Abstract:
Medical accidents are typically classified into two types: accidents caused by healthcare staff while providing services, and accidents caused by patients. Among the latter type, patient falls account for a significant percentage, and have a significant impact on patients. The goal of our research here is to establish a methodology to prevent patient falls by identifying situations that are dangerous for patients and formulating concrete countermeasures based on the results of an assessment to prevent such situations from arising.

Kato et al. (2013b) evaluated risk factors, those are included in the existing assessment sheet, through Cox regression analysis by using data from approximately 1,000 cases at Iizuka Hospital, located in Fukuoka Prefecture. However, the number of this dataset was insufficient for a detailed analysis. It was also needed to arrange the data format and consult models for recurrent event analysis. Furthermore, the statistical model and covariates need to be considered in detail.

In this paper, we tried to statistically model patient falls based on multivariate analysis by using a logistic model, the Cox model, and models for recurrent events. We first discussed the statistical model as well as the covariates to be included in it. We then developed a multiple scoring system based on the results of multivariate analysis by using data from Iizuka Hospital from 2009 to 2011. Finally, we evaluated each scoring system by calculating the correlation between scores and probability of events.

Keywords
Fall prevention, cox proportional hazard model, survival analysis, quality management system, safety management system

1. Introduction
1.1 Background
Quality of service and safety in healthcare have lately become the subjects of increased scrutiny, especially with regard to prevention and reduction of medical accidents. Medical accidents are generally classified into two types: accidents caused by medical staff while providing services, such as those caused by incorrect recordkeeping of the medication administered or the state of a patient’s health, and accidents caused by patients’ actions, such as falls, pulling out tubes, regularly inserting needles, leaving hospital prior to official discharge, or self-mutilation.

To prevent the first type of the aforementioned accidents, process approaches (e.g., the standardization of operation processes, error proofing, etc.) are considered effective. However, it is difficult to prevent accidents caused by patients using these approaches because such accidents occur when patients take high-risk actions to achieve a purpose, or act in unexpected high-risk ways without following the instructions of the medical staff.

A “fall” in the context of patient care is defined as “unintentionally coming to rest on the ground, the floor, or other lower level; it excludes coming to rest against furniture, a wall or other structure” (Wolf et al., 1996). Among the types of accidents caused by patients, falls are a significant problem accounting for 16% of medical accidents. Falls are the second-most common form of medical accidents (Kawamura, 2003), and often have serious consequences for the patient (Fujimoto, 2003), such as fractures.

The use of assessment sheets as tools to determine the risk of patient falls in order to reduce their frequency
has been proposed (Japanese Nursing Association, 2002) (Sugiyama, 2005). Although many hospitals use assessment sheets, these have not yet delivered satisfactory results. We think that this is primarily because of the impossibility of identifying dangerous situations using these sheets. As these sheets only serve to determine the risk of patient falls, it is usually difficult for users to identify the timing and nature of dangerous actions that lead to falls, as well as related considerations. Therefore, it is difficult to carry out appropriate countermeasures to prevent accidental falls based on the information provided in assessment sheets.

1.2 Related research
Kato et al. (2013a) designed a structural model to identify the risk of patient falls by analyzing cases from two hospitals. They identified three types of risks regarding patient falls in hospitals, proposed a model to determine countermeasures, and developed a prototype system based on the model. However, the scope of patients’ actions in the model was limited to urination in the initial development. Furthermore, they indicated that their methodology was too complicated to be used every day in a hospital setting.

Kato et al. (2013b) then developed an assessment system that enabled users to determine countermeasures based on assessment results from Iizuka Hospital, an acute-stage hospital in Fukuoka with approximately 1,000 beds. This system included a “table of assessment, risk, and countermeasures,” which consisted of 22 assessment items, 40 risk items, and 69 countermeasures. The degree of each factor was evaluated using Cox regression analysis on approximately 1,000 data points. Using this information, Kato et al. (2014) proposed a risk structure model for patient falls that outlined the mechanism of patient falls and the relationships between various relevant factors. Kato et al. (2014) also attempted to evaluate the effect of each risk factor that formed the risk structure model through a multivariate analysis as a first trial. However, satisfactory results have not achieved, and more detailed analysis is needed.

