Japanese Journal of Comprehensive Rehabilitation Science (2024)

Brief Report

Can AI predict walking independence in patients with stroke upon admission to a recovery-phase rehabilitation ward?

Keisuke Ono, PT, BA,[1] Ryosuke Takahashi, PT, MS,[1,2] Kazuyuki Morita, OT, Advanced Diploma,[3] Yosuke Ara, OT, BA,[2,3] Senshu Abe, PT, MS,[1,2] Soichirou Ito, PT, Advanced Diploma,[1] Shogo Uno, PT, Advanced Diploma,[1] Masayuki Abe, OT, BA,[2,3] Tomohide Shirasaka, MD[4]

[1]Physical Therapy Division, Department of Rehabilitation, Hokuto Social Medical Corporation Tokachi Rehabilitation Center, Obihiro, Hokkaido, Japan
[2]Advanced Rehabilitation Office, Hokuto Social Medical Corporation Tokachi Rehabilitation Center, Obihiro, Hokkaido, Japan
[3]Occupational Therapy Division, Department of Rehabilitation, Hokuto Social Medical Corporation Tokachi Rehabilitation Center, Obihiro, Hokkaido, Japan
[4]Rehabilitation Division, Department of Medical, Hokuto Social Medical Corporation Tokachi Rehabilitation Center, Obihiro, Hokkaido, Japan

ABSTRACT
Ono K, Takahashi R, Morita K, Ara Y, Abe S, Ito S, Uno S, Abe M, Shirasaka T. Can AI predict walking independence in patients with stroke upon admission to a recovery-phase rehabilitation ward? Jpn J Compr Rehabil Sci 2024; 15: 1−7.

Objective: This study aimed to develop a prediction model for walking independence in patients with stroke in the recovery phase at the time of hospital discharge using Prediction One, an artificial intelligence (AI)-based predictive analysis tool, and to examine its utility.

Methods: Prediction One was used to develop a prediction model for walking independence for 280 patients with stroke admitted to a rehabilitation ward-based on physical and mental function information at admission. In 134 patients with stroke hospitalized during different periods, accuracy was confirmed by calculating the correct response rate, sensitivity, specificity, and positive and negative predictive values based on the results of AI-based predictions and actual results.

Results: The prediction accuracy (area under the curve, AUC) of the proposed model was 91.7%. The correct response rate was 79.9%, sensitivity was 95.7%, specificity was 62.5%, positive predictive value was 73.6%, and negative predictive value was 93.5%.

Conclusion: The accuracy of the prediction model developed in this study is not inferior to that of previous studies, and the simplicity of the model makes it highly practical.

Key words: AI, Prediction One, consequence prediction, walk, stroke

Correspondence: Keisuke Ono, PT, BA
Physical Therapy Division, Department of Rehabilitation, Hokuto Social Medical Corporation Tokachi Rehabilitation Center, 2−1 Inadacho Baseline, Obihiro, Hokkaido 080−0833, Japan.
E-mail: pt-ono.k@hokuto7.or.jp
Accepted: January 4, 2024.
Conflict of Interest: The authors declare that there are no conflicts of interest.

Introduction

Artificial intelligence (AI) is a major "machine learning" technology that finds regularities and features in large datasets. "Neural networks," which are modeled on the neural circuits of the brain, have been developed, and "deep learning," which employs neural networks in multiple layers, has enabled the utilization of not only normalized "structured data" but also "unstructured data", such as images, videos, audio, and languages, and these have been recently implemented in various fields [1]. The use of AI is expected to improve the accuracy and quality of work, reduce work burden and labor, and resolve management issues, including the passing-on and promotion of technology [1, 2].

According to the 2021 Stroke Treatment Guidelines [3] , the medical industry has recommended that "rehabilitation programs should be planned based on the assessment of individual functional disability, impairment of Activities of Daily Living (ADL), and social limitations, as well as their prognostic value." Japan has introduced a system of rehabilitation

