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A Hybrid Data Mining Approach for Generalizing Characteristics of Emergency Department Visits Causing Overcrowding

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Abstract

Hospital emergency department (ED) crowding has led to an increase in patient waiting times; solving this problem requires a better understanding of the patient behavior. In this work, we adopt decision tree analysis which facilitate the interpretation and understanding of ED visits at Mackay Memorial Hospital, a representative ED in our country. Accordingly, a hybrid data mining approach is proposed to predict patients' length of stay (LOS) and explain their associated characteristics under various LOSs, especially for frequent and non-urgent groups with shorter stays in the ED. With two datasets from the first half-years of 2009 and 2010 containing 40,849 and 43,708 records respectively, we verify the stability and robustness of the proposed approach. We confirm the qualified rules based on patient characteristics and treatment information extracted by the decision tree induction method for the patient population that primarily causes ED overcrowding—patients with non-urgent conditions and short ED stays—in terms of accuracy, medical clinical value and relatedness. We identify that patients with short LOSs demonstrated similar characteristics in visiting ED. We also identify that attributes such as treatment frequencies of laboratory testing, age, and mode of arrival are good indicators for predicting patients' LOSs. The results clarify ED crowding in Taiwan and can guide investigations of ED overcrowding from the perspective of generalizing characteristics of visits. The results serve as a reference model for related ED research in a similar context for clinical decision support.

Keywords: Clinical Decision Support; ED Overcrowding; Hybrid Data Mining; Length of Stay; Patient Characteristics

1. Introduction

The demand for emergency medical services has increased in recent years; therefore, the emergency department (ED) has become the most important, busiest unit within most hospitals, providing emergency care and treatment to patients in need of immediate medical attention (Ashour & Okudan Kremer, 2016; Feng, Wu, &

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Chen, 2017; Hoot & Aronsky, 2008). However, EDs in Taiwan have struggled to accommodate the rapidly increasing patient demand in the past years. This demand may be attributed to the increase in the aging population, to influenza outbreaks caused by new variants of the virus, and so on. According to statistics published by Taiwan's Ministry of Health and Welfare, over the past ten years the total number of ED visits has surged from 9,800,117 in 2006 to 12,333,877 in 2016. Such increases lead to imbalanced and mismatched supply and demand, and ultimately ED crowding, that is, long-term overcrowding in hospital EDs. Accordingly, ED crowding is a national problem that requires a solution.

Hospital ED crowding has led to increased waiting times for patients; thus, solving this problem requires a better understanding of a hospital's patient flow as well as patient behavior (Xu, Wong, & Chin, 2014). Existing research on ED crowding is limited and has tended to focus on the present crowding state. Here, we seek solutions to ED overcrowding by using data mining techniques to analyze patient LOS and exploit management skills to efficiently utilize medical resources. Azari, Janeja, and Mohseni (2012) propose a novel multi-tiered data mining approach to predict patient LOS using a wide range of clustering and classification techniques. Use of this model can promote efficient management of hospital resources and planning for preventive intervention for patients with intense conditions; this study yields insight into the underlying factors that influence hospital LOS.

Based on previous researches (Ho et al., 2001; Liew, Liew, & Kennedy, 2003; Lin, Wu, Zheng, & Chen, 2011; Naghmeh & Somayeh, 2017; Richardson, 2002), we find that most studies that focus on patients who stay for a longer time in the hospital (more than 24 hours) or patients who incur heavy medical costs focus on a specific disease in the ED. In addition, most research focuses on resource allocation and patient flow-management problems in the ED (Delias, Doumpos, Grigoroudis, Manolitzas, & Matsatsinis, 2015; Feng et al., 2017). Although both problems are critical issues in EDs, they rely on a comprehensive understanding of the nature of ED visits. Some works examine the overcrowding situation in EDs in terms of the triage level (Durand et al., 2012; Sadeghi, Barzi, Sadeghi, & King, 2006; Vertesi, 2004). Triage is basically determined by physicians and ED nurses based on the severity of the patient injury or illness. Thus, triage methods include overtriage and undertriage and require more number of reliable indicator to help nurses' make judgement (Ashour & Okudan Kremer, 2016; Chonde, Ashour, Nembhard, & Oukudan Kremer, 2013; Moll, 2010). As such, the triage level is can be only one of the initial indicators to analyze the relationship of patient behavior with ED overcrowding, and we do not use triage information to subjectively investigate patient behavior in the ED.