While Kato et al. (2013b) used Cox regression analysis, their methods of analysis were not appropriately designed. Both the data model and the analysis model need to be arranged in such studies, and the results of the analyses need to be tested by data other than that used for analysis. Although there exist a few trials to identify risk factors relevant to falls (e.g., (Murata and Tsuda, 2006), (Carpenter et al., 2009), etc.), no study to date has systematically considered and implemented statistical models for fall prevention.

1.3 Purpose of this research
The goal of this study is to formulate a methodology to prevent patient falls in hospitals. In this paper, we aim to statistically model patient falls and propose a scoring system for the risk of such falls that satisfactorily addresses the issues afflicting similar proposals in the past. We use data sufficiently large for detailed analysis, and design both a data model and an analysis model using multivariate analysis involving a logistic model, a model for survival analysis, and models for recurrent events.

We designed the data model and the analysis model for patient falls based on the models described in Section 2. In Section 3, we describe our evaluation of each risk factor through multivariate analysis by using large amounts of data from Iizuka Hospital. In Section 4, we assess the accuracy of our new scoring system using new data by correlating scores and probability of events.

2. Statistical models for patient falls

2.1 Regression model
We use multivariate analysis in order to develop a scoring system for the risk of patient falls by considering conditions that affect their occurrence. Of the many types of regression analyses, logistic regression analysis is typically used to analyze the effects of explanatory variables on object variables of a binary type (e.g., dead or alive). Assessment score sheets currently used in many hospitals are typically based on the results of logistic regression analysis.

In order to evaluate the time to event in addition to the presence of events, Cox regression analysis, also known as “survival analysis,” is the basic model used. When censored cases are included in the dataset, logistic regression analysis is inapplicable, and Cox regression analysis is used to evaluate the time to event or the time to censoring. When analyzing patient falls, we assume that Cox regression analysis is appropriate because the length of stay in hospital and the time to fall vary for each patient, and therefore the dataset includes censored cases. Through Cox regression analysis, we can evaluate the likelihood of falls using each risk factor as a hazard ratio. When we can interpret the results, it is useful to consider efficient countermeasures.
We define the estimated number of days before a patient falls in hospital as the time to event. If a patient is discharged from the hospital without falling, the case is considered as “censored,” and the number of days the patient has stayed in the hospital is taken to be the time to event. The time to event is calculated using the following formula, depending on the “finish segment” (accident, reassessment, or discharge):

- accident: time to event = “accident date” - “previous assessment date”
- reassessment: time to event = “reassessment date” - “previous assessment date”
- discharge: time to event = “discharge date” - “previous assessment date”

Recurrent event analysis (or repeated event analysis) was developed as an application of Cox regression analysis. It can evaluate the time to event, which occurs on multiple occasions by considering the effects of the state variation of each patient. It is possible for a patient to fall multiple times during one hospitalization, and we thus think that models for recurrent events will be appropriate as a statistical model. In general, the Andersen–Gill (AG) model (Andersen, P.K. and Gill, R.D., 1982) and the Prentice, Williams, and Peterson (PWP) model (Prentice, R.L., et al., 1981) are representative models. Although the AG model assumes the same baseline hazard regardless of the number of times a patient has experienced an event, the PWP model assumes a different baseline hazard depending on the number of times a patient has experienced an event.

In this paper, we adopt the logistic model, the Cox model, the AG model, and the PWP model for analysis in order to evaluate the regression model best suited to represent patient falls.

### 2.2 Data model

It is difficult to segment data into discrete points because patient condition generally changes rapidly. Kato et al. (Kato et al., 2013) have developed three data models that differ according to how each model handles “reassessment,” as shown in Figure 1. In Model 1, all reassessments are considered censored. In Model 2, a reassessment is considered censored only when the conditions have changed from the previous assessment. In Model 3, reassessments are not considered at all, and typical assessment results are extracted from all results during hospitalization.

Each data model has its merits and demerits. In their study, Kato et al. (Kato et al, 2013) adopted Model 1 because it is the easiest in order to obtain data for analysis through conversion from the actual assessment data. In this study, we adopted Model 2 as well as Model 1 and compared them. Model 3 is still difficult to adopt because there are no criteria to choose a single assessment result for each patient in this model.

