A Prediction Rule for the Development of Delirium among Patients in Medical Wards: Chi-Square Automatic Interaction Detector (CHAID) Decision Tree Analysis Model

Daiki Kobayashi, M.D., Osamu Takahashi, Ph.D., Hiroko Arioka, M.D., Shinichiro Koga, Ph.D., Tsuguya Fukui, Ph.D.

Objective: To predict development of delirium among patients in medical wards by a Chi-Square Automatic Interaction Detector (CHAID) decision tree model. Methods: This was a retrospective cohort study of all adult patients admitted to medical wards at a large community hospital. The subject patients were randomly assigned to either a derivation or validation group (2:1) by computed random number generation. Baseline data and clinically relevant factors were collected from the electronic chart. Primary outcome was the development of delirium during hospitalization. All potential predictors were included in a forward stepwise logistic regression model. CHAID decision tree analysis was also performed to make another prediction model with the same group of patients. Receiver operating characteristic curves were drawn, and the area under the curves (AUCs) were calculated for both models. In the validation group, these receiver operating characteristic curves and AUCs were calculated based on the rules from derivation. Results: A total of 3,570 patients were admitted: 2,400 patients assigned to the derivation group and 1,170 to the validation group. A total of 91 and 51 patients, respectively, developed delirium. Statistically significant predictors were delirium history, age, underlying malignancy, and activities of daily living impairment in CHAID decision tree model, resulting in six distinctive groups by the level of risk. AUC was 0.82 in derivation and 0.82 in validation with CHAID model and 0.78 in derivation and 0.79 in validation with logistic model. Conclusion: We propose a validated CHAID decision tree prediction model to predict the development of delirium among medical patients. (Am J Geriatr Psychiatry 2013; 21:957–962)

Key Words: Delirium, prediction rule, CHAID

Delirium is one of the most common diseases to develop during hospitalization. It is clinically important because it increases patients’ mortality rate (odds ratio: 1.95) and prolongs length of stay (added 2.2 day per admission). The incidence of delirium varies from study to study, from 5% to 25%. Therefore, prevention and early treatment for delirium are important in patient care.

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Inoue et al. developed a prediction tool for development of delirium among hospitalized elderly medical patients based on characteristics on admission. However, their prediction tool entailed a blood test and calculation according to the second version of the Acute Physiologic Assessment and Chronic Heath Evaluation (APACHE II). Moreover, it is almost 20 years since that prediction tool was made. The content of medical care has certainly changed, necessitating new and easier prediction model fits for the current medical practice.

Chi-Square Automatic Interaction Detector (CHAID) decision tree analysis is a data mining technique with a salient advantage of advanced graphic presentation for interpretation. CHAID enables us to deal with whole variables, partition consecutive data effectively, and make decision trees by using a forward stopping or pruning rule. Moreover, CHAID is the only model to formulate multiple nodes. Unlike other techniques, the significance level can be adjusted for the number of comparisons. CHAID decision tree analysis has been applied in medical field and has been shown to be superior to logistic analysis. In addition, prediction rules with the CHAID model are highly graphic and easy to interpret in clinical settings. Because we use a prediction rule for development of delirium as a screening tool in medical wards, we have to evaluate almost all patients. In that case, prediction rules with the CHAID model are highly useful, because we evaluate patients quickly. On the other hand, other models, such as that with logistic models, require cumbersome tasks, including calculation. In this way, prediction rules with the CHAID model are more useful than other rules for screening of development of delirium.

The aim of this study is to make prediction rules for the development of delirium among medical patients using two methods, CHAID decision tree analysis and, for comparison, logistic regression analysis. We then we propose the prediction rule based on the better method for clinical use.

**METHODS**

A retrospective cohort study of all adult patients who were admitted to internal medicine units, except for intensive care and coronary care units, was conducted from April 2009 through March 2010 at St. Luke’s International Hospital, a large community hospital in Tokyo, Japan. All potential prognostic prediction parameters drawing on previous studies and physician-driven clinical relevance from the electronic chart were collected on admission. Parameters were composed of patients’ 1) demographic data, 2) current and past medical history, and 3) prescription. If patients were admitted more than once during the study period, only the most recent data were included. We collected all data from the electronic chart automatically.

Demographic data included gender, age, activities of daily living (ADLs), and blindness. ADL was evaluated with the Functional Independence Measure by nurses or physicians, and impairment was defined as the state of physical or mental condition of all patients except for those who were completely independent in ADLs. Current medical history included malignancy, metastasis, alcohol abuse, depression, and dementia, whereas past medical history included delirium. In this study, patients with malignancy were defined as those who had any kinds of malignancy. Patients with treated malignancy were not included in this category. Prescription data included benzodiazepine, anticholinergic drugs, and antihistamine drugs. These histories and prescription data were collected from the patient, patient’s family, and previous physicians according to circumstances.

