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Original Article

Predictive accuracy of multiple regression analysis stratified into four groups of admission motor FIM based on decision tree analysis

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ABSTRACT
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Objective: Factors affecting improvement in the Functional Independence Measure (FIM) differ among patient subgroups, and therefore several studies have performed multiple regression analyses after stratifying patients by relevant factors. However, the optimal variables and criteria for stratification remain unclear. Decision tree analysis can identify contributing variables and branching criteria for stratification. This study aimed to compare the predictive accuracy of multiple regression analysis stratified based on decision tree analysis with that of conventional multiple regression analysis.
Methods: We included 1,100 stroke patients admitted to a convalescent rehabilitation ward. Based on the decision tree results reported by Okamoto et al., patients were stratified into four groups according to admission motor FIM scores: 13−18, 19−30, 31−53, and 54−90. Stepwise multiple regression analysis was then performed with discharge motor FIM as the dependent variable. We compared the predictive performance of a single regression equation derived from conventional multiple regression with that of four equations derived from stratified analyses by calculating the residual sum of squares and comparing the absolute residuals using the Wilcoxon signed-rank test.
Results: The conventional single equation yielded a median absolute residual of 7.5 points and a residual sum of squares of 14.7×10^4. In contrast, the four stratified equations yielded a median absolute residual of 4.2 points and a residual sum of squares of 9.9×10^4, and the absolute residuals were significantly smaller in the stratified regression models.
Conclusion: Stratifying patients into four groups based on decision tree analysis improved the predictive accuracy of multiple regression analysis.
Key words: multiple regression analysis, decision tree analysis, stratification, predictive accuracy, Functional Independence Measure

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Introduction

The Japanese Guidelines for the Management of Stroke 2021 [1] recommend that rehabilitation programs be planned based on the evaluation and prediction of stroke pathology, individual functional impairments, activities of daily living (ADL) limitations, and social participation restrictions. Because many factors influence ADL improvement, multivariate analyses are more commonly used than univariate analyses for predicting functional recovery. Multiple regression analysis, a type of multivariate analysis, is used when the dependent variable is quantitative—such as improvement in ADL—and provides predictive equations using explanatory variables.

The Functional Independence Measure (FIM) is the most widely used clinical scale to evaluate ADL. For the dependent variable in regression models, several FIM-related indices are used, including FIM gain (discharge FIM—admission FIM), FIM effectiveness [FIMgain/(126-admission FIM)] [2], FIM efficiency (FIM gain / length of stay), and discharge FIM. Among these, discharge FIM has been the most frequently applied outcome measure [3, 4].

However, the predictive accuracy of multiple regression analysis is not sufficient to reliably predict outcomes for individual patients, although it may explain tendencies at the group level [5]. Therefore, various methods have been proposed to improve prediction accuracy. One approach is stratification of patients by specific factors. Because the influence of certain barriers to rehabilitation on FIM improvement differs across subgroups, stratifying patients based on these relevant factors may enhance prediction. Previous studies have attempted stratification by age into five groups [6], admission motor FIM into three groups [7], age and admission FIM into four groups [8], admission motor and cognitive FIM into three groups [9], presence or absence of cognitive impairment into two groups [10], or nutritional status into two groups [11]. However, the optimal stratification variable and criteria are still unclear.

Decision tree analysis is a data-driven method that exhaustively searches for the variable and cutoff value that best separates patients into two groups with the greatest between-group differences. The software automatically identifies optimal branching points and divides the dataset accordingly. While decision tree analysis does not directly predict the numeric value of discharge motor FIM, it can clarify which factors should be used for stratification.

Thus, a method can be considered in which patients are stratified appropriately based on decision tree results, and multiple regression analysis is then performed within each subgroup to predict discharge motor FIM.

In this study, we stratified stroke patients in a convalescent rehabilitation ward based on the decision tree results reported by Okamoto et al. [12], with discharge motor FIM as the dependent variable. Multiple regression analyses were conducted separately for each subgroup to obtain predictive estimates of discharge motor FIM, and the predictive accuracy was compared with that of a single regression model applied to all patients.

