

*Original Article***Formula for predicting FIM for stroke patients at discharge from an acute ward or convalescent rehabilitation ward**

Seungwon Jeong, Researcher, PhD,<sup>1</sup> Yusuke Inoue, Researcher, PhD,<sup>2</sup>  
 Katsunori Kondo, MD, PhD,<sup>2</sup> Daisuke Matsumoto, RPT, Master of Health Science,<sup>3</sup>  
 Nariaki Shiraishi, RPT, PhD<sup>4</sup>

<sup>1</sup>Department of Social Science, National Center for Geriatrics and Gerontology, Obu, Japan

<sup>2</sup>Center for Well-being and Society, Nihon Fukushi University, Nagoya, Japan

<sup>3</sup>Faculty of Health Science, Kio University, Kitakatsuragi, Nara, Japan

<sup>4</sup>Faculty of Health Science, Nihon Fukushi University, Handa, Japan

**ABSTRACT**

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**Objective:** To develop formulas for predicting Functional Independence Measure (FIM) at the time of discharge from an acute or convalescent hospital ward using multicenter data.

**Methods:** Data from 4,311 acute patients (22 hospitals) and 1,941 convalescent patients (24 hospitals) were divided into two groups (calculation group and verification group). Multiple regression analysis was performed to develop formulas for predicting discharge FIM and test their validity with data from the verification group.

**Results:** The formula derived for predicting discharge FIM for acute patients was  $85.04 + (-0.53 \times \text{age}) + (12.06 \times \text{subarachnoid hemorrhage}) + (-7.90 \times \text{complication present}) + (-0.70 \times \text{number of days from onset of stroke until admission}) + (1.24 \times \text{admission GCS}) + (-1.08 \times \text{admission NIHSS}) + (-4.15 \times \text{modified Rankin Scale score before stroke}) + (0.30 \times \text{admission motor FIM}) + (1.03 \times \text{admission cognitive FIM})$ , with  $R^2 = 0.78$ . The formula derived for predicting discharge FIM for convalescent patients was  $33.04 + (-0.34 \times \text{age}) + (-3.88 \times \text{complication present}) + (-0.11 \times \text{number of days from onset of$

$\text{stroke until admission}) + (2.44 \times \text{admission GCS}) + (-1.68 \times \text{modified Rankin Scale score before stroke}) + (0.53 \times \text{admission motor FIM}) + (1.25 \times \text{admission cognitive FIM})$  ( $R^2 = 0.66$ ).

**Conclusion:** Using a large multicenter database, we developed separate formulas for predicting FIM at discharge from an acute ward and from a convalescent ward with proven external validity.

**Keywords:** prediction of FIM at hospital discharge, stroke patients, acute rehabilitation, convalescent rehabilitation, rehabilitation patient data bank

**Introduction****1) Background**

Benchmarks can help increase the quality of medical care by enabling multicenter comparisons [1, 2]. After the start of a reimbursement system based on the quality of the convalescent rehabilitation ward in 2008, interest has been increasing in outcome measures for implementing benchmarks at various hospitals. This includes a measure of the level of functional improvement from hospital admission to discharge.

For stroke patients receiving inpatient rehabilitation care, predicting functional outcome at the time of admission is essential for setting targets and programs, managing rehabilitation processes, and preparing the discharge destination [3, 4].

Research on the functional outcome of stroke patients has been carried out since the 1980s and includes studies using a multivariate analysis approach [5–13]. Although many studies have proposed equations for predicting functional outcome, most only investigated single hospitals and therefore may not have been sufficiently externally validated for use in other hospitals or groups [3].

Correspondence: Seungwon Jeong, PhD  
 National Center for Geriatrics and Gerontology, 35 Gengo,  
 Morioka, Obu, Aichi 474–8511, Japan.

E-mail: k-jeong@ncgg.go.jp

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## 2) Study objective

This study aimed to develop formulas for predicting the functional independence measure (FIM) at hospital discharge to be used as a benchmark for assessing quality of medical care among multiple hospitals with high external validity for different hospitals and groups.

We randomly divided subjects into a calculation group and a verification group. The former was used to develop discharge FIM prediction formulas for patients on acute wards (“acute patients”) and patients on convalescent rehabilitation wards (“convalescent patients”), and the latter was used to test the validity of the formulas.