According to statistical data from the National Hospital Ambulatory Medical Care Survey (NAMCS) in 2010, a national survey about the provision and use of ambulatory medical care services in the United States, approximately 40 percent of patients who visit EDs can be categorized as non-urgent or semi-urgent, i.e., triage level 4 or 5 (Schappert, 1997). Approximately 35 percent of ED patients can be classified as non-urgent or semi-urgent cases according to statistical data from our cooperating hospital in Taiwan. Apparently, there is a similar proportion of non-urgent or semi-urgent cases of all cases in the United States and our research target. Furthermore, according to statistical data from the NAMCS in 2010, approximately 37 percent of patients remain in the ED for less than two hours. Interestingly, in our cooperating hospital in the capital of our country approximately 87 percent of patients remain in the ED for less than two hours. Preliminarily, we infer that based on the statistical data, patients with light signs and short LOS, comprise the major group causing ED overcrowding. Accordingly, we focus on patients who have shorter stays within the non-urgent group in the ED. We aim to understand the behavior of ED patients in the cooperating hospital for all kinds of illness, injury, or condition, as opposed to specific ones. To the best of our knowledge, to date there has been no similar-scale empirical study for generalizing characteristics of the non-urgent ED group by applying data mining techniques in the EDs of our country.

Specifically, one of the research questions for this work is to identify the causes of ED overcrowding and conduct analysis based on individual characteristics of patients to the ED and treatment decisions of doctors: in general, we term this ED patient characteristics and behaviors. We seek to explore the following main research questions:

(1) What types of patients and their associated characteristics and behaviors cause ED overcrowding?

(2) Will the extracted rules generated from the prediction model be helpful in the clinical diagnosis?

Thus, we deconstruct the research questions toward building the three-phases hybrid medical data mining approach into the following three phases.

(1) We preprocess the data and then mine association rules to identify frequent and infrequent ED visits. Accordingly, we identify two types of patients: typical and exceptional behavior. The idea is to consult the attending physicians of the cooperating hospital who pointed out that patients who visit the ED frequently stay for shorter times is worth investigating. We then further investigate whether there is a relationship between the two types of patients and LOSs.

(2) We adopt a k-means clustering approach to classify two types of patients based on different LOS, and then label the cluster results using linguistic terms—long, medium, or short LOS—in order to understand how patient behavior is related to their LOS in the ED. Furthermore, we analyze correlations between various LOS groups and ED crowding conditions.

(3) We build the prediction model, and then extract rules from LOS clusters of two types of patients that have a positive correlation with ED crowding. In this work, we focus on decision-tree models because the tree-like expression is easy for attending physicians to read and interpret. In addition, this use of rules makes it easier to understand ED visits.

Due to the amount and variety of ED patient data and information, as well as the data-mining results, we adopt a dashboard technique for data visualization. In this work, we propose a hybrid ED-crowding data mining and analytical approach and framework for examining ED visits based on various LOSs.

2. Literature Review

In this research, we attempt to identify solutions to ED overcrowding by using data mining techniques to analyze patients' LOSs and exploit management skills for the efficient utilization of medical resources. We reviewed articles that investigated the issues of LOSs in hospitals and articles that adopted data mining techniques in the ED, as shown in Table 1.

Table 1. Data Mining Techniques Applied in the ED

Method (technology)	Research questions	Results	Author (year)
Multivariate Logistic Regression	To identify reasons for patients staying more than 48 hours in an emergency department; factors related to patients, hospital policy, doctors, nurses, demographic data, etc. were included in the model.	Reasons for long-term stays were found to be doctors' decisions and patients feeling that their symptoms were not totally resolved within 48 hours.	Ho et al. (2001)
Bayesian Model	To compare the decision made by an automatic ED triage system with an emergency specialist. Could the ED triage system make decision in the ED?	The triage system can be used for telephone triage and triage in the ED based on the experimental results. But the efficacy of the system is unclear.	Sadeghi et al. (2006)
Neural Network	Improve the neural network model to enhance the prediction of LOS of cardiac patients in intensive care units (ICUs).	The use of the ensemble of network techniques significantly improved the classification accuracy of postoperative cardiac patients.	Rowan, Ryan, Hegarty, & O'Hare (2007)
Multivariate Quantile Regression	Adopt Quantile Regression to predict patients' LOSs in EDs; three phases of ED care, waiting time, treatment time, and boarding time, were estimated.	Providing patients with an expected LOS at triage may result in increased patient satisfaction.	Ding et al. (2009)
Propose a novel multi-tiered data mining approach to predict the LOS using a wide range of clustering and classification techniques.	Emergency department is always overcrowding.	Enable efficient management of hospital resources and planning for preventive interventions for patients with intense conditions.	Azari et al. (2012)

