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Predicting Schizophrenia at Risk of Readmissions in the Short- and Long-Term using Decision Tree Model

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Abstract

This study aims to develop readmission prediction models using a decision tree technique in data mining for predicting patients with schizophrenia at risk of readmission for four different time periods after discharge: ≤ 6 months, 6-12 months, 1-2years, > 2years. Information on the socio-demographic and clinical characteristics data were collected from the registered medical files of patients. Of the 2,285 patients admitted to Prasrimahabhodi Psychiatric Hospital between January 2007 and December 2012, 778 (34.05%) were readmissions. Almost 30% of these patients were readmitted within 6 months of discharge. The non-compliance with medication patients who were diagnoses of F20.3, F20.5 and F20.8 tend to be readmitted within 6 month, while subtype diagnoses of F20.1, F20.2 and F20.4 tend to be readmitted between 6 months and 1 year. Furthermore, patients who were subtype diagnoses of F20.2, F20.3, F20.4, F20.5 and F20.8 tend to be readmitted after 2 years. Among the patients who had low compliance to medication with diagnoses of F20.0 and F20.1 if they are unmarried, widowed and divorced, they tend to be readmitted after 2 years. The experimental results also showed that schizophrenia readmission prediction model achieved the highest accuracy, true positive rate, and true negative rate of short-term readmission up to 93.38%, 94.07% and 92.68%, and long-term readmission up to 97.40%, 98.05% and 96.44%, respectively. The implications of this study may help to increase our understanding of early intervention and will enable clinicians and practitioners in planning care.

Keywords: *Psychiatric patient, Rehospitalization, Risk factors, Data mining*

1. Introduction

Schizophrenia is a chronic, severe and debilitating mental illness affecting about 7 adults per thousand or around 24 million people worldwide, mostly in the age group 15-35 years (1). Similarly, in Thailand the prevalence of schizophrenia at ages between 15-59 is 0.8% with a male to female ratio of 1 to 1.1 (2). This disorder is associated with high rates of hospital readmission. For example, about one-half of all stabilized patients are readmitted to the hospital within 1 year (3-5). Also, patients with schizophrenia are more likely to be readmitted to the hospital than the patients with other mental disorders (6).

A hospital readmission refers to being hospitalized again after being discharged. A readmission can occur at either the same hospital or a different hospital. Hospital readmission often indicates that clinical symptoms have reached a level of severity that can no longer be managed safely at home or as an out-patient (7). Therefore, readmissions to hospitals have become an area of concern to policymakers because excess readmissions may be a sign that hospitals degrade the quality of health care and increases medical expenses (7, 8).

Numerous studies have investigated risk factors which might lead to readmissions such as premature discharge, length of stay (9, 10), a history of aggressive (11), worse condition at discharge, poor compliance to medication (12), poor compliance with outpatient appointments (13), and multiple admission (14). Furthermore, prospective cohort study of 262 adult inpatients with schizophrenia found those readmitted within three months were significantly more likely to have comorbid alcohol or substance use disorder (15, 16). Social and demographic factors, such as age of the patient, male gender, being unmarried, unemployed, chronic disability, living alone, inadequate rehabilitation, poor discharge planning (7, 8, 17-20) and unable to gain access to adequate aftercare resources (21) have also been identified as being associated with readmission.

Furthermore, there is a need to acknowledge the respective predictors for short-term and long-term risks of readmission. Such predictors could allow the identification of patients at immediate risk of readmission after discharge and those still at greater risk of readmission during a longer period of time after discharge. There have been no studies conducted using the same study cohort to compare between readmission close to and distant from discharge. In this study, we conducted a six-year psychiatric hospital-based cohort study to obtain reliable estimates of ≤6 months, 6-12 months, 1-2 years, and >2 years readmission and their significant predictors in first-time hospitalized schizophrenia patients.

