which the FIM-M gain is treated as a dependent variable in the group with low admission FIM-M scores. Admission FIM data, other clinical data, and lesion data or stroke types were defined as independent variables for this analysis. We ended the analysis when the number of people before the division (parent node) reached 20, or the number of people after the division (child node) reached 10.

Significance level was set as less than 5% in all statistical analyses.

We obtained comprehensive consent for using the patients' admission data when carrying out our research, and we ensured that no personal information was disclosed during analysis.

Results

The study subjects comprised 202 males and 129 females aged 69.7 ± 12.5 years. Time from onset to admission to our hospital was 32.6 ± 12 days. Length of stay was 66.1 ± 35.9 days. In total, 161 patients had left-hemisphere lesions and 170 patients had right-hemisphere lesions. Detailed lesion sites are presented in Table 2. The number of lesions in each patient ranged from 1 to 9. Types of cerebral infarction are shown in Table 3.

Table 2. Lesions and number of patients.

M1	81
M2	95
M3	70
I	112
C	28
L	136
IC-post	162
M4	75
M5	94
M6	76
W	243

We investigated the lesions based on ASPECTS + W (Alberta Stroke Program Early CT Score + W) and summed up the number of patients for each lesion. The total number of patients was 331.

I, insular ribbon; C, caudate; L, lentiform; IC-post, posterior limb of internal capsule; M1, anterior middle cerebral artery (MCA) cortex; M2, MCA cortex lateral to the insular ribbon; M3, posterior MCA cortex; M4, M5, M6, anterior, lateral, and posterior MCA territories immediately superior to M1, M2, and M3, rostral to the basal ganglia, respectively; W, white matter.

Table 3. Types of cerebral infarction and number of patients.

LACI (lacunar infarcts)	122
TACI (total anterior circulation infarcts)	14
PACI (partial anterior circulation infarcts)	195

TOAST (Trial of Org 10172 in Acute Stroke Treatment)

Large-artery (large-artery atherosclerosis)	96
Cardioembolism	64
Small-artery (small-artery occlusion)	12
Other (other determined etiology)	20
Undetermined (undetermined etiology)	139

The upper table shows the number of patients in each category in the OCSP classification. The lower table shows those in the TOAST classification. The total number of patients was 331.

The results are described below according to the order of data analysis.

1) The results of the analysis of variance of the discharge FIM-M score and FIM-M gain for each stroke type are shown in Figure 1. TACI and large-artery atherosclerosis showed low values.

2) We plotted the ROC curve to determine the admission FIM-M scores that resulted in discharge FIM-M scores of 70 or more. AUC was 0.94. Sensitivity was 0.786, and specificity was 0.938 in admission FIM-M scores of 49.5 points. Sensitivity was 0.786, and specificity was 0.939 for admission FIM-M scores of 50 points. Sensitivity was 0.776, and specificity was 0.946 for admission FIM-M scores of 50.5 points. Therefore, the cut-off point was set at 50 points.

3) The results of the stepwise multiple regression analyses in all patients, patients with low admission FIM-M scores (admission FIM-M score < 50 points, 165 patients), and patients with high admission FIM-M scores (admission FIM-M total score ≥ 50 points, 166 patients) are shown in Table 4.

In the case where the discharge FIM-M score was a dependent variable, the multiple regression coefficient was elevated after a stepwise multiple regression analysis when other clinical data was added to the FIM data (0.68 to 0.80: all patients; 0.46 to 0.67: patients with low admission FIM-M scores; 0.48 to 0.56: patients with high admission FIM-M scores). The admission FIM-M score showed the highest standardized partial regression coefficient, which represented the degree of influence (0.33: all patients; 0.29: patients with low admission FIM-M scores; 0.56: patients with high admission FIM-M scores). Multiple regression coefficient denoted almost no elevation when lesion data or stroke types were added to the FIM data and other clinical data (0.80 to 0.80: all patients; 0.67 to 0.68: patients with low admission FIM-M scores; 0.56 to 0.56: patients with high admission FIM-M scores).