## Methods

### 1) The Rehabilitation Patient Data Bank (Rehab DB)

For the present study, we used data from the Rehabilitation Patient Data Bank (“Rehab Patient DB”), which is a large multicenter database developed under a Health and Labour Sciences Research Grant (2007–2009).

The Rehab Patient DB was created to promote the development of evidence for rehabilitation medicine by standardizing the items and input formats for each hospital’s own database to build a larger database containing data from patients across numerous hospitals.

Data were collected from each hospital on all rehabilitation patients discharged from the hospital twice a year from January to February and from July to August (once a year from August to September starting in 2010 after management of the DB was transferred to the Japanese Association of Rehabilitation Medicine Data Management Committee) [14, 15].

### 2) Subjects

Subjects were 6,252 patients (38 hospitals) that had recorded FIM from among 8,537 patients (39 hospitals) registered in the Rehab Patient DB from 2009 to 2012.

Of those subjects, 4,311 were in the acute (22 hospitals) and 1,941 were in the convalescent ward (24 hospitals).

### 3) Variables used to create the formulas

Baseline patient characteristics, rehabilitation program and outcome of rehabilitation have been suggested as factors for assessing stroke outcome [16]. In the present study, we developed formulas from a large-scale multicenter data bank to compare and benchmark the performance of hospitals without including data on rehabilitation programs, which vary among hospitals.

The variables we used in the present study to create predictive formulas were age, sex, type of disease, presence or absence of complication, number of days from onset of stroke until admission, Glasgow Coma Scale (GCS) score at admission, National Institute of Health Stroke Scale (NIHSS) score at admission, Modified Rankin Scale (mRS) score before stroke and FIM (Table 1).

### 4) Analysis methods

First, to investigate the need for separate acute and convalescent formulas, we tested the difference between acute and convalescent patient profiles.

Next, we developed the formulas using multivariate regression analysis. To test the external validity, acute and convalescent patients were each randomly divided into two groups (calculation group and verification group).

#### (1) Differences between the profiles of acute and convalescent stroke rehabilitation patients

To examine the differences in acute and convalescent patient profiles, we performed *t*-tests and chi square tests to compare age, type of disease (cerebral infarction, brain hemorrhage, or subarachnoid hemorrhage), presence or absence of complication, number of days from onset of stroke until admission, length of hospital stay, GCS score at admission and at discharge, NIHSS score at admission and at discharge, mRS score before stroke at admission and at discharge,

**Table 1.** Variables used to create formulas.

Variable	Scale
Age	Continuous variable
Sex	Dummy variable (male=1, female=0)
FIM	Continuous variable
Number of days from onset of the stroke until admission	Continuous variable
mRS before stroke	Continuous variable
NIHSS score	Continuous variable
GCS score	Continuous variable
Type of disease	Dummy variable (cerebral infarction, brain hemorrhage, or subarachnoid hemorrhage)
Complication	Dummy variable (presence=1, absence=0)

total FIM at admission and at discharge, FIM gain and FIM efficiency (gain / length of hospital stay) between acute and convalescent patients.

## (2) Development of formulas for predicting FIM at hospital discharge

In developing formulas for predicting discharge FIM, multiple regression analysis was performed on acute and convalescent patients with (1) age, (2) sex, (3) type of disease (cerebral infarction, brain hemorrhage, or subarachnoid hemorrhage), (4) complication, (5) number of days from onset of stroke until admission, (6) admission GCS, (7) admission NIHSS, (8) mRS before stroke, (9) admission motor FIM and (10) admission cognitive FIM as independent variables.

The Rehab Patient DB data was randomly divided into two groups for each condition (calculation group [acute: N=2118, convalescent: N=941] and verification group [acute: N=1905, convalescent: N=999]). The calculation group was used to develop the formulas and the verification group was input into the formulas to test the external validity using Spearman's correlation coefficient between the predicting FIM scores at discharge and actual scores.

SPSS ver. 18.0 was used for the statistical analyses.

## Results

### 1) Profiles of acute and convalescent stroke patients

*t*-Tests and chi square tests were performed to examine the differences between the acute and convalescent patient profiles (Table 2). A significant difference was observed for all factors other than type of disease (brain hemorrhage, subarachnoid hemorrhage) and mRS before stroke.

We thus confirmed that it would be more appropriate to use a different predictive formula for each group.

### 2) Formulas for predicting discharge FIM

Patients were divided into acute and convalescent groups and the data from each calculation group was used to calculate a formula that was then used with data from each verification group to verify the validity.