During hospitalization, patients were monitored regarding the development of delirium by physicians and nurses. Delirium was diagnosed by physician based on the *Diagnostic and Statistical Manual of Mental Disorders*, Fourth Edition, Text Revision. Patients were seen at least twice a day by physicians and three times by nurses.

Descriptive statistics were used to characterize subjects’ data on admission. To make the prediction rule easy to use in the clinical setting, continuous values were categorized into groups. Consequently, age was categorized into groups by 5 years. We randomly assigned approximately two thirds of patients to a derivation group and the remaining to a validation group. Randomization was performed by computer-based random number generation. Prediction model was made from the derivation group and the predictive probability was calculated. From the result, receiver operator characteristic (ROC) curves were drawn and the value of area under the curve calculated. Then, the model developed from the derivation group was applied to the validation group.
The same procedure described above was used for CHAID decision tree analysis and logistic regression analysis. We then compared these two models in terms of clinical usability, ROC, and the value of AUC. For CHAID decision tree analysis, we used all parameters collected. The minimum parent and child nodes were determined as 50 and 20, respectively, with four layers in the final tree structure.

"Nodes" are midpoints or terminal points after bifurcation according to each factor. The parent nodes are the nodes before bifurcation, and the child nodes are ones after bifurcation. Based on the result, a group of patients was divided into one of the terminal nodes (risk groups) with predictive probability calculated. ROC curve was drawn from the predictive probability and AUC calculated.

For logistic regression analysis, we used the following method. Univariate analysis was performed to investigate the relationship between collected data and acute adverse reactions. To determine prognostic predictors, all candidate predictors with \(p < 0.2\) in univariate analysis were included in a forward stepwise logistic regression model. Only variables with subsequent \(p < 0.05\) were included in the final model. According to the result, a group of patients was calculated to predict probability, drawn ROC curve, and calculated AUC. For validation, these ROCs and AUCs were calculated based on the rules from derivation with both CHAID and logistic regression.

All analyses were conducted using SPSS software package, version 19.0 (IBM, Tokyo, Japan), except for the calculation of 95% confidence intervals (CIs), which were based on an exact binominal using Stata version 10 (STATA Corp., College Station, TX). Ethical approval was obtained from the Research Ethics Committee of St. Luke’s International Hospital, Tokyo, Japan.

**RESULTS**

Some 3,570 patients were admitted to internal medicine units between April 1, 2009, and March 31, 2010. Of these, 2,400 patients were assigned to the derivation group and 1,170 patients to the validation group. Table 1 shows patient characteristics in both groups. Ninety-one patients (3.8%, 95% CI: 3.1–4.6) developed delirium in the derivation group and 51 (4.4%, 95% CI: 3.3–5.7) in validation group. Patients with delirium in the derivation group had a mean

<table>
<thead>
<tr>
<th>TABLE 1. Patient Characteristics for the Derivation and Validation Groups</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Derivation Group (N = 2,400)</strong></td>
</tr>
<tr>
<td>-------------------------------</td>
</tr>
<tr>
<td><strong>Delirium</strong> (N = 91)</td>
</tr>
<tr>
<td>General information</td>
</tr>
<tr>
<td>Age, year (SD)</td>
</tr>
<tr>
<td>Gender male</td>
</tr>
<tr>
<td>ADL impairment</td>
</tr>
<tr>
<td>Blind</td>
</tr>
<tr>
<td>Disurea</td>
</tr>
<tr>
<td>History</td>
</tr>
<tr>
<td>Delirium</td>
</tr>
<tr>
<td>Underlying condition</td>
</tr>
<tr>
<td>Malignancy</td>
</tr>
<tr>
<td>Metastasis</td>
</tr>
<tr>
<td>Hypertension</td>
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<tr>
<td>Dyslipidemia</td>
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<tr>
<td>Diabetes mellitus</td>
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<tr>
<td>Alcohol abuse</td>
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<tr>
<td>Depression</td>
</tr>
<tr>
<td>Dementia</td>
</tr>
<tr>
<td>Medication</td>
</tr>
<tr>
<td>Benzodiazepine</td>
</tr>
<tr>
<td>Anticholinergic</td>
</tr>
<tr>
<td>Antihistamine</td>
</tr>
</tbody>
</table>

Notes: Values are N, with percents in parentheses, unless otherwise noted.
age of 76.8 years (standard deviation: 14.2) and those without delirium, 65.3 years (17.0). For validation group, mean age was 78.3 (9.1) in patients with delirium and 64.8 (18.0) in those without delirium. Other variables are described in Table 1. Table 2 shows the comparison between the groups.