In the case where the FIM-M gain was a dependent variable, the multiple regression coefficient was low in the stepwise multiple regression analysis, using only the FIM data, in all patients and for those with low admission FIM-M scores (0.27: all patients; 0.05: patients with low admission FIM-M scores). The relationship between the admission FIM-M score and the FIM-M gain is shown in Figure 2. As a result, FIM-M gain was widely distributed in the low admission FIM-M scores. On the other hand, the higher the admission FIM-M score was, the lower the FIM-M gain was in patients with high admission FIM-M scores (≥50). This relationship was consistent with the high multiple regression coefficient of 0.70 obtained by adding only the FIM data for patients with high admission FIM-M scores in Table 4.

4) The median FIM-M gain in all patients was 27 points. High recovery was defined as a score of 27 points or more and low recovery as less than 27 points. The search results of the factors that predicted a high recovery group by logistic regression analysis are shown in Table 5. Odds ratios of the trunk function (verticality) were low when only the FIM data and other clinical data were added as independent variables (0.059) and also when the lesion data or stroke types were added to the FIM data and other clinical data (0.073). Caudate, posterior limb of internal capsule (IC-post), M5, and lesion side (right lesion) were included as significant independent variables among the lesion data or stroke types.

5) Sensitivity and specificity of this model were calculated. Sensitivity increased from 0.70 to 0.79 and specificity increased from 0.73 to 0.77 by adding the lesion data or stroke types to the FIM data and other clinical data. This means that the prediction accuracy improved.

6) In the decision tree analysis, the tree was first branched by the FIM data and other clinical data, such as admission verticality score, age, admission FIM-M motor score, admission SIAS-M score, and admission visuospatial score, followed by the branch for the lesion data and stroke types such as IC-post (Figure 3).

Discussion

When we predicted the discharge FIM-M score in this study, we were able to obtain higher multiple regression coefficients by adding other clinical data to the FIM data as independent variables (Table 4). Meyer et al. [3] stated that the influence of the same admission FIM score on the ADL outcome varied in relation to the degree of impairment or period from the onset. Thus, we considered that the addition of other clinical data would be important for improving the prediction accuracy of the discharge FIM-M score. On the other hand, the addition of lesion data or stroke