Methods

We included stroke patients admitted to the convalescent rehabilitation ward at K Hospital between April 1, 2016, and July 31, 2025, after treatment at an acute care hospital. To minimize the influence of exceptional cases, patients with subarachnoid hemorrhage, a duration from onset to admission of less than 5 days or more than 60 days, a length of stay of less than 14 days or more than 180 days, or an admission motor FIM score of 91 were excluded. The remaining 1,100 patients were analyzed in this study.

1. Stratification of patients based on decision tree analysis

Okamoto et al. [12] conducted a decision tree analysis using 2,650 stroke patients admitted to and discharged from the convalescent rehabilitation ward at F Hospital between September 2004 and March 2017. Patients with bilateral hemiplegia, no paralysis, recurrent stroke, acute deterioration during hospitalization, or discharge FIM lower than admission FIM were excluded from the original 5,191 patients. Discharge motor FIM was used as the dependent variable, and age, days from onset to admission, stroke subtype, each item of the Stroke Impairment Assessment Set (SIAS), total SIAS motor function score, individual 18 FIM items, motor FIM, and cognitive FIM were included as explanatory variables. The decision tree analysis first divided patients into those with admission motor FIM <31 and ≥31. The <31 group was further divided into <19 and ≥19, and the ≥31 group into <54 and ≥54. Based on these results, in this study, patients were stratified into four groups according to admission motor FIM: 13−18, 19−30, 31−53, and 54−90.

2. Stepwise multiple regression analysis

Stepwise multiple regression analysis (variable reduction method) was performed with discharge motor FIM as the dependent variable. The explanatory variables included six factors: age, admission motor FIM, admission cognitive FIM, days from onset to admission, pre-onset modified Rankin Scale, and Brunnstrom stage of the affected lower limb. Statistical analyses were performed using 4 Steps Excel Statistics [13] with a significance level of 5%. Multicollinearity was assessed using the variance inflation factor (VIF), with VIF ≥10 considered indicative of multicollinearity. IBM SPSS Statistics version 23 was used for this assessment. The magnitude of each factor's influence was evaluated using standardized regression coefficients, representing the relative strength of association with the dependent variable.

3. Comparison of predictive accuracy between a single regression equation and four equations stratified by admission motor FIM

Scatter plots of observed versus predicted discharge motor FIM values were generated for a single regression equation applied to all patients and for four regression equations stratified by admission motor FIM. Predictive accuracy was evaluated by comparing the absolute residuals and the residual sum of squares (RSS) between the single and stratified models. The Wilcoxon signed-rank test was used to statistically compare absolute residuals, with a significance level set at 5%.

This study was approved by the Clinical Research Review Committee of the hospital to which the authors belong (approval number JMC411−2509).

Results

The basic characteristics of the study patients are shown in Table 1.

The variance inflation factor (VIF) was below 3.81 for all variables, indicating no multicollinearity. Results of the stepwise multiple regression analysis

Table 1. Baseline characteristics of the participants.

Number of patients	1,100
Type of stroke	Infarction 699, hemorrhage 401
Sex	Male 644, female 456
Age	70.9±13.4 (73)
Admission motor FIM	51.2±24.9 (53)
Discharge motor FIM	71.3±22.7 (80)
Motor FIM gain	20.1±15.4 (18)
Admission cognitive FIM	23.5±8.4 (25)
Discharge cognitive FIM	27.9±7.4 (31)
Pre-onset mRS	0.6±1.1 (0)
BRS of the affected lower limb	4.7±1.6 (5)
Days from onset to admission	16.3±7.3 (15)
Length of stay	78.1±43.5 (73)

Values are presented as the number of patients or mean ± standard deviation (median).
FIM: Functional Independence Measure
mRS: modified Rankin Scale, BRS: Bruunstrom stage

Table 2. Stepwise multiple regression analysis with discharge motor FIM as the dependent variable.