The tools used the most for analysis of risk factors for readmission are traditional hypothesis-driven statistical methods such as regression analysis, logistic regression and cox proportional hazards regression (3, 4, 7). However, most models have produced conducting results with poor prediction accuracies that prevent their generalization. In this study, models to predict the risk of readmission were constructed using a decision tree method which decides the most significant independent variable in each stage of predicting dependent variables. We utilized existing hospital data from Prasrimahabhodi Psychiatric Hospital during 2007 and 2012. The development of models that are capable of accurately predicting patients at risk of readmission will enable clinicians, practitioners and policy makers to improve clinical outcomes and increase effective budgeting.

2. Methods

2.1 Data Source

Patient data used for this study was acquired from the Prasrimahabhodi Psychiatric Hospital's database between January 1, 2007 and December 31, 2012. This is a large database of psychiatric patients from all regions. Access to research data was approved by the ethics committee of the hospital's review board. Fields' identifying patients were omitted from the dataset to preserve privacy. The data also underwent several stages of quality checks to delete duplicated records and correct errant variable coding. Inpatient records of all admissions and discharges of inpatients with a primary diagnosis of schizophrenic disorder (ICD-10 diagnosis code F20) diagnosed by an experienced psychiatrist were identified and retrieved from the IT department.

2.2 The Hospital

The Prasrimahabhodi Psychiatric Hospital is a 550-bed tertiary health institution located in the northeast of Thailand. It is one of seventeen mental hospitals belonging to the Thai Department of Mental Health under the Public Health Ministry.

2.3 Sample

The original dataset were collected from medical files of 2,285 schizophrenia patients who were admitted to the Prasrimahabhodi Psychiatric Hospital from January 1, 2007 to December 31, 2012. The patients with readmission during the same hospitalization episode were taken as the study sample. The authors kept the first time episode in 2007 as the index hospitalization. Only the first readmission was used for analysis. Out of the 2,285 patients, 841 (36.80%) were readmissions. The authors excluded 51 cases with duplicate data, 1 case with no information on age and 10 cases of outlier (over 3 standard deviations away from the mean) that had longer period between admissions than 2,000 days. The remaining sample of 778 schizophrenic cases (92.50% of the original readmitted sample) was used.

After cleaning, the dataset included information on the socio-demographic (age, gender, marital status, educaiton and occupation) and clinical characteristics (diagnosis, cause readmission, length of stay and types of payment scheme). Hospital readmission was examined for four different time periods: ≤6 months, 6-12 months, 1-2 years, and >2 years after the initial discharge, respectively. For each of these four time periods, readmissions were considered only for those patients readmitted to hospital with a primary diagnosis of schizophrenia via an emergency department.

3. Decision tree techniques

Decision tree refers to a technique that can formulate a tree structure for classifying instances (22). It provides the most promising results. For this reason, several research studies have effectively utilized this technique to build the prediction model in the medical domain. For example, Bellaachia and Guven (23) utilized C4.5 to build a 5-year breast cancer survivability prediction model from SEER databases. Their results presented that the accuracy of C4.5 decision tree was superior to Neural Networks and Naïve Bayes. Likewise, Yao, Liu, Lei and Yin (24) employed C4.5 to construct a decision tree model for predicting the inpatient length of stay. The result is an interpretable tree-shaped model that identifies a small set of attributes that have high predictive power for the target variable. Their results also demonstrated that this tree model can be understood and accepted better by managers and assist the health care personnel to arrange and make full use of hospital data to enhance the organization profit.

Nowadays C4.5 (25) (called J48 in WEKA) is become the state of the art to generate a decision tree (23, 24, 26). It is used to build a tree structure for classifying a data set related to a class variable consisting of node and leaves. The node model generated from C4.5 represents rules which categorize data according to variables while leaves represent the condition in each rule. The algorithm of this technique starts with partitioning the instances into smaller subsets by utilizing Gain Ratio for selecting the best variable with unequal class labels form a large number of instances. Then recursive approach applies the top-down greedy algorithm to build the tree (22).