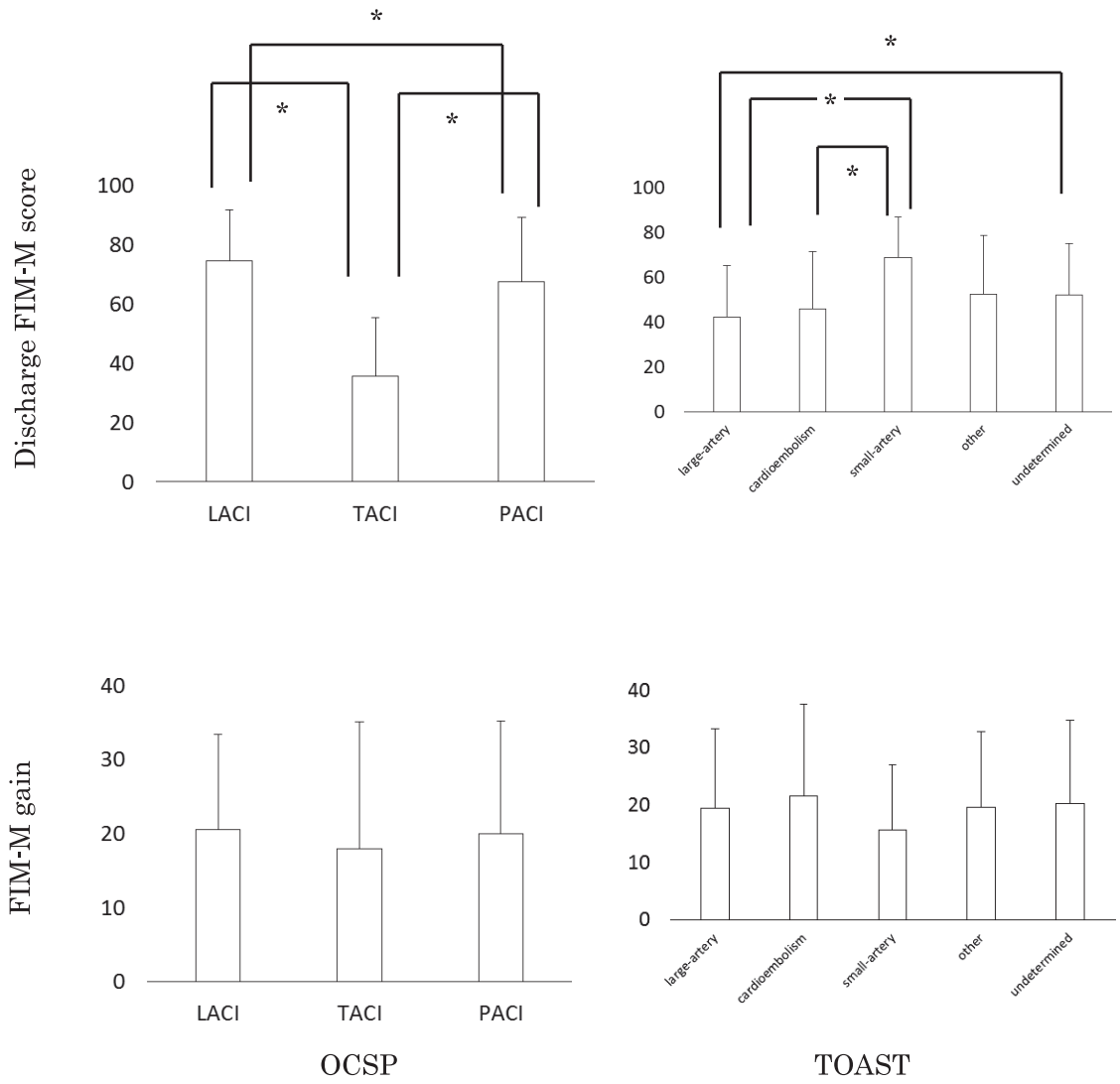

Figure 1. Discharge FIM-M score and FIM-M gain according to the type of cerebral infarction.
The left panel shows the results of the OCSP (Oxfordshire Community Stroke Project) classification, and the right panel shows those of the TOAST (Trial of Org 10172 in Acute Stroke Treatment) classification. Data is presented as mean ± standard deviation. *: $p < 0.05$.
LACI, lacunar infarcts; TACI, total anterior circulation infarcts; PACI, partial anterior circulation infarcts; large-artery, large-artery atherosclerosis; small-artery, small-artery occlusion; other, other determined etiology; undetermined, undetermined etiology.
The TACI group in the OCSP classification and the large-artery atherosclerosis (large-artery) group in the TOAST classification have significantly low discharge FIM-M scores.

types did not increase the multiple regression coefficients. Hand et al. [11] reported that the ADL outcome was closely related to the National Institutes of Health Stroke Scale (NIHSS) [26], which represents the neurological severity only in patients with mild or moderate impairment. However, even information such as the findings on diffusion-weighted MR images also became a significant independent variable for predicting the ADL outcome in severely impaired stroke patients because the NIHSS score deviated to a high score. We considered that adding imaging findings to the ADL on admission in predicting ADL outcomes, without limiting patients, including those with severe impairment, was not effective because information obtained from the images comprised impairment or ADL scores.

In contrast, the multiple regression coefficient for predicting the FIM-M gain with only the FIM data as an independent variable showed a low value of 0.05 in the group with low admission FIM-M scores (Table 4). There is a low linear relationship between the admission FIM-M score and FIM-M gain, and the use of a stepwise multiple regression analysis was believed to be difficult [18]. Additionally, the FIM-M gain was widely distributed at low admission FIM-M scores in this study (Figure 2). Therefore, when we predicted the FIM-M gain in the group with low admission FIM-M scores, it was difficult to use the stepwise

Table 4. The results of prediction of ADL outcome by stepwise multiple regression analysis.