	single equation	13−18	19−30	31−53	54−90
Admission motor FIM	0.367 (0.404)	2.085 (0.180)	0.680 (0.124)	0.591 (0.276)	0.228 (0.405)
Admission cognitive FIM	0.653 (0.243)	0.595 (0.159)	0.384 (0.143)	0.465 (0.224)	0.134 (0.109)
Age	–0.343 (–0.202)	–0.734 (–0.465)	–0.693 (–0.472)	–0.469 (–0.452)	–0.125 (–0.267)
BRS of the affected lower limb	2.492 (0.180)	1.792 (0.136)	n.s.	1.243 (0.121)	0.850 (0.079)
Pre-onset mRS	–2.572 (–0.128)	–1.544 (–0.106)	–3.934 (–0.280)	–2.222 (–0.191)	–1.557 (–0.217)
Days from onset to admission	–0.272 (–0.087)	–0.458 (–0.181)	–0.346 (–0.155)	–0.196 (–0.089)	–0.053 (–0.058)
Constant term	55.6	58.5	91.2	68.6	70.8
Coefficient of determination	0.740	0.449	0.487	0.497	0.498

Values for each factor are shown as unstandardized coefficient (standardized coefficient); n.s., not significant; Abbreviations are as shown in Table 1.
13−18, 19−30, 31−53, 54−90: Predictive equations for patients with admission motor FIM scores in these ranges.

with six explanatory variables and discharge motor FIM as the dependent variable are shown in Table 2. For the single regression equation applied to all patients, all six variables were significant, and the coefficient of determination (R^2) was 0.740. The variable with the largest standardized regression coefficient was admission motor FIM. A scatter plot of observed versus predicted discharge motor FIM values is shown in Figure 1a. The mean ± SD of the absolute residuals was 9.0 ± 7.2 points (median 7.5 points) (Figure 2), and the residual sum of squares (RSS) was 14.7×10^4.

In the four regression analyses stratified by admission motor FIM, the variable with the largest standardized regression coefficient was age for patients with admission motor FIM scores of 13−18, 19−30, and 31−53, and admission motor FIM for patients with scores of 54−90 (Table 2). Scatter plots of observed versus predicted discharge motor FIM for the four stratified equations are shown in Figures 3a-d. Compared with the single regression equation applied to all patients, the stratified equations provided more accurate predictions for patients with discharge motor FIM near 91 (Figure 1b). The mean ± SD of absolute residuals was 6.5 ± 6.9 points (median 4.2 points) (Figure 2), and the RSS was 9.9×10^4. Absolute residuals for the four stratified equations were significantly smaller than those for the single equation ($p < 0.0001$).

Discussion

Several studies have reported creating multiple predictive equations by stratifying patients [6−11]; however, the optimal stratification variables and the number of groups have not been clearly established. In the decision tree analysis by Okamoto et al. [12], which used discharge motor FIM as the dependent variable, both the first and second splits were based solely on admission motor FIM. Based on this report, the present study stratified patients into four groups according to admission motor FIM and performed multiple regression analyses. This approach yielded significantly smaller absolute residuals than conventional regression analysis, indicating higher predictive accuracy.