#### (1) Formula for predicting discharge FIM for acute phase stroke rehabilitation patients

The following formula for predicting discharge FIM for acute patients was created with only the variables that were statistically significant.

Formula for predicting discharge FIM for acute patients =  $85.04 + (-0.53 \times \text{age}) + (12.06 \times \text{subarachnoid hemorrhage}) + (-7.90 \times \text{complication present}) +$

**Table 2.** Profiles of acute and convalescent stroke rehabilitation patients.

Variable		Acute (mean)	Convalescent (mean)	<i>p</i> -Value
Age		72.5	69.6	<i>p</i> <.001
Type of disease	cerebral infarction	65.5%	62.2%	<i>p</i> <.05
	brain hemorrhage	25.0%	26.6%	n.s.
	subarachnoid hemorrhage	4.4%	5.3%	n.s.
Complication present		15.0%	23.0%	<i>p</i> <.001
Number of days from onset of stroke until admission		3.0	33.9	<i>p</i> <.001
Length of hospital stay		32.1	96.8	<i>p</i> <.001
GCS at admission		13.1	13.7	<i>p</i> <.001
GCS at discharge		13.9	14.1	<i>p</i> <.001
NIHSS at admission		8.5	3.8	<i>p</i> <.001
NIHSS at discharge		6.2	2.5	<i>p</i> <.001
mRS before stroke		1.0	0.9	n.s.
mRS at admission		3.9	3.5	<i>p</i> <.001
mRS at discharge		3.0	2.7	<i>p</i> <.001
Total FIM score at admission		56.0	63.3	<i>p</i> <.001
Total FIM score at discharge		82.7	88.1	<i>p</i> <.001
FIM gain		25.9	24.5	<i>p</i> <.05
FIM efficiency		1.4	0.3	<i>p</i> <.001

$(-0.70 \times \text{number of days from onset of stroke until admission}) + (1.24 \times \text{admission GCS}) + (-1.08 \times \text{admission NIHSS}) + (-4.15 \times \text{mRS before stroke}) + (0.30 \times \text{admission motor FIM}) + (1.03 \times \text{admission cognitive FIM})$ , with  $R^2 = 0.78$ .

For acute patients, discharge FIM tended to be higher with (1) younger age, (2) absence of complication, (3) fewer days from onset of stroke until admission, (4) higher admission GCS, (5) lower admission NIHSS, (6) lower mRS before stroke, (7) higher admission motor FIM and (8) higher admission cognitive FIM. As for differences with type of disease, discharge FIM had a high likelihood of being higher in subarachnoid hemorrhage patients than in cerebral infarction or brain hemorrhage patients.

Looking at the standard partial regression coefficient that shows the strength of the relative association of independent variables with discharge FIM, the strongest effect was from admission cognitive FIM (0.31). The next strongest effect was from NIHSS at admission (-0.24), followed by admission motor FIM (0.19), age (-0.17), mRS before stroke (-0.15), admission GCS (0.09), presence of complication (-0.07) and day of illness after onset at admission (-0.04), in descending order (Table 3).

When the formula developed with data from the calculation group was used on data from the verification group, a high correlation was found between the discharge FIM prediction values and actual values (0.88,  $R^2 = 0.77$ ).

#### (2) Formula for predicting discharge FIM for convalescent phase stroke rehabilitation patients

The following formula for predicting discharge

**Table 3.** Standard partial regression coefficient of the formula for predicting discharge FIM for acute phase stroke rehabilitation patients.

Variable	beta	
Age	-0.17	$p < .001$
Sex	0.01	n.s.
Cerebral infarction	0.02	n.s.
Brain hemorrhage	0.02	n.s.
Subarachnoid hemorrhage	0.06	$p < .01$
Complication present	-0.07	$p < .01$
Number of days from onset of stroke until admission	-0.04	$p < .001$
GCS at admission	0.09	$p < .001$
NIHSS at admission	-0.24	$p < .001$
mRS before stroke	-0.15	$p < .001$
Admission motor FIM	0.19	$p < .001$
Admission cognitive FIM	0.31	$p < .001$
$R^2$	0.78	$(p < .001)$

FIM for convalescent patients was created with only the variables that were statistically significant.