doi.org/10.11336/jjcrs.15.1

performance indexes to calculate outcomes based on the functional independence measure (FIM) and length of hospital stay, which serves as a requirement for facility standards in recovery-phase rehabilitation wards. Improvement of the accuracy and quality of rehabilitation planning based on outcome prediction has become increasingly important for managing issues and ensuring good outcomes [4, 5]. Although outcome prediction has been substantially reported [4, 7−11], including in Niki's study [6], Sasaki [12] reported that "there is still no perfect level of prognosis prediction." The author considers that it is necessary to continue working on outcome predictions from various perspectives and methods. Various reports on the use of "Prediction One" (Sony Network Communications Corporation, Tokyo, Japan) in consequence prediction have been published [13-15]. Prediction One is an AI predictive analytics software that automatically adjusts and standardizes variables, building optimal predictive models from multiple on-board algorithms. Although the process of building a prediction model is difficult to track because of the nature of machine learning, Prediction One shows the "prediction contribution," which indicates the degree to which each item contributes to the prediction results. In analyses using Prediction One, the coefficient of determination for the model predicting independence at discharge from a recovery unit on admission was 0.972 [13], that for independence at 6 months after surgery in patients with cerebral hemorrhage was 0.997 [14], and that for independence at 6 months after surgery for subarachnoid hemorrhage was 0.994 [15]. All of these models are reportedly highly accurate, and their use in predicting outcomes is highly anticipated. However, the practicality of prediction models created in previous studies, the improvement of physical and mental functions, and the use of these models to predict the consequences of walking independence remain to be studied.

This study aimed to develop an AI-based prediction model for walking independence using Prediction One for patients with stroke admitted to the rehabilitation ward of the Tokachi Rehabilitation Center (hereafter "the center"), including physical and mental functions, and to examine its practicality.

Methods

1. Participants

The participants of this study were 414 patients with stroke who were admitted to the center's rehabilitation ward from April 1, 2020, and discharged until February 28, 2023, all of whom presented an FIM locomotion score of ≤ 5 at admission.

2. AI-based prediction model

Among the 414 participants, 280 were discharged from the hospital until March 31, 2022, and their FIM locomotion score at discharge was classified into two categories: ≥ 6, independent; and ≤ 5, non-independent. Prediction One was used to create a prediction model with independence at discharge as the predictor variable. Fifty-eight items, selected based on the assumption that they would be used in practical applications, were employed to construct the prediction model, items with an overall collection rate < 50% from the psychosomatic function information collected from regular medical records at the time of admission were excluded (Table 1). Owing to the nature of machine learning, tracking the process of constructing and selecting a prediction model is difficult. The items were selected manually based on whether the prediction accuracy of Prediction One improved or remained unaltered.

3. Confirmation of the accuracy of the prediction model developed (Table 2)

Among the 414 participants, we used the prediction model to measure the predicted and actual walking independence at the time of hospitalization for 134 patients hospitalized from April 1, 2022 and discharged until February 28, 2023. The indices used to assess accuracy and their definitions were as follows: "sensitivity" was defined as the percentage of participants who were actually independent for walking and also had an "independent" prediction result (true positive); "specificity" was defined as the percentage of participants who were non independent for walking and also had a "non-independent" prediction result (true negative); "correct response rate" was defined as the ratio of the number of participants divided by the sum of the true positives and true negatives (additive value); "positive predictive value" was defined as the percentage of participants who actually became independent for walking among those with an "independent for walking" predicted outcome (positive); "negative predictive value" was defined as the percentage of participants who actually became non-independent for walking among those with a "non-independent for walking" predicted outcome (negative). The results of each calculation were expressed as percentages. The above-mentioned five items, "sensitivity," "specificity," "correct response rate," "positive predictive error rate," and "negative predictive error rate," were assessed for actual accuracy when the prediction model was utilized.

Results

1. Characteristics of the participants (Table 3)

Among the patients assessed to create the prediction model, 156 were male and 124 female and their mean age was 74.9 ± 14.0 years. A total of 188 patients presented cerebral infarction, 69 cerebral hemorrhage, and 23 other diseases. The mean period from disease

Table 1. Items used to create the prediction model (Fifty-eight items).