4. Evaluation criteria

In order to assess prediction models during fine-tuning and final evaluation, it is necessary to select appropriate evaluation measures. Measures commonly used for classifier performance evaluation include precision, sensitivity/recall, specificity, accuracy and AUC (27). In this study, stratified 10-fold cross validation was utilized to divide data set into training and test session in order to reduce the bias and variance of prediction results in the evaluation process (22, 28). Accuracy, true positive rate and true negative rate are employed.

The accuracy presents the basic performance as the percentage of correctness of outcomes among the test sets. It commonly has values ranging from 0 till 100%. The zero accuracy model is unable to predict the right classes. One hundred percent accuracy refers to the model that can predict all correct classes.

True positive (TP) rate is the evaluation method in binary classification problems to indicate the performance of predicting the patient who will readmit within 6 months, 6-12 months, 1-2 years, and more than 2 years. The true positive rate of prediction models can be interpreted into percentage which has value between 0 and 100%. One hundred percent refers to the best predicting model while 0 refers to the worst predicting model.

True negative (TN) rate is the evaluation method in binary classification problems to indicate the performance of predicting the patient who will readmit within 6 months, 6-12 months, 1-2 years, and more than 2 years. The true negative rate of the prediction model can be interpreted into percentage which has value between 0 and 100. One hundred percent refers to the best predicting model while 0 refers to the worst predicting model.

5. Results

5.1 Characteristics of Sample

Patient characteristics are displayed in Table 1. Among the 778 readmitted patients, 584 (75.06%) were male, and 512 (65.81%) were unmarried. The mean age of patients was 33.74 years old (SD=26.72; range: 12.17 to 71.58). There was a slight majority of patients who were readmitted (54.24%) had primary school level. Fifty-three percent of them were farmer and 25.06% were unemployed. In total, 702 (90.23%) readmitted schizophrenic patients were paid by the Universal Coverage Scheme (UCS) and 5.91% were self-payment.

Three hundred and forty-five patients (44.34%) were diagnosed with schizophrenia, unspecified (F20.9) and 38.69% were diagnosed with paranoid schizophrenia (F20.0). The common reasons for readmission were non-adherence with medication (50.51%) and relapse episode (31.88%). The average LOS was 26.72 days (SD=16.48; range: 1 to 98) while the median LOS was 22 days. Short-term readmissions represented the largest single category, with almost 30% of individuals being readmitted within 6 months of discharge from hospital and 25% after one and two years. The average interval between the first and the second admission was 516.87days (SD=466.27; range: 1 to 1,914).

5.2 Preparation for building the model

In this study, readmission dataset was divided into two subclasses in order to provide short term readmission (called subclass 1) and long term readmission (called subclass 2) prediciton models. Subclass 1 (short - term) is divided into two categories including readmitted to the hospital within 6 months called class 0 and readmitted between 6 and 12 months called class 1. Subclass 2 (long - term) also is divided into two categories including readmitted between 1 and 2 years called class 0 and readmitted after 2 years called class 1. In order to prepare the data for building the model, there are 4 steps involved as follows.

1. Transform each subclass into 0 and 1 using the number of days readmited wtihin 180 days (or 6 months) for subclass 1 and 670 days (or 2 years) for subclass 2 after discharge from hospital;
2. Select the 6 significant variables (except class variable) with Gain Ratio;
3. Automatic removal of misclassified data using the SVM technique; and
4. Resampling the data with the Synthetic Minority Oversampling Technique

The completed analysis data was reduced from 778 to 698 records ensuring data integrity. In subclass 1, class 0 consists of 205 (29.37%) patients and class 1 consists of 138 (19.77%) patients. For subclass 2, class 0 comprises 177 (25.36%) patients and class 1 comprises 178 (25.50%) patients. The significant variables are presented in table 2.