Predictors	Outcomes					
	Discharge FIM-M score			FIM-M gain		
Patients (*n*)	all (331)	Admission FIM-M score<50 (165)	Admission FIM-M score>=50 (166)	all (331)	Admission FIM-M score<50 (165)	Admission FIM-M score>=50 (166)
Models using only FIM data						
Admission FIM-M score	+(0.67)	+(0.67)	+(0.66)	−(0.67)	NS	−(0.85)
Admission FIM-C score	+(0.20)	NS	+(0.13)	+(0.30)	+(0.22)	+(0.09)
R^2	0.68	0.46	0.48	0.27	0.05	0.7
Models using FIM data and other clinical data						
Admission FIM-M score	+(0.33)	+(0.29)	+(0.56)	−(0.89)	−(0.35)	−(0.93)
Admission FIM-C score	+(0.12)	+(0.12)	NS	NS	+(0.16)	NS
Age	−(0.17)	−(0.27)	−(0.23)	−(0.26)	−(0.36)	−(0.17)
Days to admission to our hospital	−(0.07)	NS	−(0.17)	NS	NS	−(0.13)
Admission SIAS-M score	+(0.17)	+(0.23)	NS	+(0.28)	+(0.31)	NS
Admission position score of lower extremity in SIAS	NS	NS	+(0.14)	NS	NS	+(0.10)
Admission verticality score in SIAS	+(0.19)	+(0.27)	+(0.16)	+(0.41)	+(0.36)	+(0.12)
Admission visuospatial score in SIAS	+(0.11)	+(0.11)	NS	NS	+(0.15)	NS
R^2	0.8	0.67	0.56	0.46	0.41	0.75
Models using FIM data, other clinical data and lesion data or stroke types						
Admission FIM-M score	+(0.33)	+(0.29)	+(0.56)	−(0.89)	−(0.34)	−(0.93)
Admission FIM-C score	+(0.12)	+(0.19)	NS	NS	+(0.25)	NS
Age	−(0.17)	−(0.26)	−(0.23)	−(0.26)	−(0.35)	−(0.17)
Days to admission to our hospital	−(0.07)	NS	−(0.17)	NS	NS	−(0.13)
Admission SIAS-M score	+(0.17)	+(0.25)	NS	+(0.28)	+(0.34)	NS
Admission position score of lower extremity in SIAS	NS	NS	+(0.14)	NS	NS	+(0.10)
Admission verticality score in SIAS	+(0.19)	+(0.27)	+(0.16)	+(0.41)	+(0.36)	+(0.12)
Admission visuospatial score in SIAS	+(0.11)	+(0.10)	NS	NS	+(0.13)	NS
Lesion sites (right to left)	NS	−(0.11)	NS	NS	−(0.15)	NS
ASPECTS+W on DWI	NS	NS	NS	NS	NS	NS
OCSP classification	NS	NS	NS	NS	NS	NS
TOAST classification	NS	NS	NS	NS	NS	NS
R^2	0.8	0.68	0.56	0.46	0.42	0.75

We used the discharge FIM-M score and FIM-M gain as factors in predicting the ADL outcome.

The results of the prediction of discharge FIM-M score are shown in the three rows on the left side, and those of FIM-M gain in the three rows on the right side. Each of the three rows represents results for all patients, for patients with low admission FIM-M scores (less than 50 points in admission FIM-M total score), and for patients with high admission FIM-M scores (more than 50 points in admission FIM-M total score).

The results are also shown for the stepwise multiple regression analysis when we introduced only "FIM data," "FIM data" and "other clinical data," and "FIM data," "other clinical data," and "lesion data or types of cerebral infarction" as independent variables (predictors).