Total FIM score	Gender
Motor FIM score	Height
Cognitive FIM score	Weight
FIM items Eating	Body Mass Index
Grooming	Paralyzed side
Bathing	Maximum period of hospitalization
Dress-upper	History of stroke
Dress-lower	Place of residence at onset
Toileting	Place of stay prior to hospitalization (e.g., at the hospital)
Bladder	City/town/village of residence
Bowel	Walking aids used prior to hospitalization
(Bed · Chair · Wheelchair)	Lower limb orthosis used prior to hospitalization
Transfers (Toilet)	Leg joints of lower limb orthosis used prior to hospitalization
Transfers (Tub)	History of falls within one year of admission
Locomotion (walk)	Presence of nasogastric tube
Stairs	Cognitive-related Behavioral Assessment
Comprehension	Action Research Arm Test
Expression	Fugl Meyer Assessment (FMA) upper extremity
Social interaction	FMA upper extremity items shoulder · elbow · forearm
Problem Solving	wrist
Memory	Hand
Age	FMA lower extremity
Intelligence Quotient (IQ)	FMA balance
Mini Mental State Examination Japan (MMSE-J)	FMA sensation
Functional Assessment for Control of Trunk (FACT)	Gravity sway test of standing holding with closed eyes
Berg Balance Scale (BBS)	Gross muscle strength (Non-paralyzed side)
Comfortable walking speed	Gross muscle strength (Paralyzed side)
Maximum Walking Speed	

※Items with an overall collection rate <50% from the psychosomatic function information collected from regular medical records at the time of admission were excluded

Table 2. Interpretation of results for accuracy verification items.

Items	Interpretation of results
Sensitivity	Certainty in prediction walking independence
Specificity	Certainty in prediction walking non-independence
Correct response rate	Prediction accuracy of judgment of walking independence
Positive predictive error rate	Prediction accuracy of walking independence
Negative predictive error rate	Prediction accuracy of walking non-independence

onset to hospitalization was 26.9 ± 17.2 days, mean hospital stay was 94.8 ± 50.0 days, and mean FIM locomotion score at admission was 2.3 ± 1.7 points. A total of 159 patients were independent for walking at the time of discharge, and 121 were not. Among the participants assessed to verify the accuracy of the model, 73 were male and 61 female, with a mean age of 76.4 ± 12.4 years; 96 of them presented cerebral infarction, 34 cerebral hemorrhage, and 14 other diseases. The mean period from disease onset to hospitalization was 25.9 ± 20.1 days, the mean length of hospitalization was 78.9 ± 51.9 days, and mean FIM locomotion score at admission was 2.6 ± 1.7 points. Seventy patients were independent for walking at discharge, whereas 64 were not.

2. Prediction model (Tables 4 and 5)

The prediction accuracy (area under the curve, AUC) of the model developed using Prediction One to assess 58 items was 88.3%. The top prediction contributions were the FIM items “memory,”, “bed transfer,”, “problem-solving,”, “functional assessment for control of trunk (FACT), ”, and “expression”. The number of items used in Prediction One was reduced from 58 to 28, and the AUC of the new model was 91.7%. The top prediction contributors were the FIM

Table 3. Characteristics of the participants.

	Prediction model	Actual accuracy of the prediction model
Gender	Male: 156 Female: 124	Male: 73 Female: 61
Age (year)	74.9 ± 14.0	76.4 ± 12.4
Disease classification	Cerebral infarction: 188 Cerebral hemorrhage: 69 Other: 23	Cerebral infarction: 96 Cerebral hemorrhage: 34 Other: 14
Disease onset to hospitalization (day)	26.9 ± 17.2	25.9 ± 20.1
Hospital stay (day)	94.8 ± 50.0	78.9 ± 51.9
FIM locomotion item at admission (point)	2.3 ± 1.7	2.6 ± 1.7
Independence for walking at the time of discharge	Independent: 159 Non-independent: 121	independent: 70 Non-independent: 64

Table 4. The prediction accuracy (AUC) of the model developed using Prediction One and the items used.