Formula for predicting discharge FIM for convalescent patients =  $33.04 + (-0.34 \times \text{age}) + (-3.88 \times \text{complication present}) + (-0.11 \times \text{number of days from onset of stroke until admission}) + (2.44 \times \text{admission GCS}) + (-1.68 \times \text{mRS before stroke}) + (0.53 \times \text{admission motor FIM}) + (1.25 \times \text{admission cognitive FIM})$ , with  $R^2 = 0.66$ .

Similar to acute patients, for convalescent patients, discharge FIM tended to be higher with (1) younger age, (2) absence of complication, (3) fewer days from onset of stroke until admission, (4) higher admission GCS, (5) lower mRS before stroke, (6) higher admission motor FIM and (7) higher admission cognitive FIM. For convalescent patients, there was no statistically significant effect of age, type of disease or admission NIHSS.

Looking at the standard partial regression coefficient that shows the strength of the relative association of independent variables on discharge FIM, the strongest effect was from admission motor FIM (0.38) and admission cognitive FIM (0.36), followed by age (-0.13), admission GCS (0.13), number of days from onset of stroke until admission (-0.10), mRS before stroke (-0.08) and presence of complication (-0.05), in decreasing order (Table 4).

When the formula developed with data from the calculation group was used on data from the verification group, a high correlation was found between the discharge FIM prediction values and actual values (0.84,  $R^2 = 0.71$ ).

**Table 4.** Standard partial regression coefficient of the formula for predicting discharge FIM for convalescent phase stroke rehabilitation patients.

Variable	beta	
Age	-0.13	$p < .001$
Sex	-0.01	n.s.
Cerebral infarction	0.04	n.s.
Brain hemorrhage	0.04	n.s.
Subarachnoid hemorrhage	0.04	n.s.
Complication present	-0.05	$p < .05$
Number of days from onset of stroke until admission	-0.10	$p < .001$
GCS at admission	0.13	$p < .001$
NIHSS at admission	0.03	n.s.
mRS before stroke	-0.08	$p < .001$
Admission motor FIM	0.38	$p < .001$
Admission cognitive FIM	0.36	$p < .001$
$R^2$	0.66	$(p < .001)$

## Discussion

Using the Rehab Patient DB, which is a large data bank with many participating hospitals, we were able to develop formulas for predicting FIM at hospital discharge that takes into account the issue of external validity for use in different hospitals and in target groups that differ from the group used for developing the formulas.

### 1) Profiles of acute and convalescent stroke rehabilitation patients

An examination of the differences between acute and convalescent stroke rehabilitation patient profiles revealed that these two profiles differ significantly.

The mean length of hospital stay of convalescent patients was roughly three times longer at 96.8 days than that of acute patients (32.1 days). As the number of days of illness when admitted to a convalescent setting was 33.9 days, it is likely that convalescent patients were transferred from an acute setting, and that the total length of hospital stay including the time in the acute setting is actually 130.7 days. There was a large variation in the standard deviation of the number of days of illness at admission to a convalescent rehabilitation ward, at 29.8 days.

The mean length of hospital stay on an acute ward was roughly equal to the number of days from onset of stroke until admission, suggesting that FIM at discharge from an acute ward (82.7) and FIM at admission to a convalescent ward (63.3) are measured at around the same period. As there is only a small difference between the admission FIM of acute patients (63.3) and that of convalescent patients (56.0), it is possible that many patients in convalescent wards are those that showed slow recovery in acute wards and were subsequently transferred to the convalescent setting because they could not be sent home. Reasons for this may be dizziness or nausea in patients with a cerebellar hemorrhage or infarction that can prevent starting rehabilitation early in the acute phase [17].

Compared to 1.4 for acute patients, the FIM efficiency for convalescent patients was 0.3. Although the mean discharge FIM of 88.1 for convalescent patients is higher than the 82.7 for acute patients, it is likely that many patients took their time recovering gradually after moving to the convalescent setting.

These results showed that the patient profiles differ between acute and convalescent wards, suggesting the need for two separate formulas to predict discharge FIM. However, it should be noted that all the acute patient data had only a rehabilitation request, therefore the data set did not include patients with severe or mild stroke. Also, patients who were not eligible for rehabilitation were not referred to the convalescent ward.

### 2) Formula for predicting discharge FIM

In acute stroke rehabilitation patients, admission cognitive FIM had the highest coefficient (0.31), followed by admission NIHSS (-0.24), admission motor FIM (0.19), age (-0.17), mRS before stroke (-0.15), admission GCS (0.09), and number of days from onset of stroke until admission (-0.04), in decreasing order. Even adjusting for type of disease, presence of complication and GCS at hospital admission, admission cognitive FIM still had a large coefficient with respect to discharge FIM, suggesting that discharge FIM may be higher for acute patients with milder cognitive impairment.