(continued)

Table 1. Data Mining Techniques Applied in the ED (continued)

Method (technology)	Research questions	Results	Author (year)
A computerized asthma detection system that triggered NHLBIadopted	Examined whether an automatic disease detection system increases clinicians' use of paper based guidelines and decreases time to a disposition decision.	Identified 1,100 patients with asthma exacerbations, of which 704 had a final asthma diagnosis determined by a physician-established reference standard. The positive predictive value for the probabilistic system was 65%.	Dexheimer et al. (2013)
Artificial neural network (ANN), Nonlinear least square regression (NLLSR), Multiple linear regression (MLR), Mean average percentage error (MAPE)	What are the variables directly associated with patient arrivals in the ED? What is the nature of association between these variables and patient arrivals? Which variable is the most influential and why?	Provides comprehensive comparison of four types of relative importance (RI) using different computational methods. Aid in strategic decision-making on ED resource planning in response to predictable arrival variations.	Xu, Wong, & Chin (2013)
Naïve Bayes (NB), BayesNet, Support vector machine learner, Decision tree algorithms	Proposed an approach based on supervised classification methods in order to predict the patients' length of stays at the pediatric emergency department.	The results show that BayesNet and NB give the best results. Some of the decision tree methods achieve similar results with Bayes methods which can be suitable for the prediction of patient's length of stay.	Benbelkacem, Kadri, Chaabane, & Atmani (2014)
Non-dominated sorting genetic algorithm II (NSGA II), multi-objective computing budget allocation (MOCBA)	Proposed a multi-objective stochastic optimization model that minimizes patient LOS and MWCs simultaneously to solve medical resource allocation problems in ED systems.	The results show that the NSGA II_MOCBA algorithm generates better and more suitable allocation solutions for ED decision-makers than the current solution implemented in EDs does.	Feng et al. (2017)

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Table 1. Data Mining Techniques Applied in the ED (continued)

Method (technology)	Research questions	Results	Author (year)
Supper vector machine, Ensemble Methods (Baysian Boosting, Ada Boost, Vote, Stacking)	Proposed a model consists of eight different steps of pre-processing and ensemble methods to explore the important factors affecting the LOSs of patients with pneumonia in an Iranian hospital.	The proposed model show how different scenarios of data pre-processing can affect the scale of performance model. The Bayesian boosting ensemble method achieved the best results for predicting patient LOS.	Naghmeh & Somayeh (2017)
Logistic regression, Decision tree, Gradient boosted machine	Adopted three algorithms, i.e., logistic regression, decision tree, and gradient boosted machine (GBM), to build the prediction model for patient admissions based on factors related to hospital admissions.	The results show that the GBM achieved the best prediction capability but logistic regression has better interpretability for predicting hospital admission.	Graham, Bond, Quinn, & Mulvenna (2018)
Multivariate logistic regression model	Adopted a multivariate logistic regression analysis method to evaluate factors predicting hospital admission for three independent groups of patients in the Netherlands.	The results show that the admission probability for ED patients can be calculated using the proposed prediction tool.	Kraaijvanger et al. (2018)

Ho et al. (2001) explored the reasons why patients stay in an emergency department longer than 48 hours. The factors investigated included the patients themselves, hospital policies, doctors, nurses, and demographic data, among others. They adopted logistic regression analysis for 223 samples and found that the reasons for longer stays were most often based on doctors' decisions and patients experiences that their symptoms had not totally resolved within 48 hours. Thus, it is suggested that it is very important in Taiwan to educate patients about self-care in order to decrease the rate of ED stays that exceed 48 hours. Ding et al. (2009) addressed the importance of analyzing the length of stay (LOS) to understand the behaviors of patients in the ED. This research provides good departure points for understanding patient behaviors based on the LOS factor.