	Prediction model with 58 items		Prediction model with 28 items
AUC (%)	88.3		91.7
Items	Total FIM score	Gender	Total FIM score
	Motor FIM score	Height	Motor FIM score
	Cognitive FIM score	Weight	Cognitive FIM score
	FIM items	Body Mass Index	FIM items
	Eating		Eating
	Grooming	Paralyzed side	Grooming
	Bathing	Maximum period of hospitalization	Bathing
	Dress-upper	History of stroke	Dress-upper
	Dress-lower	Place of residence at onset	Dress-lower
	Toileting	Place of stay prior to hospitalization (e.g., at the hospital)	Toileting
	Bladder	City/town/village of residence	Bladder
	Bowel	Walking aids used prior to hospitalization	Bowel
	Transfers (Bed · Chair · Wheelchair)	Lower limb orthosis used prior to hospitalization	Transfers (Bed · Chair · Wheelchair)
	Transfers (Toilet)	Leg joints of lower limb orthosis used prior to hospitalization	Transfers (Toilet)
	Transfers (Tub)	History of falls within one year of admission	Transfers (Tub)
	Locomotion (walk)	Presence of nasogastric tube	Locomotion (walk)
	Stairs	Cognitive-related Behavioral Assessment	Stairs
	Comprehension	Action Research Arm Test	Comprehension
	Expression	Fugl Meyer Assessment (FMA) upper extremity	Expression
	Social interaction	FMA upper extremity items shoulder · elbow · forearm	Social interaction
	Problem Solving	wrist	Problem Solving
	Memory	Hand	Memory
	Age	FMA lower extremity	Age
	Intelligence Quotient (IQ)	FMA balance	IQ
	Mini Mental State Examination Japan (MMSE-J)	FMA sensation	MMSE-J
	Functional Assessment for Control of Trunk (FACT)	Gravity sway test of standing holding with closed eyes	FACT
	Berg Balance Scale (BBS)	Gross muscle strength (Non-paralyzed side)	BBS
	Comfortable walking speed	Gross muscle strength (Paralyzed side)	Comfortable walking speed
	Maximum Walking Speed		Maximum Walking Speed
	Comfortable walking speed cadence		
	Maximum walking speed cadence		

Table 5. Top 5 predictive contributions presented in Prediction One.

	Prediction model with 58 items	Prediction model with 28 items
1st place	FIM items “memory”	FIM items “memory”
2nd place	FIM items “bed transfer”	FIM items “cognitive total”
3rd place	FIM items “problem-solving”	MMSE-J
4th place	FACT	FIM items “dress-lower”
5th place	FIM items “expression”	FIM items “locomotion”

items “memory,”, “cognitive total,” “Mini Mental State Examination Japan (MMSE-J),” and FIM items “dress-lower” and “locomotion”.

3. Actual accuracy of the prediction model (Tables 6 and 7)

To validate the accuracy of the prediction model, the model created using 28 items was utilized. The predicted results were “independent” for 91 patients, and “not independent” for 43; of these patients, 67 were actually independent and 40 were not independent at the time of discharge. Twenty-four participants whose predicted outcome was “independent” were “non-independent” at the time of hospital discharge, and 3 of the participants whose predicted outcomes were “non-independent” were independent at the time of discharge. The correct response rate was 79.9%, sensitivity 95.7%, specificity 62.5%, positive predictive value 73.6%, and negative predictive value 93.5%.

Discussion

1. AI-based prediction model for walking independence using Prediction One

Practical examples of the use of Prediction One in financial institutions presented an AUC of 85% or higher [16]. The prediction model in this study had an AUC of 91.7%, which we considered to be highly accurate, similar to previous studies employing Prediction One [13−15]. For the cutoff values of the endpoints used to determine walking independence in patients with stroke hospitalized in recovery wards, Kitaji [10] reported that for patients with a first stroke, the berg balance scale (BBS) had an AUC of 97.9% with a cutoff of 45.5 points, and the timed up and go test (TUG) had an AUC of 97.6% with a cutoff of 15.6 seconds in the maximum walking speed condition. In patients admitted to a convalescent ward for cerebrovascular disease, musculoskeletal disease, disuse syndrome, Hasegawa [17] reported an AUC of 89.9% with a cutoff of 72% for the Balance Evaluation Systems Test (BESTest), an AUC of 84.7% with a cutoff of 14 points for the Brief-BESTest, and an AUC of 84.1% with a cutoff of 18 points for the Mini-

Table 6. Breakdown of accuracy verification results.

		Actual Results		
		Independent	Non-independent	Total
AI Prediction Results	Independent	67	24	91
	Non-independent	3	40	43
	Total	70	64	

Table 7. Accuracy validation results.

	Prediction model with 28 items
Correct response rate (%)	79.9
Sensitivity (%)	95.7
Positive predictive error rate (%)	73.6
Specificity (%)	62.5
Negative predictive error rate (%)	93.0

Table 8. AUC comparison with previous studies.