For convalescent stroke rehabilitation patients, the coefficient was large for admission cognitive FIM (0.36), similar to acute patients, but was larger for admission motor FIM (0.38) and the coefficient for admission NIHSS was not significant. These differences in coefficients suggest that separate formulas should be developed for acute and convalescent patients.

The explanatory power ( $R^2$ ) was 0.78 for the acute formula and 0.66 for the convalescent formula. This does not differ greatly from the results of external validity tests on the verification group data (acute:  $R^2 = 0.77$ , convalescent:  $R^2 = 0.71$ ), indicating that external validity is not low. Compared to a study by Heinemann *et al.* ( $R^2 = 0.19-0.73$ ) [13], predicted ADL outcome at hospital discharge found by Miyakoshi *et al.* ( $R^2 = 0.43$ ) [16], prediction of FIM at hospital discharge found by Fujiwara *et al.* ( $R^2 = 0.66-0.75$ ) [18], prediction of FIM at hospital discharge found by Tsuji *et al.* ( $R^2 = 0.68$ ) [19] and the results of a review by Sonoda ( $R^2 = 0.7-0.9$ ) [12], the formulas developed in the present study are considered to be within the accuracy range of existing predictive formulas. The formula for predicting discharge FIM developed in the present study can therefore be used as a multicenter benchmark of hospital performance.

The reason for the lower predictive power of the convalescent formula compared to the acute formula may be the presence of factors that could not be measured at admission but that strongly influence FIM at discharge, such as amount and quality of training with a physical therapist over the 90-day-long stay at the convalescent ward or whether or not training is provided on weekends and holidays, i.e. factors that vary among hospitals.

### 3) Significance and limitations of this study

Until now, no multicenter database including acute and convalescent patients in the field of rehabilitation medicine existed in Japan and predictive formulas created with data on patients from a single hospital were not validated for use on patients at other hospitals. Moreover, the limited number of patients at single hospitals prevented the thorough testing of external validity on a group of patients that differed from those

used to develop the predictive formulas.

In contrast, we used data from the Rehab Patient DB, which is a large-scale multicenter data bank, enabling a comparison of the characteristics of acute and convalescent patients that confirmed the disparity between their profiles. We then applied these findings to develop two separate formulas for predicting discharge FIM for acute patients and convalescent patients, respectively. The study yielded useful predictive formulas with confirmed external validity for use in various hospitals and on different groups of patients.

This study has five limitations:

- (1) We did not stratify the data by type of disease. While it would have been possible to stratify the data this way, we chose not to do so because our objective was to use the results for a benchmark that could be applied at all hospitals and fewer formulas would be easier to implement.
- (2) In the present study, predictive formulas were developed from patient variables. Although performance varies among hospitals [2], the objective of developing and applying the predictive formulas was to create a benchmark for comparing hospitals. We therefore deliberately avoided using variables such as rehabilitation program that vary among hospitals. If performance was the same at all hospitals, the outcome (discharge FIM) would also be the same. Future studies are needed to analyze the difference between predicted values and actual values and determine what characteristics of hospitals, such as amount of training or other aspects of the rehabilitation program, lead to higher discharge FIM scores (actual scores).
- (3) The formulas developed in the present study had an  $R^2$  of only 0.66–0.78 without including variables on the amount of training or other aspects of the rehabilitation program. This may not be sufficient for use in predictions on an individual level.
- (4) The admission FIM for acute patients used in the present study was measured on average on the third day after onset. It is thus possible that there was an effect of the level of bed rest on admission FIM. Future studies may be needed to examine this possibility in detail.
- (5) Although we verified the external validity for hospitals participating in the Rehab Patient DB project, those hospitals may be a biased representation of diligent hospitals. The results therefore cannot be generalized to patients at hospitals with different characteristics.

### Conclusion

We divided data from 39 hospitals into a calculation group and a verification group and developed separate formulas for predicting FIM at hospital discharge from patient information at hospital admission for acute

patients ( $R^2 = 0.78$ ) and convalescent patients ( $R^2 = 0.66$ ) and tested the external validity of the formulas. Collection of more data and further research are needed to develop an even more accurate model.

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