The fact that the first two splits in Okamoto et al.'s

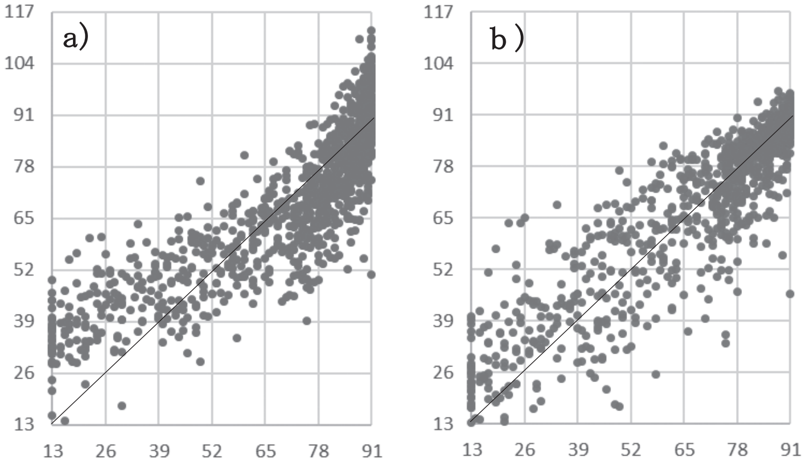

Figure 1. Scatter plots of observed versus predicted discharge motor FIM values.
a) Single regression equation, b) Combined results of four regression equations.
X-axis: Observed discharge motor FIM; Y-axis: Predicted discharge motor FIM. Diagonal line: points lie on this line if predictions are accurate.

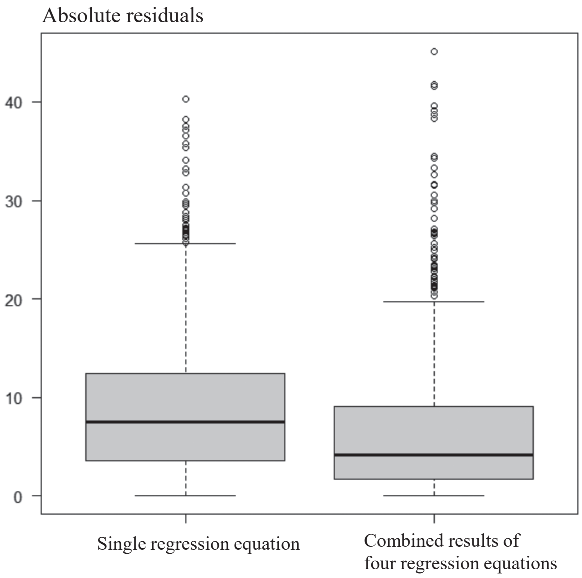

Figure 2. Absolute residuals.
Box-and-whisker plots: Horizontal line = median; Box = 25th−75th percentiles; Whiskers = 10th and 90th percentiles; Dots = outliers

decision tree analysis were solely based on admission motor FIM highlights its critical importance for predicting discharge motor FIM. In the third split, verticality and age were involved, and in the fourth split, admission cognitive FIM and FIM memory contributed [12]. To our knowledge, no other studies have performed decision tree analysis with discharge motor FIM as the dependent variable in stroke patients admitted to convalescent rehabilitation wards.

In the present study, standardized regression coefficients were largest for admission motor FIM in the single regression equation; however, after stratifying patients into four groups by admission motor FIM, age had the largest standardized coefficient in the 13−18, 19−30, and 31−53 point groups, whereas admission motor FIM remained most important in the 54−90 point group (Table 2). This finding—that age is the second most important factor after admission motor FIM—is consistent with the results of the decision tree analysis [12].

Multiple regression analysis assumes a linear relationship between explanatory and dependent variables. Therefore, in the case of a non-linear relationship between admission motor FIM (explanatory variable) and discharge motor FIM (dependent variable), dividing the data into intervals and fitting separate regression lines may better approximate the underlying curve.

A previous report combining decision tree and multiple regression analysis was published by Otsubo et al. [10]. In that study, the first split in the decision tree was based on the presence of dementia, and two predictive equations were generated accordingly. However, differences in predictive accuracy between the stratified and conventional regression models were not evaluated. In that analysis, decision tree analysis used motor FIM gain and motor FIM efficiency as dependent variables, with age, sex, length of stay, cognitive function, renal function, hypertension, number of medications at discharge, and use of sleep or anticholinergic drugs at discharge as explanatory variables. A limitation was that admission motor FIM, the most important factor, was not included as an explanatory variable.