Table 1. Patient characteristics

Characteristics	Coding	Frequency	%
Gender	ged		
Male	1	584	75.06
Female	2	194	24.94
Marital status	mar		
Single	1	512	65.81
Married	2	132	16.97
Divorced	3	22	2.83
Widowed	4	51	6.56
Separated	5	58	7.46
Other	9	3	0.36
Education level	edu		
No schooling	1	19	2.44
Primary	2	422	54.24
Secondary	3	250	32.13
Occupational	4	51	6.56
Faculty	5	32	4.11
Unknown	9	4	0.51
Occupation	occ		
Unemployed	1	195	25.06
Farmer	2	414	53.21
Worker	3	132	16.97
Business owner	4	25	3.21
Civil servant	5	12	1.54
Diagnostic subtypes	dia		
F20.0 (Paranoid schizophrenia)	F20.0	301	38.69
Hebephrenic schizophrenia	F20.1	59	7.58
Catatonic schizophrenia	F20.2	5	0.64
Undifferentiated schizophrenia	F20.3	32	4.11
Post-schizophrenic depression	F20.4	12	1.54
Residual schizophrenia	F20.5	6	0.77
Other schizophrenia	F20.8	18	2.31
Schizophrenia, unspecified	F20.9	345	44.34
Payment methods	pay		
Self-payment	1	46	5.91
Civil Servant Medical Benefit	2	21	2.70
Universal Coverage	3	702	90.23
Social Security	4	8	1.03
Unknown	9	1	0.13

Characteristics	Coding	Frequency	%
Reason for readmission	res		
Non- compliance to medication	1	393	50.51
Relapse episode	2	206	26.48
Relapse episode after received post-discharge treatment from primary healthcare	3	42	5.40
Alcohol/Substance use	4	22	2.83
Referred from primary healthcare	5	12	1.54
Immature discharged due to escape from hospital	6	1	0.13
Length of stay cut-off within60 days	7	1	0.13
Unknown	9	101	12.98
Readmission time interval, median (403 days), mean (516.87± 466.27 days)			
≤6 months	0	228	29.30
6-12 months	1	136	17.48
1-2 years	0	200	25.71
>2 years	1	214	27.51
		mean	Standard deviation
Age (years)		33.74	10.31
Hospital LOS (days), median (22 days)		26.72	16.48

Table 2. Significant variables

No	Subclass 1	Subclass 2
1	Reasons for admission	Diagnosis
2	Diagnosis	Reasons for admission
3	Types of payment	occupation
4	Marital status	Sex
5	Sex	Marital status
6	Occupation	Types of payment
7	Classed	Classed

Table 3. Mean and standard deviation of TP, TN and accuracy of the decision tree readmission prediction models obtained after the 10-fold cross validation

Model	TP%	TN%	Accuracy%
Short term	98.07±0.02	97.03±.021	97.66±0.09
Long term	94.93±0.54	93.33±0.70	93.83±0.47

5.3 Validation of Models

WEKA explorer was used as a data mining tool to evaluate to performance and effectiveness of the model. This is because the WEKA program has well-known experimenter to build and evaluate the prediction models (29). Table 3 summarizes the average values and standard deviation of true positive rate, true negative rate and accuracy obtained for the short and long term subsets after the 10 fold cross validation. The experimental results showed that the true positive rate of schizophrenia readmission prediction models generated from J48 is unstable while the true negative rate is stable but has a high variance especially in round three. However, the true positive rate was significant in result with average up to 99.64% and 97.91% for the true negative rate. Additionally, the experimental results showed that the accuracy of the prediction models is stable. It has an average of up to 98.76% and also less variance. The average accuracy of the short- term was 97.66 and 93.83 for the long- term readmission.

5.4 Schizophrenia readmission prediction models

Our findings display that nearly 30% of schizophrenia patients were readmitted within 6 months after discharge. There were no statistical differences in age, gender, payment methods and LOS. The decision tree for inpatient readmission in figure 1 presents that the patients were readmitted within 6 months with all reasons for readmission except for non-compliance to medication patients. Readmission rate was 13.75% in the relapse episode groups.