Dexheimer et al. (2013) proposed an automatic asthma detection system might prompt providers to initiate treatments earlier and remove the burden of guideline initiation from the triage nurse. Ideally the system would detect asthma patients during the triage process, which is most often the earliest time of a clinician interacting with a patient. It primary objective was to examine whether a workflow-embedded, informatics-supported framework including automatic disease detection system and a locally adapted protocol based on the NHLBI guideline can decrease the time to disposition decision. Xu, Wong, and Chin (2013) adopted a data-driven approach to identify key variables that are the main variables to predict daily patient arrival according to one year's data from a local ED. They use an artificial neural network (ANN) approach to model the association between these contributing variables and daily patient arrivals and finally compare four types of relative importance (RI) of key variables by ANN, i.e., ANN-based RI, thus confirming its superiority over two benchmarking methods in terms of modeling accuracy. The model is helpful for ED decision-making on resource planning and flow adjustment in the process of achieving excellent service from the perspective of patient behavior. Feng et al. (2017) first proposed a multi-objective stochastic optimization model that minimizes patient LOS and Medical Wasted Costs (MWCs) simultaneously to solve the problems of the medical resource allocation in the ED of Taiwan. That is, a multi-objective simulation optimization algorithm that combine NSGA II with MOCBA algorithms was developed to search the Pareto set of non-dominated medical resource allocation solutions by allocating simulation replications/budgets effectively. Finally, the hybrid method, i.e., NSGA II_MOCBA algorithm, generates more accurate and more suitable allocation solutions for ED decision-makers than the current solution implemented in EDs does. However, this research did not select the proper feature automatically in the first step.

Graham, Bond, Quinn, and Mulvenna (2018) used three algorithms, i.e., logistic regression, decision tree, and gradient boosted machine (GBM), to build the prediction model for patient admissions to two major hospitals' EDs in Northern Ireland. The research identified factors related to hospital admissions including hospital site, patient age, arrival mode, triage, care group, previous admissions in the past months and years. The results show that the GBM algorithm achieved the best prediction capability, but decision tree and logistic regression also performed well. The research suggests that practical implementation of the models can help advance resource planning and the avoidance of bottlenecks in patient flow. Kraaijvanger et al. (2018) adopted a multivariate logistic regression analysis method to evaluate factors predicting hospital admission for three independent groups of patients in the Netherlands. Four contributing factors for admission that could be determined at triage were identified as follows: age, triage, arrival mode, and main symptom, and 1,261 visits were included in the derivation of the rule. The results show that the admission probability for ED patients can be calculated using the prediction tool. Both researches provide insights into selecting attributes for predicting patients' LOSs and hospital admission.

Based on previous research, we find that most studies that have focused on patients who stay for a longer time in the hospital. In this research, we will put our emphasis on patients who have shorter stays within the non-urgent group in the ED to have a comprehensive understanding of the nature of ED visits. We aim to understand the behaviors of patients in the ED of the cooperating hospital for all kinds of illness, injury, or condition instead of specific ones. In addition, our proposed framework can help researchers conduct more effective feature selections for further data mining or simulation tasks.

3. Methods

3.1 Hybrid data mining and analytical ED framework

The emergency department (ED) is generally the most important and busiest unit in a hospital, providing emergency care and treatment to patients needing immediate medical attention. However, EDs in Taiwan have not been able to accommodate rapidly the increasing patient demand in recent years. Recently, an increasing number of researchers and practitioners have pointed out the importance of domain knowledge for closing the gap between academic and real domain problems. The domain-driven knowledge discovery approach is proposed to tackle the problem of traditional knowledge discovery in databases (KDD) for finding actionable knowledge (Cao, 2010; Cao et al., 2007). Expert domain knowledge is incorporated into the data-mining process to conduct intelligent data analysis and to transform data into information by utilizing domain knowledge (Bellazzi et al., 2011; Cao, 2010; Cao et al., 2007; Tan, Gao, & Koch, 2015). Carter and Sholler's (2016) study reveals that theory and domain knowledge play an important role during the early stages of data analysis. In addition, the data used to perform an analysis are objective, while the results of the analysis are evaluated by subjective processes. Accordingly, we sought to integrate the domain knowledge of attending physicians in the emergency department (ED) into the data-mining process; to this end, we propose the hybrid data-mining and analytical approach for investigating the phenomenon of ED overcrowding in terms of the available data and domain knowledge.

Basically, we partition the dataset to identify frequent ED patient behavior by the Apriori Algorithm. The algorithm can efficiently analyze relationships among several attributes in terms of rules. This represents one of our contributions in this research to propose a partition method from the perspective of ED-visit behaviors. After identifying frequent ED patient behaviors, we then conduct LOS labeling tasks. This phase may be conducted manually. However, the aim of our research is to explore the variations of LOSs from our available data using the clustering technique to reflect the actual situation of our research target instead of dividing LOSs subjectively. Following the results of Phases 1 and 2, we also select a rule-based approach to predicting patients' LOSs using decision-tree methods. In addition, it can help us identify important rules and attributes to help predict patients' LOSs and explain patients' behaviors. The core of this research is to propose a rule-based approach by deploying the three-phase framework to explain patients' behaviors in the ED. The procedures and the rationale behind the design of the approach are introduced below, as shown in Figure 1.