"+" represents a positive effect on the discharge FIM-M score and FIM-M gain when the presence or increasing value of an independent variable was found. "−" represents a negative effect.

Values enclosed in ( ) show the standardized partial regression coefficients representing the influence. R^2 shows the multiple regression coefficients.

We statistically processed the right side as 1, and the left as 0 regarding the lesion site. We statistically processed the category determined for each patient as 1, and other categories as 0 regarding the OCSP and TOAST classifications.

NS, not significant; FIM-M, motor subscore of the Functional Independence Measure; FIM-C, cognitive subscore of the Functional Independence Measure; SIAS, Stroke Impairment Assessment Set; ASPECTS, Alberta Stroke Program Early CT Score; DWI, diffusion-weighted image; OCSP, Oxfordshire Community Stroke Project; TOAST, Trial of Org 10172 in Acute Stroke Treatment.

When we added other clinical data to the FIM data, multiple regression coefficients increased in the case of the discharge FIM-M score as a dependent variable. When we introduced only the FIM data, multiple regression coefficients were low in the FIM-M gain of all patients and patients with low admission FIM-M scores.

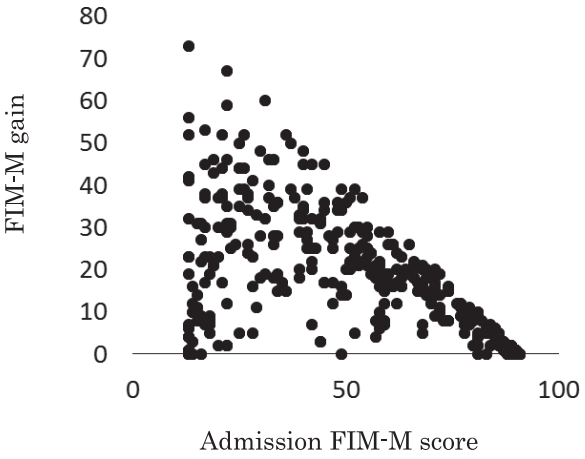

Figure 2. Relationship between admission FIM-M score and FIM-M gain.
The horizontal axis shows the admission FIM-M score and the vertical axis indicates the FIM-M gain. FIM-M gain was widely distributed in the low admission FIM-M scores (<50).

multiple regression analysis. It was necessary to identify another method of analysis, that is, to change the statistical approach, and stratify patients with limited conditions. Thus, we introduced the logistic regression analysis and decision tree analysis to analyze the FIM-M gain in the group with low admission FIM-M scores.

In the logistic regression analysis of FIM-M gain in the group with low admission FIM-M scores, the lesion became a significant independent variable when lesion data or stroke types were added to the FIM data and other clinical data.

As to the lesions obtained as a significant independent variable, IC-post is a pyramidal tract route, and M5 is an area that contains the motor and sensory cortex [27, 28]. Therefore, we considered that these lesions had an effect on FIM-M gain via their association with motor function. Cheng et al. [29] reported that the site rather than the size of cerebral infarction had an impact on ADL outcome, and especially lesions in the corona radiata, posterior limb of internal capsule, and insula affected mRS after one month from the onset of the cerebral infarction.

Table 5. Variables and influences which predicted high recovery of FIM-M gain.

	OR	95%CI	*p*
Models using FIM data and other clinical data			
Age	0.934	0.9–0.97	0
Admission Verticality score 0 in SIAS	0.059	0.007–0.509	0.01
Admission Visuospatial score 0 in SIAS	0.188	0.057–0.616	0.006
Models using FIM data, other clinical data and lesion data or stroke types			
Age	0.92	0.885–0.964	0
Admission FIM-M score	0.93	0.884–0.979	0.006
Admission FIM-C score	1.085	1.015–1.159	0.017
Admission SIAS-M score	1.096	1.024–1.174	0.008
Admission Verticality score 0 in SIAS	0.073	0.008–0.694	0.023
Admission Visuospatial score 0 in SIAS	0.213	0.055–0.831	0.026
Right lesion	0.299	0.126–0.712	0.006
C	6.725	1.509–29.966	0.012
IC-post	0.293	0.122–0.705	0.006
M5	0.369	0.145–0.938	0.036