Among the non-compliance to medication group if the patients are subtype diagnoses of F20.3, F20.5 and F20.8, they tend to be readmitted within 6 months while the patients who are subtype diagnoses of F20.1, F20.2, and F20.4 tend to be readmitted after 6 months. Additionally, for the F20.0 group, if patients are married and separated status, they tend to be readmitted within 6 months, while patients who are unmarried, divorced and widowed, they tend to be readmitted after 6 months. Besides, for the F20.9 group, if patient are single, married, divorced they tend to be readmitted within 6 months while patients who are widowed and separated tend to be readmitted after 6 months.

The decision tree for inpatient readmission in figure 2 all subtype diagnoses of schizophrenia were associated with number of readmissions after 2 years except for subtype diagnoses of F20.0, F20.1 and F20.9. Among the F20.0 and F20.1 groups, if the patients have relapse episode and problems with alcohol or drugs, they tend to be readmitted before 2 years while F20.9 subtype patients who simply drink alcohol or have drug misuse, they tend to be readmitted before 2 years. In addition, in F20.0 and F20.1 subtypes if the patients had non-compliance issues recorded and separated status, they tend to be readmitted before 2 years.

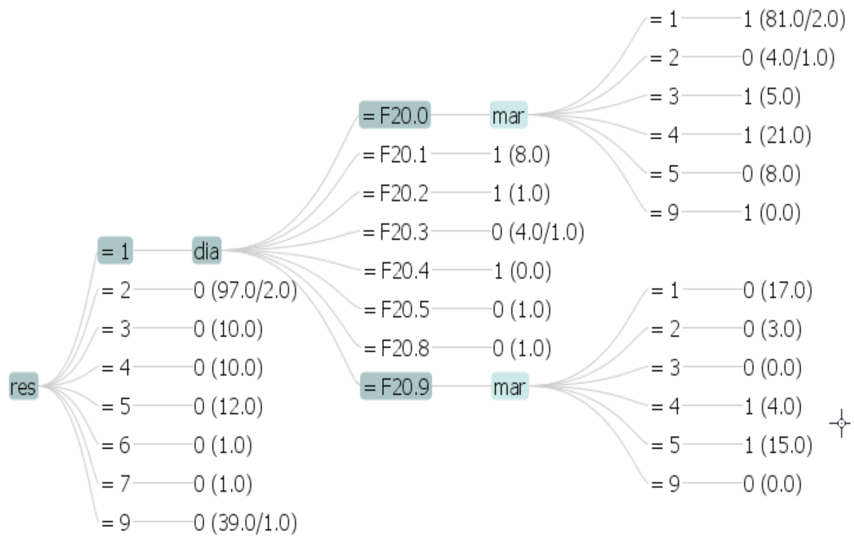

Figure 1. Decision tree model for less than 1 year readmission subclass

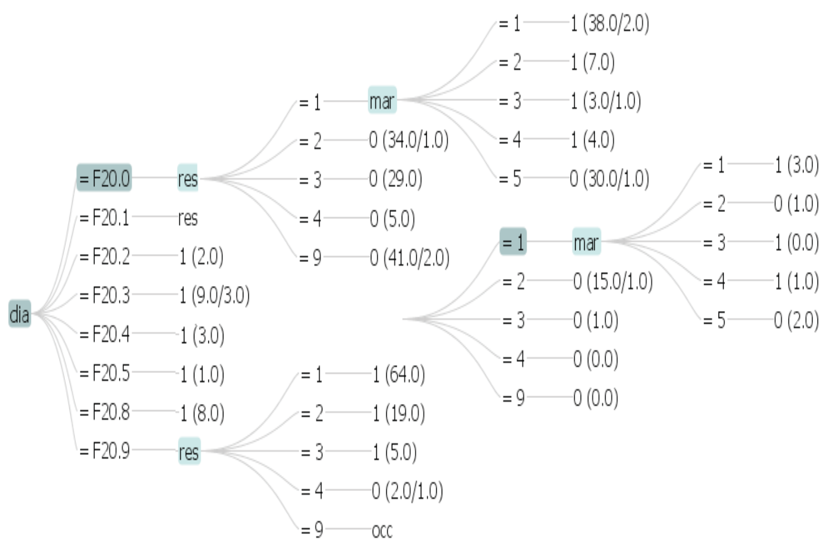

Figure 2. Decision tree model for more than 1 year readmission subclass

6. Discussions

Within the study period, 34.05% schizophrenia patients were readmitted after discharge, a finding that conformed with previous studies (۳۰ ,۵-۳). Also, nearly 30% of these patients were readmitted within 6 months, 25% after 1 year, and 25% after 2 years. Conversely, Lien et al.(19) conducted a comprehensive literature and had found that the readmission rates for psychiatric patients are close to 40% after 1 year, and 50% after 2 years.

In the current study, the predictive variables of readmission were reasons for readmission, subtypes of schizophrenia and marital status. The study did not find any significant difference in the readmission between different age groups, types of payment, education levels, and occupation of patients with schizophrenia. The findings are congruent with those of previous studies that the education status of the patient had no statistically significant correlation with the readmission rate(17). The present results contradicted some of the reports such as a history of aggression(11), a history of multiple admission and younger age group(7, 8, 14), shorter hospitalization and medical comorbidity(9) more likely to be readmitted.