CHAID decision analysis was constructed with all candidate predictors. The result is shown in Figure 1. Delirium history, age (<50 years, 50 < Age ≤ 75 years, >75 years), underlying malignancy, and ADL impairment were included in the decision tree, and six terminal nodes were made. According to the incidence, we divided them into quite low risk (incidence of delirium: 0.2%), low risk 1 (1.1%), low risk 2 (1.3%), moderate risk (2.9%), high risk (8.7%), and quite high risk (40.0%). In the validation group; the incidence in each risk group was similar to derivation group (quite low risk: 0.0%; low risk 1: 1.8%; low risk 2: 1.5%; moderate risk: 2.5%; high risk: 9.4%; and quite high risk: 46.4%) (Fig. 2). ROC curves in both groups are shown in Figure 3. AUC was 0.82 (95% CI: 0.77–0.86) for the derivation group and 0.82 (95% CI: 0.76–0.88) for the validation group.

Logistic regression analysis was conducted with selected variables. Table 3 shows the result of the analysis. Delirium history, ADL impairment, alcohol abuse, malignancy, and dementia were detected. From the result, predictive probability was calculated among each patients, and ROC curves were drawn for both the derivation and the validation groups (Fig. 4). AUC was 0.78 (95% CI: 0.73–0.82) for the derivation group and 0.79 (95% CI: 0.72–0.86) for the validation group.

### TABLE 2. Comparison between the Groups

<table>
<thead>
<tr>
<th></th>
<th>Derivation Group (N = 2,400)</th>
<th>Validation Group (N = 1,170)</th>
<th>Name of Test</th>
<th>df</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Development of delirium</td>
<td>91 (3.8)</td>
<td>51 (4.4)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.42</td>
</tr>
<tr>
<td>Age, year (SD)</td>
<td>65.7 (17.0)</td>
<td>65.4 (17.9)</td>
<td>t test</td>
<td>0.60</td>
<td></td>
</tr>
<tr>
<td>Gender male</td>
<td>1,435 (59.8)</td>
<td>671 (57.4)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.16</td>
</tr>
<tr>
<td>ADL impairment</td>
<td>1,452 (61.3)</td>
<td>746 (66.4)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.06</td>
</tr>
<tr>
<td>Blind</td>
<td>1 (0.0)</td>
<td>0 (0.0)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.49</td>
</tr>
<tr>
<td>Disurea</td>
<td>38 (1.6)</td>
<td>13 (1.1)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.26</td>
</tr>
<tr>
<td>Past history</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Delirium</td>
<td>50 (2.1)</td>
<td>28 (2.4)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.55</td>
</tr>
<tr>
<td>Underlying condition</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Malignancy</td>
<td>645 (26.9)</td>
<td>286 (24.4)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.12</td>
</tr>
<tr>
<td>Metastasis</td>
<td>14 (0.6)</td>
<td>9 (0.8)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.52</td>
</tr>
<tr>
<td>Hypertension</td>
<td>1,133 (47.2)</td>
<td>511 (43.7)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>&gt;0.05</td>
</tr>
<tr>
<td>Dyslipidemia</td>
<td>645 (26.9)</td>
<td>302 (25.8)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.50</td>
</tr>
<tr>
<td>Diabetes mellitus</td>
<td>737 (30.7)</td>
<td>309 (26.4)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>&gt;0.05</td>
</tr>
<tr>
<td>Alcohol abuse</td>
<td>16 (0.7)</td>
<td>15 (1.5)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.06</td>
</tr>
<tr>
<td>Depression</td>
<td>231 (9.6)</td>
<td>118 (10.1)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.66</td>
</tr>
<tr>
<td>Dementia</td>
<td>104 (4.3)</td>
<td>68 (5.8)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.05</td>
</tr>
<tr>
<td>Medication</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Benzodiazepine</td>
<td>489 (20.4)</td>
<td>241 (20.6)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.88</td>
</tr>
<tr>
<td>Anticholrine</td>
<td>137 (5.7)</td>
<td>61 (5.2)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.54</td>
</tr>
<tr>
<td>Antihistamine</td>
<td>57 (2.3)</td>
<td>11 (0.9)</td>
<td>(\chi^2)</td>
<td>1</td>
<td>0.14</td>
</tr>
</tbody>
</table>

Notes: Values are N, with percents in parentheses, unless otherwise noted.
DISCUSSION

In this study, we evaluated two prediction models to estimate the probability of development of delirium in patients who were admitted to internal medicine units. CHAID decision tree compared with logistic regression model had a better value of AUC.

We believed the CHAID decision tree was one of the most variable and easiest methods to predict the development of delirium.