Phase 1. Data preprocessing and partitioning: In this phase we partition the dataset to identify frequent ED patient behavior in terms of rules. First, we clean the data to eliminate noisy, incomplete, and inconsistent data. We select attributes based on the experience of attending physicians at the cooperating hospital. Table 2 lists the basic demographic attributes of ED patients with descriptive statistical data from January 1, 2010

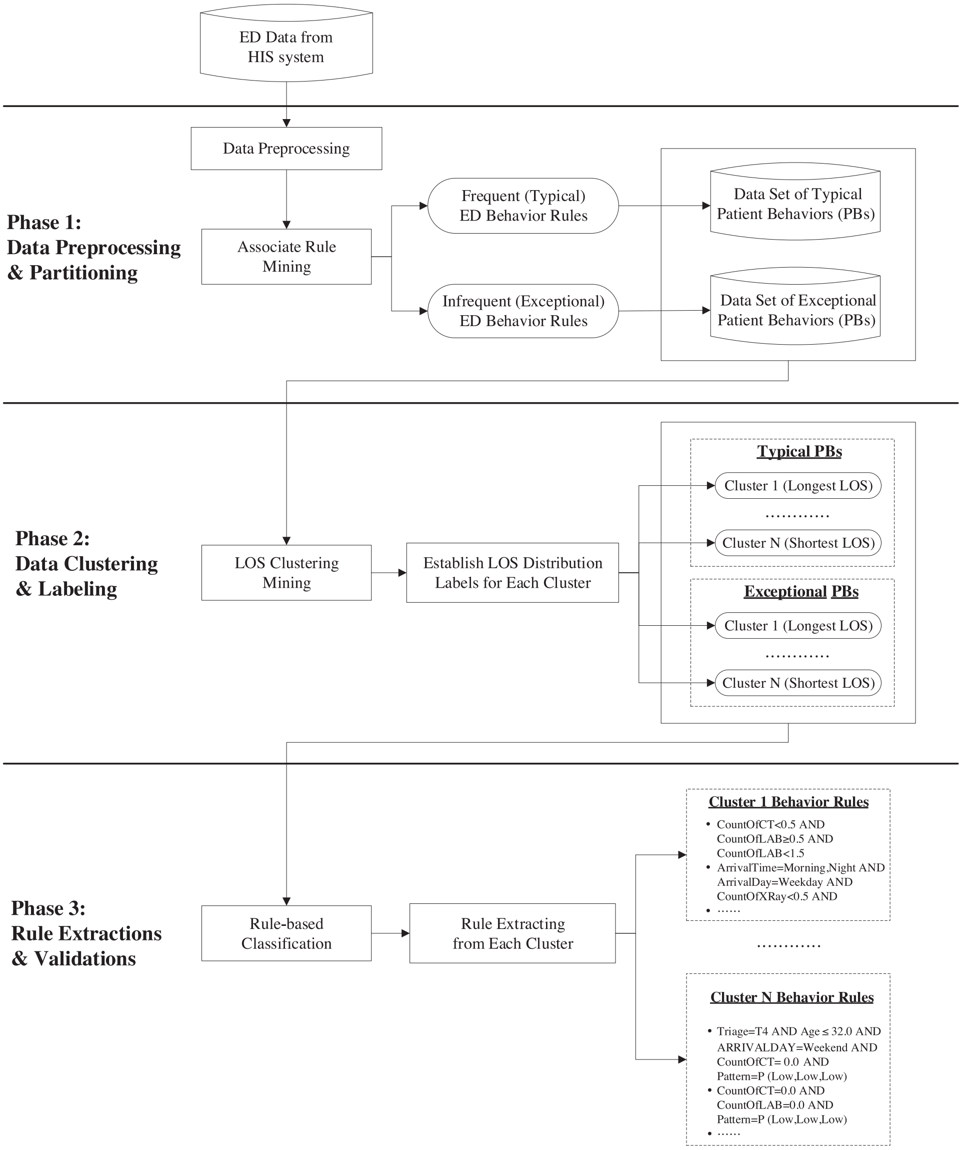

Figure 1. Three-phases Hybrid Data Mining and Analytical Process for ED Overcrowding

to June 30, 2010. The attributes are selected from the hospital's ED database and treated as input variables of an association-rule- mining algorithm; 11 attributes are selected. Then, we use the Apriori Algorithm to partition the dataset into frequent and infrequent ED patient groups. Accordingly, we identify two types of patients: typical and exceptional patients. We then investigate whether

Table 2. Basic Individual and Treatment Attributes with Descriptive Statistical Data of ED Patients (First Six Months of 2010 at Mackay Memorial Hospital)