We investigated independent variables and influences that predicted high recovery of FIM-M gain (≥27 points) in patients with low admission FIM-M scores (<50 points).
We showed significant independent variables when we introduced only the FIM data and other clinical data and when we added the lesion data or stroke types to the FIM data and other clinical data. We calculated the odds ratios (OR), 95% confidence intervals (CI), and *p*-values. An independent variable with an odds ratio of more than 1 predicted a high recovery, and less than 1 predicted a low recovery. In addition, when an odds ratio was much larger or smaller than 1, the independent variable had a large impact on the FIM-M gain.
With respect to verticality and visuospatial scores, we statistically processed a score of 0 as 1 and a score of 1–3 as 0. In addition, we statistically processed the presence of lesions as 1 and the absence of lesions as 0 for each location.
FIM-M, motor subscore of the Functional Independence Measure; FIM-C: cognitive subscore of the Functional Independence Measure; SIAS, stroke impairment assessment set; C, caudate; IC-post: posterior limb of internal capsule; M5, lateral MCA territories immediately superior to the M2, rostral to the basal ganglia.
Odds ratio of the trunk function (verticality) was low. C, IC-post, M5, and right-hemisphere lesion (right lesion) were included as significant independent variables among the lesion data or stroke types.

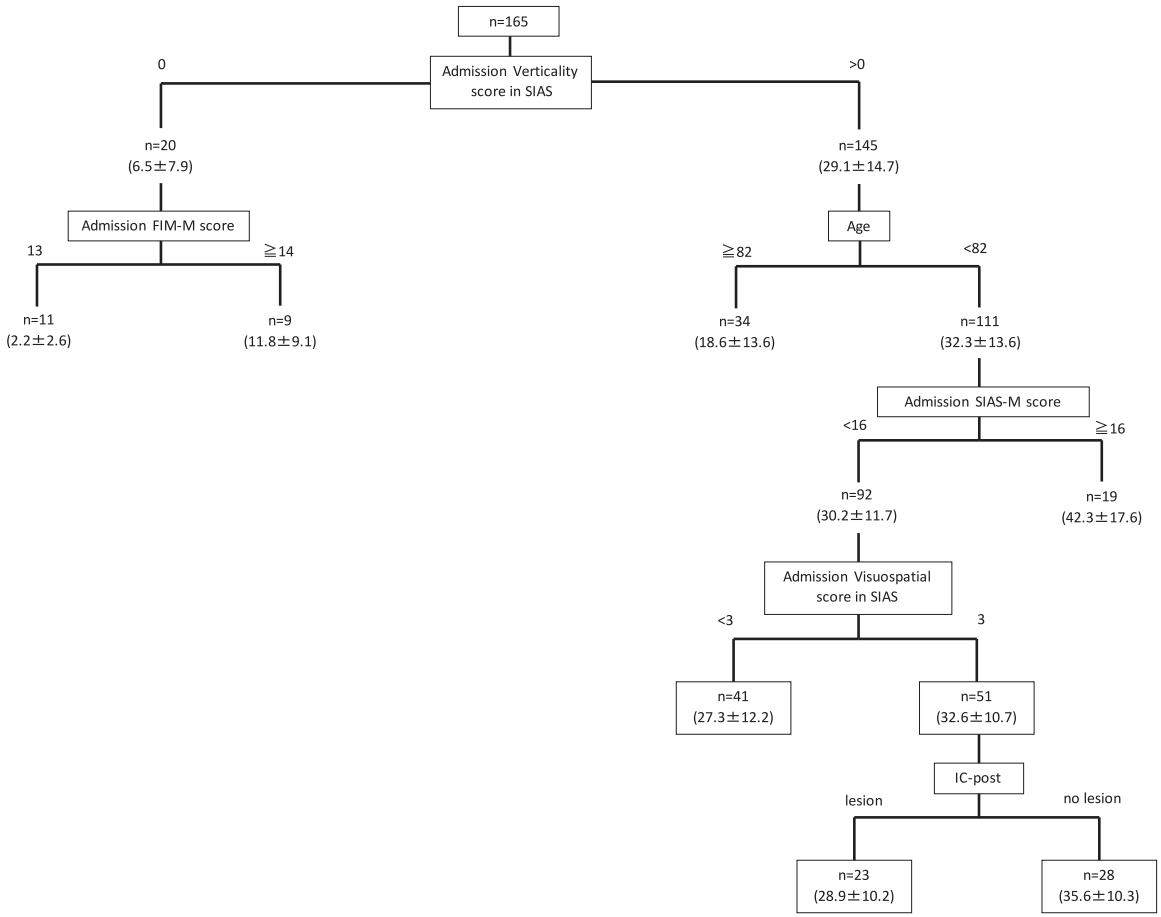

Figure 3. Results of decision tree analysis for the group with low admission FIM-M scores.
FIM-M gain in the group with low admission FIM-M scores was defined as a dependent variable. "Admission FIM data", "other clinical data", and "lesion data or stroke types" were defined as independent variables for this analysis. The status of the branches is shown here.
Values enclosed in ( ) are presented as mean ± standard deviation of the FIM-M gain.

Terasaka et al. [24] reported on acute stroke patients who were able to obtain a high FIM-M gain despite a low discharge FIM-C score. They speculated that mild paralysis could be the cause of this phenomenon. This situation is also applicable when severe paralysis on admission recovers during admission. We then considered that imaging findings are useful for detecting such cases.

Meanwhile, FIM-M gain was a predictor of high recovery when the lesion was present in the caudate (Table 5). Caudate lesions lower the status of ADL on admission; however, this negative effect is easy to resolve during admission. The caudate is a region involved in memory and cognition. There are reports that unilateral caudate lesions started to influence cognitive function after more than a year since onset [30], and that the improvement of symptoms such as apathy was gradual in patients with bilateral caudate lesions [31]. These reports are not inconsistent with our speculations.