There were four potentially predictable variables in the CHAID model: delirium history, age, underlying malignancy, and ADL impairment. The logistic model had five variables: delirium history, dementia, underlying malignancy, alcohol abuse, and ADL impairment. All these variables were reported to be related to the development of delirium in the previous studies.19-21 Therefore, we believed both models were clinically reasonable.

The CHAID decision tree when compared with the logistic regression model has some advantages. First, the technique can partition consecutive data into the best predictive group.4 Second, CHAID can partition continuous data as multiple nodes, whereas the logistic regression model cannot.5,22 From this

FIGURE 2. Algorithm for development of delirium in the validation group.

1,170 patients in Validation group
(Delirium incidence, 4.4%)

Delirium history

No delirium history

28 patients
(incidence, 46.4%)
Quite high risk

1,142 patients
(incidence, 3.3%)

Age ≥ 50 (years)

50 < Age ≤ 75 (years)

Age < 75 (years)

240 patients
(incidence, 0.0%)
Quite low risk

560 patients
(incidence, 2.0%)
Malignancy

342 patients
(incidence, 7.9%)
ADL impairment

Non-malignancy
Malignancy
Independent ADL
Impair ADL

397 patients
(incidence, 1.8%)
Low risk 1

163 patients
(incidence, 2.5%)
Moderate risk

65 patients
(incidence, 1.3%)
Low risk 2

277 patients
(incidence, 9.4%)
High risk

FIGURE 3. Receiver operating characteristic (ROC) curves and the area under the curves (AUCs) in both derivation and validation groups with the CHAID model.

1.0

0.8

0.6

Sensitivity

0.4

0.2

0

1-Specificity

0.8

0.6

0.4

0.2

0

1

Derivation group
(AUC 0.82, 95%CI: 0.77-0.86)

Validation group
(AUC 0.82, 95%CI: 0.76-0.88)

Derivation group
(AUC 0.78, 95%CI: 0.73-0.82)

Validation group
(AUC 0.79, 95%CI: 0.72-0.86)

FIGURE 4. Receiver operating characteristic (ROC) curves and the area under the curves (AUCs) in both derivation and validation groups with the logistic regression model.

TABLE 3. Logistic Regression Analysis Conducted with Selected Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Wald</th>
<th>df</th>
<th>Odds Ratio</th>
<th>95% CI</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Delirium history</td>
<td>95.68</td>
<td>1</td>
<td>14.35</td>
<td>8.41–24.47</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>ADL impairment</td>
<td>31.94</td>
<td>1</td>
<td>5.81</td>
<td>3.16–10.69</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Alcohol abuse</td>
<td>11.21</td>
<td>1</td>
<td>5.47</td>
<td>2.02–14.79</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Malignancy</td>
<td>19.75</td>
<td>1</td>
<td>2.34</td>
<td>1.61–3.41</td>
<td>&lt;0.01</td>
</tr>
<tr>
<td>Dementia</td>
<td>4.68</td>
<td>1</td>
<td>1.86</td>
<td>1.06–3.28</td>
<td>0.03</td>
</tr>
</tbody>
</table>
advantage, in this study, the age variable was divided into three nodes. After division, child nodes have different incidence of delirium. In contrast, prediction rule with logistic regression does not easily deal with continuous data, such as age, because of the difficulty of calculation in the clinical setting. Moreover, CHAID decision trees are easy to use in clinical settings, because these are graphic. According to a previous review, a good clinical prediction rule needs to be easy to incorporate into routine clinical practice. With the logistic regression model, the point of each risk factor needs to be remembered and then calculated in the clinical settings, which takes a lot of time when compared with the CHAID model. In this way, the CHAID decision tree analysis was a more effective prediction rule in this study.

Comparing the CHAID model with a previous study, we found this model is easier to use in clinical settings. In that study the prediction model was composed of four variables: vision impairment, severe illness (APACHE II), cognitive impairment, and a high blood urea nitrogen-to-creatinine ratio. However, APACHE II scoring needs 13 physiologic variables, and measurement of blood urea nitrogen-to-creatinine ratio needs a blood test. In contrast, our study also had four variables, but all were easily calculated. In this way, our model is more useful in clinical settings.

There were some limitations in our study. First, our prediction model needs previous and current medical history. These may be less accurate, because of memory bias. However, in clinical settings, physicians would take a history like we did. Therefore, in this way our model may be clinically effective. Second, our study was retrospective and conducted only in one hospital, at which most patients were Japanese. Although both large in scale and validated, prospective studies at multiple centers and with heterogeneous populations are needed in the future to further refine the model.

We propose a validated CHAID decision tree prediction model, which was more reliable than logistic regression model, for development of delirium. Using the model, this set of predictors is easy to use in the clinical setting and may facilitate appropriate care for high-risk patients.

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