	Attributes	Domain values	Instances
Basic individual information for treatment	Mode of Arrival	Walk in / Come	9,785
		Referral from other hospitals	953
		Referral from out-patient clinic	545
		Medical referral 119	4,369
		Escorted to the hospital	28,056
	Age	0–12	6,749
		13–18	8,687
		19–25	12,872
		26–40	12,671
		41–64	1,290
		64 above	1,659
		Min: 0, Max 105, Mean: 43.417	
	Arrival Time	Morning (midnight – 8 am)	9,854
		Afternoon (8 am – 4 pm)	15,655
		Night (4 pm – midnight)	18,199
	Arrival Day	Weekday	29,691
		Weekend (Monday through Friday)	14,017
	Temperature	Fever (Above 38º Centigrade)	3,909
		Non-Fever	39,799
Basic treatment information	Pattern	P (X-ray_Level, CT_Level, LAB_Level)	
	X-RAY_Level	Divided into three intervals:	
		Low (0–2)	42,861
		Mid (3–5)	840
		High (6–8)	7
		Min: 0, Max 8, Mean: 0.822	
	CT_Level	Divided into three intervals:	
		Low (0–1)	43,607
		Mid (2)	99
		High (3–4)	2
		Min: 0, Max 4, Mean: 0.089	

(continued)

Table 2. Basic Individual and Treatment Attributes with Descriptive Statistical Data of ED Patients (First Six Months of 2010 at Mackay Memorial Hospital) (continued)

Attributes	Domain values	Instances
LAB_Level	Divided into three intervals:	
	Low (0–5)	43,362
	Mid (6–10)	343
	High (11–15)	3
	Min: 0, Max 15, Mean: 1.093	
Disposition	Ward admission (intensive care unit [ICU] & cardiac catheterization, or surgery)	842
	Inpatient	5,482
	Discharge	33,812
	Death	27
	Non-admission	738
	Against medical advice	2,460
	Refund and discharged	75
	Transfer to another hospital	272
Triage	1 level (T1)	539
	2 level (T2)	6,034
	3 level (T3)	21,788
	4 level (T4)	12,980
	5 level (T5)	2,367
Target	Disposition	

there is a relationship between the two types of patients and LOS to answer our research question. In most work non-urgent patient behavior in the EDs is examined in terms of the triage level (Durand et al., 2012; Sadeghi et al., 2006; Vertesi, 2004). However, in this work we do not use triage information to subjectively partition the dataset. Basically, attending physicians and nurses judge the severity of patient conditions and then determine the priority of patient treatments. Some indicators, for instance the subjective pain score for determining triage levels, are based on the experience of the attending physicians and nurses. Accordingly, we adopt the Apriori Algorithm to partition the dataset from the view point of characteristics and behaviors to determine the major group behind ED overcrowding.

Phase 2. Data Clustering and Labeling: The aim of this phase is to explore LOS variations from our available data using clustering to reflect the real situation of our research target instead of dividing LOSs subjectively. In this phase, we use k-means clustering to cluster the separated dataset of typical and exceptional ED visits into three groups based on the LOS and then label the cluster results using linguistic terms – long, medium, or short LOS. Note that both association rule mining (Phase 1) and clustering (Phase 2) are descriptive data mining methods, which help us to explore the data and then mine interesting associations, trends, or rules. We then analyze the correlation between various ranges of LOS and ED crowding conditions to answer the second research question: Which major group causes ED crowding? Understanding the characteristics and treatment information for the majority of ED visits group will be important to hospitals that aim to resolve ED overcrowding conditions by developing strategies or establishing practice policies.

Phase 3. Rule Extraction and Evaluation: In the remaining phase, we adopt and refine the rule-based classification algorithms J48, CART, and JRip in the Weka data mining tool to build the model and then extract the rules to predict patient LOS. Note that the J48 algorithm is an open source Java implementation of the C4.5 algorithm in the Weka tool. We evaluate the accuracy of each model to select the best one, and we consult with the attending physicians to validate the rules. Furthermore, we preliminary build a rule-based medical decision support dashboard application to help ED staff interact with the system via visualization techniques based on the analytical results.

In this work, we investigate if patients have similar individual characteristics and treatment process between the years in the ED and examine the stability and robustness of each phase of the proposed approach for analyzing ED visits by applying it to datasets with information from 2009 and 2010.

3.2 Data preprocessing and partitioning

We have records of all visits to the ED of the study hospital from January 1, 2010 to June 30, 2010. The data were collected from the HIS system of Mackay Memorial Hospital. As shown in Table 2, they include patients' basic individual and treatment information. The attributes are selected from the hospital's ED database and are treated as variables (attributes) in the association rule mining algorithm.