![Figure 1: Data segment](image)
Furthermore, it is possible for the same patient to be hospitalized multiple times during the observation period. Figure 2 shows the two data models for repeated event analysis. In the “Same Patient Model”, multiple hospitalizations of the same patient are considered as one, whereas “Different Patient Model” considers each hospitalization as that of a new patient, even if the same patient is hospitalized several times. In this study, we choose the Different Patient Model because the same patient is often hospitalized for diseases or injuries different from his/her previous hospitalizations, because of which his/her state has presumably changed.

Figure 2: Multiple hospitalizations

### 2.3 Data format

The data format we used for the logistic model, the Cox model, the AG model, and the PWP model is shown in Table 1. Each model commonly needs an “event” and covariates for analysis. Moreover, the Cox model needs “time,” the AG model needs “start,” “stop,” and “ID,” whereas the PWP model needs “start,” “stop,” “ID,” and “stratum.” Since we adopted the Different Patient Model in Figure 2, “start,” “stop,” “ID,” and “stratum” were set such that different hospitalizations were considered those of different patients each time. The terms in quotes are defined as follows:

- **event**: whether accidents have occurred during the observation period
- **time**: length of the observation period in days
- **start**: commencement date of the observation period for each patient
- **stop**: end date of the observation period for each patient
- **ID**: patient ID
- **stratum**: number of accidents for each patient before the observation period

### 2.4 Additional variables and stratification factors

We assume that the occurrence mechanism of patient falls is different if the “clinical department” or “hospital ward” to which the patient belongs is different because the patient type or the nursing system would be different in this case. In general, a ward occupies an entire floor of a hospital building and contains several departments.

The effects dependent on the “clinical department” can be construed as part of the effects based on the patient’s characteristics, and effects depending on the “hospital ward” can be interpreted as effects dependent on

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the nursing system. In this paper, we adopted clinical department as additional variable and stratification factor.

In general, there are three methods to include these additional factors into the Cox regression analysis and the recurrent event analysis (Nakazawa, 2007). The hypotheses of each method for baseline hazard and covariate effects are summarized in Table 2.

In Method (1), different baseline hazards and variable effects are assumed, because of which we cannot compare the scores of different departments or groups. In Method (2), different baseline hazards and common variable effects are assumed such that we can compare the scores of different departments or groups. In Method (3), common baseline hazards and common variable effects are assumed such that we can discuss the absolute score between different departments or groups. Therefore, if it is realistic to assume that the baseline hazard is common to all departments or groups, Method (3) is the most suitable. In this paper, we adopted Methods (2) and (3), and evaluated the most appropriate method for modeling patient falls.

Table 1: Data format for logistic model, Cox model, AG model, and PWP model

| dataID | time | event | start | stop | ID | stratum | deliria | impaired judgment | over 65 years old |
|--------|------|-------|-------|------|----|---------|---------|-------------------|-------------------|
| 1      | 2    | 0     | 0     | 2    | 1  | 1       | 0       | 0                 | 1                 |
| 2      | 1    | 0     | 0     | 1    | 2  | 1       | 0       | 0                 | 1                 |
| 3      | 1    | 0     | 0     | 1    | 2  | 1       | 0       | 0                 | 1                 |
| 4      | 1    | 0     | 1     | 2    | 3  | 1       | 0       | 0                 | 1                 |
| 5      | 2    | 1     | 2     | 4    | 3  | 1       | 0       | 0                 | 1                 |
| 6      | 2    | 0     | 4     | 6    | 3  | 2       | 1       | 0                 | 1                 |
| 7      | 7    | 1     | 6     | 13   | 3  | 2       | 1       | 0                 | 1                 |
| 8      | 5    | 0     | 13    | 18   | 3  | 3       | 1       | 0                 | 1                 |
| 9      | 3    | 0     | 0     | 3    | 4  | 1       | 0       | 1                 | 0                 |
| 10     | 4    | 0     | 3     | 7    | 4  | 1       | 0       | 1                 | 0                 |
| 11     | 2    | 0     | 7     | 9    | 4  | 1       | 0       | 0                 | 0                 |