We calculated the sensitivity and specificity to examine whether the prediction accuracy of the FIM-M gain improved when we added lesion data or stroke types to the FIM data and other clinical data. Sensitivity and specificity are indexes used to determine the accuracy of a model obtained by logistic regression analysis. The higher the value is, the higher the accuracy of the model [32]. In this study, both sensitivity and specificity increased by adding the lesion data and stroke types to the FIM data and other clinical data. From these results, the prediction accuracy of the ADL outcome could be improved when we introduce lesion data or stroke types after the stratification of patients with admission ADL.

Decision tree analysis is a method of dividing the dependent variables into two groups based on the independent variable values. It has the advantage of representing the branch logic in independent variables and visualizing which variable is important [33, 34]. Since the relationship between FIM-M gain and independent variables was not linear and the decision tree analysis was one of the nonlinear analyses used, we conducted this analysis. Our results revealed that the branches for the FIM data and other clinical data were located in the upper layer, and the branches for the lesion data or stroke types appeared in the lower

layer (Figure 3). This indicates that we should consider the lesion data or stroke types as well as the FIM data and other clinical data when predicting the FIM-M gain in patients with low admission FIM-M scores.

The results of the odds ratios in the logistic regression analysis and the branch in the decision tree analysis demonstrated that trunk function (verticality) showed the strongest contribution to the FIM-M gain as an independent variable in patients with low admission FIM-M scores. Importance of sitting ability was frequently presented in previous studies about stroke outcome [35, 36], and "sitting up and maintaining a sitting position without assistance" was set in the logic that predicts independent walking as a principal factor by Niki [37]. Di Monaco et al. [38] reported that outside of the admission FIM score, only the trunk function, such as in the Trunk Impairment Scale and Postural Assessment Scale, was a significant factor that influenced the discharge FIM-M score or FIM change. The Trunk Impairment Scale measures static and dynamic balance in the sitting position, so it is similar to the SIAS trunk function item that rates the ability to maintain a sitting position by checking the trunk verticality. Trunk function is considered an easy item in SIAS [39]. Therefore, it is possible that poor trunk function consequently predicts a low ADL outcome.