	Cutoff	AUC (%)
Prediction model for this study	—	91.7
BBS	45.5 points	97.9
TUG (Maximum Walking Speed)	15.6 seconds	97.6
TUG (Comfortable walking speed)	21.6 seconds	96.4
BESTest	72%	89.9
Brief-BESTset	14 points	84.7
Mini-BESTest	18 points	84.1

BESTest (Table 8). Compared to previous studies, which have often reported high accuracies, our prediction model using an assessment at the time of admission to the rehabilitation ward was considered "non-inferior," if not superior. An improvement in prediction accuracy was achieved with a reduction in the number of evaluated items; we believe that this will reduce the burden of evaluation work in clinical practice. Regarding items related to the prediction model, the top three items contributing to prediction in Prediction One were related to cognitive and higher brain functions.

The highest ranking item in the predictive model before the item reduction was the FIM item "memory," Because the binary classification in this study was based on FIM locomotion scores of ≥ 6 and ≤ 5 points, walking independence required the ability to move completely by oneself without being watched by a caregiver. In such cases, even if the participant reached a level of independence in terms of physical function, the patient may not be judged to be walking independently because of a decreased danger perception caused by cognitive and higher brain functions. Assessing the presence of cognitive decline is effective to predict walking independence [9], suggesting that items related to cognition and higher brain function may be highly relevant in predicting the outcome of walking independence.

2. Accuracy of the prediction model

The "sensitivity," of the model, which indicates the probability of error in predicting independence, was high. Therefore, we can conclude that most patients who were independent at the time of discharge were also predicted to be independent at the time of admission. The predictive accuracy of the "non-independent" outcome was high, and a patient predicted to be non-independent at the time of admission had a high probability of actually becoming non-independent for discharge. Conversely, the "specificity," of the model, which indicates the probability of error in non-independence, was approximately 60%, indicating that the certainty of predicting non-independence was low, as some patients who were judged to become independent at admission may be non-independent at discharge. Since the contributions of the prediction model indicated that the association between cognition and higher brain functions may be high, we believe that the positive predictive value may be improved by considering additional details of cognition and higher brain functions, and clarifying factors that inhibit independence. Yoshimatsu [9] reported a sensitivity of 63.1% and specificity of 89.8% for predicting gait independence using a decision tree (Yoshimatsu model) in patients with stroke admitted to and discharged from a recovery rehabilitation ward. Sakamoto [18] compared a prediction model (Sakamoto model) that predicted the outcome of walking based on a patient's ability to position themselves into an end-sitting position with two other prediction models: one that introduced the variable "whether or not the patient can stand on the bed" (Niki model), reported by Niki [6] in 1982; and one that employed the "static sitting position holding" (Ishigami model), reported by Ishigami [19, 20] in 1996. The comparison was made at disease onset, 2 weeks after admission, and 1 month later. All models were created for patients with acute stroke, and the comparison 1 month after onset, which is similar to the time of admission to a recovery rehabilitation ward, showed that the Niki, Ishigami, and Sakamoto models had sensitivities of 96.0%, 100%, and 96.0%, respectively, and specificities of 63.0%, 16.0%, and 59.0%, respectively (Table 9). Therefore, the accuracy of prediction in our model was considered "non-inferior," if not superior, to those of these previous studies. The correct response rate of the prediction of independence was approximately 80%, which was considered sufficient for clinical use in view of the above-mentioned points.

3. Limitations and future prospects

As mentioned above, tracking the process of constructing and selecting a prediction model using Prediction One is difficult, because of the nature of machine learning. The selection of evaluation items to be used in the development of a prediction model is a manual process involving trial and error by an analyst to determine whether the selected items are optimal. The purpose of this study was not to verify the superiority of the prediction of outcomes using AI over other methods, but rather to verify the clinical practicality of employing AI to predict outcomes.

In the future, we will continue to evaluate variances in clinical practice results, analyze error factors, reexamine evaluation items, and update the prediction model. We would like to clarify the characteristics of

Table 9. Comparison of prediction accuracy with previous studies.

	Sensitivity (%)	Specificity (%)
Prediction accuracy of this study	91.7	91.7
Yoshimatsu model	63.1	89.8
Niki model	96.0	63.0
Ishigami model	100	16.0
Sakamoto model	96.0	59.0

the use of AI itself through the results of clinical practice, verify for which outcomes AI is useful for predicting, and improve the ability and methods of interpretation of AI-derived presentations by recipient healthcare providers. We aim to increase the possibility of using AI to predict outcomes.