3.2.1 Data preprocessing

We clean data to minimize noisy, incomplete, and inconsistent data, after which we discretize numerical data, such as age; the number of various types of medical equipment used, such as X-ray and CT machines; the frequencies of laboratory testing, and so on. Notably, the frequency of medical resource use is combined into a treatment pattern and expressed as *P(#* of X-RAYLevel, # of CTLevel, # of LABLevel), which form the derived attribute *Pattern*. This attribute is used because doctors generally keep records when conducting each treatment in a medical order each time to the patient. We also keep the frequencies of three treatment attributes without discretization. The attributes for the algorithm included types of patients' individual information (age, arrival time, etc.), and medical diagnosis (frequencies of LAB-Level, triage, etc.). Accordingly, the data preprocessing attributes include mode of arrival, age, arrival day, arrival time, temperature, triage, frequencies of X-RAY, CT-Level, and LAB-Level, P(# of X-RAY Level, # of CT Level, # of LAB Level), and disposition. Because this research mainly focused on the patients' individual information to the ED to understand the ED overcrowding condition in Taiwan, most selected attributes are belong to this type of attributes. We collected 43,708 of 43,885 valid medical records from Mackay Memorial Hospital covering the first half year of 2010.

3.2.2 Data partition

We propose a novel way to divide an unbalanced dataset by using rules that are extracted from the Apriori algorithm instead of using one or more attributes to partition the unbalanced dataset. These rules are termed patient behavior rules for characterizing of ED visits. Then two types of ED visits—typical and exceptional groups—are identified based on the support and confidence values. Rules with higher support and confidence values are represented as typical rules; others are represented as exceptional rules. Shown in Table 3 are rules with 100% confidence. Here, as shown in the last two columns in Table 3, the target attribute of the rule is the disposition status. Generally, the strength of an association rule is measured in terms of support and confidence.

In Appendix A, we explain how to tune the association rule mining parameters to select rules, that is, the patterns of patient behavior. Due to the diversity of ED patients, and the fact that each rule is composed of multiple attributes, we set the support value from 0.001 to 0.1 and then adjust the confidence value to extract the rules first. Accordingly, there are nine sets of parameters, labeled "A" to "I," as shown in the Appendix A of Table A. To determine the sets of indicators by which to partition the data set, we evaluate the support and confidence, check Pearson's correlation coefficient value, and check the set coverage. As shown in Table A in the Appendix A as well as Table 4, we rename set F to A' and set H to B'. Set A' has the highest Pearson (*R*) and coverage values and the highest number of rules. However, set B', which has only 1,311 rules, yields 77.36% coverage of the original data without loss of precision. Finally, Sets A' and B' in Table 4 are used to extract rules for sampling the data.

Notably, as shown in Table 4, we use the same support and confidence values to partition the dataset for the first half of 2009, and derive

Table 3. Examples of Rules of Patient Behaviors in the ED

Antecedent part (attributes)						Consequent part (target attribute)	
Mode of arrival	T	Age	Pattern	Temperature	Support	Disposition	Support
Escorted in to the hospital	5	19–25	P (L, M, H)	Non-Fever	76	Discharge	76
Medical referral 119	5	13–18	P (L, M, H)	Non-Fever	42	Discharge	42
Walk in / Come	4	19–25	P (L, M, H)	Fever	39	Discharge	39

Note. T = triage

Table 4. Parameter Tuning in Association Rule Mining to Select Rules

Support		Confidence	Rules	Coverage	Pearson (T)	Pearson (E)
DataSet (2009)						
A’’	0.0010	0.6000	31,040	79.42%	0.9679	0.1774
B’’	0.1000	0.7000	1,599	76.74%	0.9552	0.1422
DataSet (2010)						
A’	0.0010	0.6000	38,716	80.28%	0.9469	0.2469
B’	0.1000	0.7000	1,311	77.36%	0.9249	0.1708

similar results for the first half year of 2010. Thus, the two sets of support and confidence values can be applied to other datasets to identify typical and exceptional ED visits. We apply rules from B’ to explain patient behavior, because B’ uses fewer rules to represent most of the population without loss of precision. The next section provides an analysis of the clinical values and the accuracy of the rules extracted by the two sets of indicators.

3.2.3 Types of ED visits

In the following, we discuss the analysis results in Table 5 that identify the typical and exceptional groups from the first half of 2010.