Table 2: Method of including the effects of additional variables and stratification factors

|               | Baseline Hazard $h_0(t)$ | Covariates’ Effect $\beta_1, \beta_2, \cdots$ | Comparison of Scores among Groups |
|---------------|--------------------------|-----------------------------------------------|----------------------------------|
| (1) Separate  | different among groups    | different among groups                         | impossible                       |
| (2) Strata    | different among groups    | common among groups                            | impossible                       |
| (3) Covariates| common among groups       | common among groups                            | possible                         |

2.5 Criteria for variable selection

Although there are many criteria for variable selection in regression analysis, the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC) are representative. In general, the number of variables included in a regression formula using BIC is smaller than that using AIC.

In this paper, we adopted both AIC and BIC for each model and evaluated the method more suited to modeling patient falls.

3. Risk scoring system based on the results of multivariate analysis

3.1 Data collection and arrangement

We collected 150,883 sets of assessment data and 2,085 sets of accident data for hospitalized patients. The data were from Iizuka Hospital from 2009 to 2011. The assessment data contained information regarding risk factors, patient ID, and the date of assessment. The accident data contained information regarding accidents,
patient ID, and the date of each accident. We connected these data and restructured them by adding information regarding the date of patient discharge from the hospital information system for each patient ID. We examined and excluded improper data, and finally obtained 109,474 sets of data for analysis, which included 1,429 events (data-1, based on Model-1, in Figure 1).

Data were available for multiple assessments of each patient because risk assessment was conducted for each patient every three or seven days. We integrated the records with past records if the assessment results for all risk factors were identical to those in the previous dataset. Finally, 85,525 sets of data were obtained for analysis, including 1,429 accidents (data-2, based on Model-2, in Figure 1).

In data-1, some data items were missing. Important among these, such that their absence could have affected the analysis, were the number of missed accidents. Missed accidents are of two types. One occurs when the accident data cannot be associated with assessment data. This type is impossible to complement because it is caused by missing in original data. The other type of missed accidents occurs when time is zero. We complemented some accident data, whose time was zero, by integrating them with past data if the patient’s condition had not changed (Model-2 was partially implemented) in order to increase accident information for analysis.

We then stratified the data by clinical department, and integrated them according to “large group,” and “small group,” as shown in Table 3, based on the technical knowledge of members of the Medical Safety Promotion Office (MSPO), since we assumed that the occurrence mechanism of patient falls depended on the “department.”

### Table 3: Data summary based on clinical departments

| Department Group | data-1 | data-2 |
|------------------|-------|-------|
| Large Group      |       |       |
| 1. Cerebral Nerve Group |       |       |
| neurology        | 7033  | 51007 | 84   | 5312  | 51007 | 84   |
| neurosurgery     | 4890  | 36137 | 71   | 4165  | 36137 | 71   |
| 2. Surgery Group |       |       |
| 2.1 Orthopedic Surgery |       |       |
| orthopedic surgery | 7151 | 45118 | 62   | 6151  | 45118 | 62   |
| surgery          | 13847 | 62799 | 137  | 11145 | 62799 | 137  |
| 2.2 Other Surgeries |       |       |
| surgery          | 13847 | 62799 | 137  | 11145 | 62799 | 137  |
| 3.1 Cardiovascular |       |       |
| cardiovascular surgery | 8592 | 41023 | 80   | 6607  | 41023 | 80   |
| surgery          | 2634  | 16343 | 53   | 2199  | 16343 | 53   |
| 3.2 Other Internal Medicine |       |       |
| cardiovascular surgery | 8592 | 41023 | 80   | 6607  | 41023 | 80   |
| surgery          | 2634  | 16343 | 53   | 2199  | 16343 | 53   |
| 4. Psychiatry Group |       |       |
| psychiatry        | 4828  | 97700 | 279  | 2151  | 97700 | 279  |
| 5. Pediatrics Group |       |       |
| pediatrics        | 5251  | 21322 | 9    | 3894  | 21322 | 9    |
| pediatrics surgery | 584   | 1883  | 0    | 524   | 1883  | 0    |
| 6. Ophthalmology |       |       |
| ophthalmology     | 1968  | 7812  | 3    | 1885  | 7812  | 3    |
| 6.1 Ophthalmology |       |       |
| ophthalmology     | 1968  | 7812  | 3    | 1885  | 7812  | 3    |
| 6.2 Others |       |       |
| obstetrics        | 1125  | 3285  | 1    | 971   | 3285  | 1    |
| emergency         | 1006  | 5494  | 8    | 863   | 5494  | 8    |
| 6. Other Groups |       |       |
| obstetrics        | 1125  | 3285  | 1    | 971   | 3285  | 1    |
| emergency         | 1006  | 5494  | 8    | 863   | 5494  | 8    |
| 7. Other Groups |       |       |
| obstetrics        | 1125  | 3285  | 1    | 971   | 3285  | 1    |
| emergency         | 1006  | 5494  | 8    | 863   | 5494  | 8    |
| Total             | 109474| 880672| 1429 | 85525 | 880672| 1429 |
As shown in Table 3, there were a total 32 of department in Iizuka Hospital, integrated into six large groups and nine small subgroups. The shaded names indicate departments with insufficient number of data items for events (minor departments), which were hence difficult to separately analyze. Therefore, we adopted two types of datasets for each data item in data-1 and data-2. One consisted of data-1 and data-2 by themselves, whereas the other excluded data from minor departments. We called these four datasets “data-1_total,” “data-1_mindel,” “data-2_total,” and “data-2_mindel.”