References

1. Ministry of Economy, Trade and Industry. AI/IoT Utilization Feasibility Study Report in Western Honshu. Available from: https://www.chugoku.meti.go.jp (cited 2023 April 8).
2. Survey report commissioned by the Ministry of Economy, Trade and Industry. Commissioned Business Report on Research on Business Strategies for the Growth of SMEs and Micro Businesses FY2016. Available from: https://dl.ndl.go.jp/pid/11274286/1/1 (cited 2023 April 8).
3. Japan Stroke Society Stroke Guideline Committee, Editor. Stroke Treatment Guidelines 2021; 2021. P. 46−47.
4. Miura H, Shimazaki T, Yasuoka Y, Baba H, Motomiya M, Furutani Y.Influence of mobility means on activities of daily living in elderly people before injury to musculoskeletal diseases- Examination of musculoskeletal rehabilitation patients-. Physiotherapy - clinical, research, education 2020; 27: 51−5. Japanese.
5. Kaifukuki Rehabilitation Ward Association. Investigation report on the current situation and issues of convalescent rehabilitation wards [revised version]. Available from: http://plus1co.net/d_data/2019_zitai_book_kaitei.pdf (cited 2023 April 9).
6. Niki R. Early prediction of independence in stroke rehabilitation patients. Rehabil Med 1982; 19(2): 201−23. Japanese.
7. Arai T, Kaneko S, Fujita H. Factors necessary for independent walking in patients with femoral neck fracture —investigation by decision tree analysis—. J Jpn Geriatrics Soc 2011; 48(5): 539−44. Japanese.
8. Koyama T. Predicting outcomes in stroke patients—FIM, Diffusion Tensor Method MRI, Returning Home—. Jpn J Rehabil Med 2018; 55(9): 773−82. Japanese.
9. Yoshimatsu T, Kabe N, Hashimoto Y. Makizako H. Prediction of gait independence of stroke patients through signal detection analysis in the convalescent period. Phys Ther Sci 2018; 33(1): 145−50. Japanese.
10. Kitaji Y, Hara T, Sato Y, Shigekuni K, Kiyohuji Y, Furukawa H, et al. Cut-off value of performance test for judgment of walking independence in patients with hemiplegia after cerebrovascular disease who are hospitalized in convalescent rehabilitation wards. Phys Ther 2011; 38(7): 481−8. Japanese.
11. Doumen K. Stroke Functional Evaluation and Prognostic Prediction Manual 2013. Japanese.
12. Sasaki N. Current issues in stroke prediction. Jpn J Rehabil Med 2023; 60: 222−9. Japanese.
13. Katsuki M, Narita N, Ozaki D, Sato Y, Jia W, Nishizawa T, et al. Deep Learning-Based Functional Independence Measure Score Prediction After Stroke in Kaifukuki (Convalescent) Rehabilitation Ward Annexed to Acute Care Hospital. Cureus 2021; 13: 16588.
14. Katsuki M, Kakizawa Y, Nishikawa A, Yamamoto Y, Uchiyama T. Postsurgical functional outcome prediction model using deep learning framework (Prediction One, Sony Network Communications Inc.) for hypertensive intracerebral hemorrhage. Surg NeurolInt 2021; 12(203): 1−11.
15. Katsuki M, Kawamura S, Koh A. Easily Created Prediction Model Using Automated Artificial Intelligence Framework (Prediction One, Sony Network Communications Inc, Tokyo, Japan) for Subarachnoid Hemorrhage Outcomes Treated by Coiling and Delayed Cerebral Ischemia. Cureus 2021; 13(6): 15695.
16. Prediction One implementation case study. Available from: https://predictionone.sony.biz/case/11joyobank/ (cited 2023 September 27).
17. Hasegawa S, Kouchi H, Usuda S. Accuracies of the Balance Evaluation Systems Test (BESTest), Mini-BESTest, and Brief-BESTest in discriminating the ambulatory independence of patients in a convalescence rehabilitation ward. Phys Ther Sci 2017; 32(4): 477−81. Japanese.
18. Sakamoto M, Yuki T. Comparison of the accuracy of 3 models for predicting independent ambulation among acute stroke patients. Phys Ther Sci 2013; 28(5): 657−63. Japanese.
19. Ishigami S. Acute rehabilitation and prognosis. Rehabil Med 1996; 33(9): 605−8. Japanese.
20. Ishigami S. We use stroke prognosis predictions. J Clin Rehabil 2001; 10(4): 334−7. Japanese.