Neither the ASPECTS + W score itself nor the types of cerebral infarction were significant in any of the statistical analyses. ASPECTS + W is proposed as a simple way to semi-quantify early ischemic changes. Tei et al. [1] reported that ASPECTS became a significant variable for the prediction of mRS three months after the onset of cerebral infarction. In contrast, Schiemanck et al. [10] reported that the area of cerebral infarction in the MCA was not a significant variable for predicting BI after one year. Several studies reported that the size of cerebral infarction could be underestimated depending on the time when the MRI was performed and the thickness of the slice [10, 40], and that the images of cerebral infarction did not necessarily reflect the brain function [29]. These findings led to the discrepancy between the size of cerebral infarction and ADL outcome. There is no need to add the ASPECTS + W score to the FIM data and other clinical data for predicting ADL outcomes, because the information included for the lesion size consequently reflected the admission FIM-M score. To summarize, the admission FIM-M score of patients with large lesions tended to be low.

We used OCSP and TOAST classifications to express the types of cerebral infarction. The former is a classification purely based on clinical symptoms. It is easy to use and closely related the responsible vessels [8]. The latter is a classification based on clinical findings, imaging findings, and auxiliary laboratory findings. It is used in determining the treatment strategy [9]. Lauretani et al. [8] reported lower discharge ADL in the TACI group compared to other groups in the OCSP classification. They pointed out that various symptoms in TACI led to lower discharge ADL. Similarly, the discharge FIM-M score in the TACI group was low in this study. However, TACI was not a significant factor when we performed stepwise multiple regression analysis and logistic regression analysis because the number of patients with TACI was extremely small. Pinto et al. [9] reported that admission and discharge ADL scores were lower in the cardiogenic embolism group in the TOAST classification compared to the ADL scores in other groups. In contrast, intragroup variations in ADL outcomes were reported in the TOAST classification [12]. There is no consensus regarding which group has the low discharge ADL. The differences in outcome parameters, time of evaluation, and variation of responsible vessels that induced cerebral infarction [1, 10, 11] might be the causes of the discrepancies. Tei et al. [1] reported that the TOAST classification did not significantly contribute to the prediction of mRS three months after the onset. As types of cerebral infarction, as in the OCSP and TOAST classifications, are very rough evaluations, it is also difficult to uniformly determine impairments. Therefore, we considered that it was of little importance to add the types of cerebral infarction to the ADL and impairments as independent variables for predicting ADL outcomes.

The limitation of this study is that a validation group was not set. In this study, we focused on clarifying the variables and conditions that contributed to improved prediction accuracy as a first stage of enhancing the accuracy of the created prediction equation itself. To validate the prediction equation, it is necessary to divide the patients into two groups in advance and to create the prediction equation using about half the total number of patients. Furthermore, we limited the patients only to those with MCA cerebral infarction and again divided the patients based on admission FIM-M scores. Under such conditions, when we divided the remaining patients into two groups, the number of patients in each group became too small. In the future, we will increase the number of cases and validate the prediction equation using the data on patients who were not included when creating the equation.

Conclusions

In this study, we investigated the factors that contributed to improved prediction accuracy of ADL outcome, using the discharge FIM-M score and FIM-M gain as outcome parameters in patients with first-time unilateral infarctions in the MCA. Trunk function and presence of lesions contributed to improved accuracy when we predicted the FIM-M gain in patients with low admission FIM-M scores. Therefore, it is important to consider items other than

clinical data to improve ADL prediction accuracy after limiting the patients.

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