To improve the predictive accuracy of multiple regression analysis, it is essential to use appropriate explanatory variables. Based on reviews of multiple regression analysis, commonly used and significant

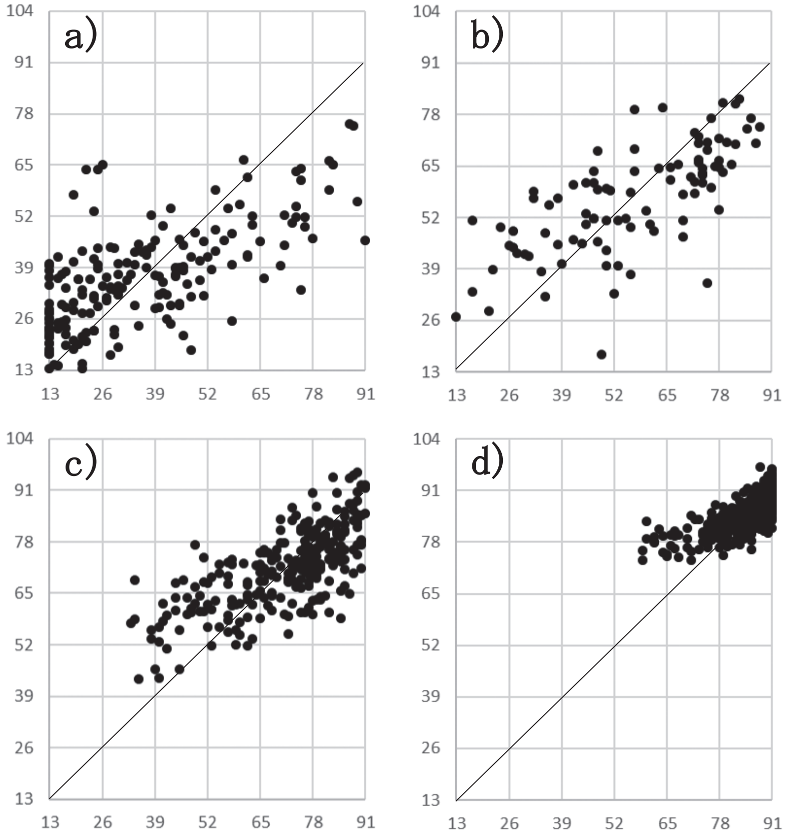

Figure 3. Scatter plots of actual and predicted discharge motor FIM scores using four predictive equations.
X-axis: Actual discharge motor FIM score; Y-axis: Predicted discharge motor FIM score.
Predictions for patients with admission motor FIM scores of: a) 13−18, b) 19−30, c) 31−53, d) 54−90.

explanatory variables should be employed [3, 4].

Machine learning has shown utility for non-linear predictions [14]. In particular, artificial neural networks, support vector regression, and Gaussian process regression have demonstrated higher predictive accuracy than multiple regression analysis [15]. However, machine learning presents challenges, including the "black box" nature of predictions and limitations in applying the model only within hospitals that have implemented the software. In contrast, multiple regression analysis provides explicit predictive equations, allowing the effects of individual factors to be understood and enabling use of published models in other institutions. It also allows assessment of external validity—the applicability of results to populations beyond the original study cohort [16].

While machine learning is expected to become increasingly valuable for prognostic prediction, multiple regression analysis remains highly useful when the goal is to evaluate the influence of factors on rehabilitation outcomes. Therefore, efforts to enhance the predictive accuracy of multiple regression analysis are warranted.

Conclusion

Because the impact of inhibitory factors on rehabilitation outcomes is not uniform across all patients, stratification of patients is sometimes attempted. Decision tree analysis is useful for providing an evidence-based method for patient stratification. Admission motor FIM, as an explanatory variable, has a non-linear relationship with discharge motor FIM, the dependent variable, and therefore represents the most important factor for stratification in multiple regression analysis, which assumes linearity. In this study, stratifying patients into four groups based on admission motor FIM scores (13−18, 19−30, 31−53, and 54−90) improved the predictive accuracy of multiple regression analysis for discharge motor FIM. Our findings demonstrate that the approach of performing multiple regression analysis after stratifying factors based on decision tree results is useful.

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