3.2 Results of multivariate analysis

We conducted multivariate analysis on 176 models using the R software package. We used four datasets, data-1_total, data-1_mindel, data-2_total, and data-2_mindel, and four base models, the logistic model, the Cox model, the AG model, and the PWP model, three factors as additional variable or stratification factors, large group (“large”), small group (“small”), and department (“dept”), and two criteria for stepwise variable selection, AIC and BIC.

For example, an item of the analysis results obtained using the Cox model with no stratification factors with BIC as criterion is shown in Table 4. As shown in Table 4, seven risk factors were part of the regression formula, and the concordance index was 0.679. As above, we derived 176 regression models.

### Table 4: Example of the results of multivariate analysis

| Covariates               | Hazard Ratio | Lower 95%CI | Upper 95%CI | p Value |
|--------------------------|--------------|-------------|-------------|---------|
| do not use nurse call    | 1.386        | 1.194       | 1.61        | 1.90E-05|
| do anything by oneself   | 1.414        | 1.207       | 1.656       | 1.79E-05|
| wamble                   | 1.749        | 1.524       | 2.008       | 3.55E-15|
| using portable toilet    | 1.641        | 1.45        | 1.856       | 4.60E-14|
| younger than 9 years old | 0.4009       | 0.2313      | 0.6947      | 2.22E-15|
| history of falls         | 1.586        | 1.415       | 1.777       | 4.60E-14|
| using sleeping pills     | 1.535        | 1.373       | 1.716       | 4.60E-14|

3.3 Risk scoring system

In the results of the regression analysis using the logistic, Cox, AG, and PWP models, the “odds ratio” or “hazard ratio” expressed the effect of each risk factor on patient fall at a given point in time. Therefore, it was reasonable to calculate the total risk score for each patient as the product of the hazard rates of all risk factors, as shown in Figure 3.

**Figure 3: Example of a risk scoring system**
As shown in Figure 3, we calculated the total risk score for each patient based on the results of the multivariate analysis. The total risk score was calculated as the product of the “risk score” for each covariate (assessment item). If a covariate applied to a patient, the risk score for the covariate was determined as the left-sided value (the “apply” column in the center table, equal to the “hazard ratio”); if it did not apply to the patient, the risk score was determined as the right-sided value (the “not apply” column, equal to 1).

Since we conducted multivariate analysis using multiple models, we obtained 176 sets of formulae for risk scoring (we called this a “risk scoring system”) in addition to the two existing systems.