The influence of relapse episode on the risk of readmission is not debated. The findings indicated that relapse episode contributes to the risk of readmission within 6 months even when the patients have high compliance to medication level. This result is consistent with previous studies that risk of relapse rate was 79% in the discontinuation of medicine group and 41% in the maintenance group over 1 year following first-episode psychosis for schizophrenia(27), and mean time the relapse of untreated psychosis was 129 ± 199 days for the first-episode(11) and 163 ± 10.9 days for the second episode(14).

Besides, another finding in this study was time taken for readmission of non-compliance to medication group were different from subtypes of schizophrenia. For example in subtypes of F20.3, F20.5 and F20.8 tended to be readmitted within 6 months while F20.9 tended to be readmitted after 2 years. These findings are consistent with those of Beratis et al.(31) who found that residual schizophrenia (F20.5) was more likely to have a frequency of negative symptoms and multiple admissions and Mortensen et al.(32) who found that readmission risk was lower after the first discharge for the simple (F20.6), paranoid (F20.0), and latent subtypes than for other groups. These results are different from those of Doering et al. (33) who found that diagnosis of residual type (F20.5) decreased the risk of relapse. A possible explanation for this finding could be that F20.3 and F20.5 subtypes are undifferentiated and chronic undifferentiated conditions with negative symptoms may increase in severity. F20.8 subtype, on the other hand, is the other schizophrenia in which has no specific diagnostic criteria (34).

Consistent with the findings of other studies about comorbid substance use and early readmission in patients with schizophrenia (35), the study found that F20.0 and F20.9 subtypes with compliance to medication who had problem with alcohol or drug misuse were more likely to be readmitted before 2 years. The result is also similar to a systematic review of longitudinal studies of Alvarez-Jimenez et al. (36) that persistent substance use significantly increase the risk for relapse in first-episode psychosis.

Some limitations were, first, that the results of the study cannot be generalized, as the data used were of patients from a single hospital. Second, the study could not include all the variables that reflect the state of the patients mentioned in prior research such as the severity of the disease. Third, a high number of duplicate and missing data may have contributed to uncontrolled bias. Present associations do not necessarily correspond to cause-effect relations in the readmission phenomenon. There is the possibility that third variables may influence the observed differences. This may be minimized in further studies if other kinds of variables are taken into account. This study was, however, an initial effort to study the theme of readmission using the data mining technique in Thailand that can increase our understanding of what is important in risk of readmission

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