4. Evaluation of scoring systems

4.1 Data for evaluation

We prepared the data obtained from Iizuka Hospital in 2012, which consisted of approximately 50,000 sets of assessment data. We arranged the data in the same manner as described in Section 3.1, and retrieved 33,984 sets of data with 441 events (data-2). We calculated risk scores for these new datasets, using the 176 new scoring system obtained in Section 3.3, and the two existing scoring systems at Iizuka Hospital.

4.2 Method and results of evaluation

Since the odds ratio or hazard ratio expresses the immediate value of patient fall risk, there is a linear relationship between ln (total score) and ln (probability of events = event/time) if the scoring system has high-resolution capability. To evaluate the resolution capability, we calculated the determination coefficient for the above relationship for each risk scoring system. In order to ensure scale invariance (1 to 30), we applied a standardization whereby the maximum value of each scoring system was 30.

We calculated the total risk score for the data using the 176 scoring systems. For each score set, we approximated each score by every 1.0 point, and grouped all data according to these approximated scores. Each group contained the following information: number of assessments and time, and the number of events for each scoring system. Using this information, we calculated the determination coefficient. The relevant part of the results is shown in Table 5 (in descending order by determination coefficient).

5. Discussion and future research

5.1 Effectiveness of the statistical models

The results of the evaluation confirmed the effectiveness of our new scoring systems. As mentioned above, the results of the evaluation using the determination coefficient for the total score and probability of events, a risk scoring system using data-2_total, the Cox model, adding a small group as a stratification factor, and AIC as selection criteria yielded the best results.

On the whole, the Cox and AG models were superior to the others. Because the PWP model assumed different baseline hazard depending on the frequency of events, there was a high probability that the number of events in the analysis data was insufficient. The determination coefficient of the logistic model was lower than those of other models. We think that this indicated that the time to event in multivariate analysis is a more appropriate measure of the magnitude of each risk factor involved in patient falls.

As mentioned in Section 2.4, we assumed that the occurrence mechanism of patient falls might be different if the “clinical department” or “hospital ward” to which the patient belonged was different, since the patient type or nursing system would be different in such a case.

While we adopted the clinical department as an additional variable and stratification factor in this paper, we think that further consideration of this issue is needed. Since we designed a scoring system to assess patient fall risk, which should include all risk factors based on the patient’s characteristics, effects dependent on the “clinical department” should be part of the effects based on the patient’s characteristics. It is also reasonable that effects dependent on the “hospital ward” should not be included in the list of effects dependent on the patient’s characteristics, but should independently be made part of the scoring system because they depend on the nursing system.
### Table 5: Example of the results of evaluation

| ID    | Analysis Model                      | Number of Covariates | Sample Size | Determination Coefficient |
|-------|-------------------------------------|-----------------------|-------------|---------------------------|
| 53    | data-2_total_Cox_strata_small_AIC   | 15                    | 28          | 0.839                     |
| 15    | data-1_total_AG_strata_large_AIC    | 16                    | 28          | 0.829                     |
| 59    | data-2_total_AG_strata_large_AIC    | 16                    | 28          | 0.829                     |
| 52    | data-2_total_Cox_strata_large_AIC   | 17                    | 27          | 0.814                     |
| 35    | data-1_mindel_Cox_var_dept_AIC      | 34                    | 34          | 0.809                     |
| 9     | data-1_total_Cox_strata_small_AIC   | 17                    | 28          | 0.803                     |
| 54    | data-2_total_Cox_strata_dept_AIC    | 15                    | 28          | 0.802                     |
| 77    | data-2_mindel_Cox_var_large_AIC     | 20                    | 28          | 0.798                     |
| 10    | data-1_total_Cox_strata_dept_AIC    | 16                    | 29          | 0.772                     |
| 21    | data-1_total_PWP_total_AIC          | 17                    | 31          | 0.766                     |
| 33    | data-1_mindel_Cox_var_large_AIC     | 20                    | 28          | 0.765                     |
| 103   | data-1_total_AG_strata_large_BIC    | 7                     | 27          | 0.760                     |
| 147   | data-2_total_AG_strata_large_BIC    | 7                     | 27          | 0.760                     |
| 124   | data-1_mindel_AG_total_BIC          | 7                     | 26          | 0.750                     |
| 128   | data-1_mindel_AG_var_large_BIC      | 7                     | 26          | 0.750                     |
| 129   | data-1_mindel_AG_var_small_BIC      | 7                     | 26          | 0.750                     |
| 130   | data-1_mindel_AG_var_dept_BIC       | 7                     | 26          | 0.750                     |
| 168   | data-2_mindel_AG_total_BIC          | 7                     | 26          | 0.750                     |
| 172   | data-2_mindel_AG_var_large_BIC      | 7                     | 26          | 0.750                     |
| 173   | data-2_mindel_AG_var_small_BIC      | 7                     | 26          | 0.750                     |
| 174   | data-2_mindel_AG_var_dept_BIC       | 7                     | 26          | 0.750                     |
|       | data-1_current                      | 26                    | 30          | 0.700                     |
|       | data-2_current                      | 26                    | 30          | 0.700                     |

#### 5.2 Value of the application of the results

We found that some new models had higher determination coefficients. While many hospitals currently use assessment score sheets, the results show that it is possible to improve existing assessment score sheets by using data from each hospital.

Moreover, there was a smaller number of covariates in the regression formula than in the assessment score sheet, which is useful in reducing the number of assessment items while obtaining reasonably accurate predictions regarding patient falls because nurses generally very busy for many kind of works on the field site. In future work, we need to assess the effectiveness of our new assessment sheet, which will have fewer assessment items based on the results of this study, by using in daily operation at Iizuka Hospital.

#### 5.3 Application Scope

We believe that it is inadvisable to implement the proposed risk scoring system in other hospitals without modifications because our system was formulated by considering circumstances unique to Iizuka Hospital. We believe that our assessment can be applied to other hospitals with minor changes, primarily involving the addition of factors unique to each hospital. However, the risk scoring system will need to be redesigned for each hospital by using data to reflect its specific situation.

The method of developing risk scoring systems detailed in this paper can be applied to other hospitals. In the future, we aim to develop risk scoring systems for several hospitals, as well as a method to design an optimal scoring system for each hospital according to its unique characteristics.

In many hospitals, assessment data and accident data are accumulated together. To apply our method, the data need to be prepared for analysis in the format shown in Table 1, and summarize in the format shown in Table 3. To this end, both assessment data and accident data need to share an ID for each patient and a date to form the relation. These requirements are basic to data collection, and should be easy to implement in many hospitals.
5.4 Accuracy of analysis

While preparing the data for analysis, we noticed two types of instance of missed data. One occurred when accident data could be associated with assessment data. We think that this type of missed data occurred randomly and had little effect on our analysis.

The other type of missed data occurred when the time was zero. In this paper, we complemented some accident data, the time for which was zero, by integrating them with past data if the patient’s condition had not changed. Therefore, this type of missed data remaining two cases: the case where an accident occurred on the day on which the first assessment was conducted, and the case where the accident occurred on the day on which the reassessment was conducted and the patient’s condition had changed.

These cases suggest the potential for bias in the data, which can affect the results of the analysis. However, it is also inevitable when we try to analyze the time to event, and should be considered a limitation of statistical methods of the sort we used.

6. Conclusion

In this paper, we statistically modeled the occurrence mechanism of patient falls in hospitals based on multivariate analysis involving a logistic model, the Cox model, the AG model, and the PWP model by using large amounts of case data from Iizuka Hospital. By using the determination coefficient for correlativity between total risk score and event probability as the means of assessment, we found that some of our new scoring systems were better at evaluating patient fall risk with smaller number of covariates than those currently being used. This result suggests that it is possible to improve existing assessment score sheets through statistical analysis using the data from each relevant hospital.

In future research, we will implement our scoring system by considering the number of covariates, an explanation of the hazard ratio of each covariate, and the statistical sense of the model. We will then assess the effectiveness of these new assessment sheets in terms of prediction accuracy and the time required to make assessments by implementing them in the day-to-day operation at Iizuka Hospital.

Furthermore, we plan to develop scoring systems for multiple hospitals and establish a general method to develop customizable scoring systems according to the characteristics of each hospital. We believe that our methodology and scoring system will improve the quality of patients’ stay in hospitals and, therefore, the quality of healthcare.

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