(1) **The typical group:** Clearly, as shown in Table 5, the distribution of the typical group over the five triage levels is similar to that of the total population. The table also shows that whether typical or exceptional, most patients belong to the third triage level. Apart from Triage 3, most of the population of this group belongs to the semi-urgent Triage 4. Interestingly, for the typical group, we find that most patients are “discharged”.

(2) **The exceptional group:** As shown in Table 5, the triage level distribution of the exceptional group is different from that of the total population. Apart from Triage 3, most of this group belongs to the emergency Triage 2. They are characterized by various dispositions but not “discharge.”

(3) Table 6 reveals that, based on our data partition method, the data distribution is smilar between the two years. We confirm that our model is useful and stable in generating representative results for analyzing patients’ behaviors in the ED.

4. Results

We address the process, results, and findings of Phase 2 and Phase 3 of the framework.

4.1 Data clustering and LOS labels

We cluster typical and exceptional patient groups based on LOS. We further divide the data for the two patients types under each LOS to answer our first research question.

Clustering results: We adopt the k-means algorithm to cluster data into three LOS-based groups. The three resultant groups are labeled based on the ED LOS: LOS short (Cluster 0), LOS medium (Cluster 1), and LOS long (Cluster 2). Shown in

Table 5. Typical and Exceptional Groups for Five Triage Levels Compared to Total Population in 2010

	Rule sets	Triage 1	Triage 2	Triage 3	Triage 4	Triage 5
Total		1.23%	13.81%	49.85%	29.70%	5.42%
Typical	A’	0.50%	10.58%	49.83%	**32.73%**	6.36%
	B’	0.45%	9.91%	49.85%	**33.29%**	6.50%
Exceptional	A’	4.04%	**26.08%**	49.92%	18.16%	1.80%
	B’	3.92%	**27.10%**	49.84%	17.43%	1.71%

Table 6. The Percentage of Data for the Shortest LOS for the Overall Data Population in 2009 and 2010

Year	Data set	Cluster 0 (Short)	
		Typical	Exceptional
2009	A’	90.84%	75.02%
	B’	91.02%	71.51%
2010	A’	91.08%	74.98%
	B’	91.16%	71.52%

Table 7 is the average LOS of the typical and exceptional groups of two datasets in the first half of 2010: exceptional patients stay much longer than typical patients, regardless of the LOS cluster. We apply the 2010 clustering results to 2009 and analyze the patient distribution among the three groups based on the kernel values of the 2010 clustering results. Table 8 shows the statistical data of each dataset of the three clusters for typical and exceptional patient groups: the two years clearly have a similar percentage of patients in each cluster. This again indicates that patient behavior differs little between the two years.

Correlation analysis: We analyze correlations based on patient LOS—short, medium and long—of the typical and exceptional groups of the two sets of data in the first half-years of 2009 and 2010, as shown in the Table B in the Appendix B. Cluster 0 clearly is most highly positively correlated with the total population. This suggests that ED overcrowding is caused by patients with shorter LOSs, especially for the typical group. We assume that if the group is highly correlated with the data population, this group could be responsible for the overcrowding conditions. Additionally, investigation of the correlation values of two years confirms similar results for the two years. The attending physician suggested that it would be helpful and interesting to investigate typical patients to understand the hospital ED overcrowding conditions. We extract rules from the group with short LOS to investigate

Table 7. Average LOS of Each Cluster of Two Sets of Data in the First Half Year of 2010 (Unit: hour (hr.))

Type of patients	Sets	Cluster 0 (short)	Cluster 1 (medium)	Cluster 2 (long)
Typical	A’	2hr	18hr	54hr
	B’	2hr	15hr	49hr
Exceptional	A’	4hr	23hr	56hr
	B’	4hr	24hr	57hr

Table 8. Population Distribution of the Three Clusters of Two Sets of Data in the First Half-Years of 2009 and 2010

Year	Sets	Cluster 0 (short)	Cluster 1 (medium)	Cluster 2 (long)
Typical				
2009	A’	90.84%	7.72%	1.44%
	B’	91.02%	8.25%	0.73%
2010	A’	91.08%	7.46%	1.46%
	B’	91.16%	8.04%	0.80%
Exceptional				
2009	A’	75.02%	18.87%	6.10%
	B’	71.51%	20.53%	7.97%
2010	A’	74.98%	17.49%	7.53%
	B’	71.52%	19.40%	9.07%

the characteristics of ED visits for medical treatment and then provide suggestions for medical ED management.

4.2 Experimental design and results for prediction model

We adopt rule-based classification methods to construct the model and extract rules for future prediction in the last phase (Phase 3). We conduct two sets of experiments based respectively on the partitioning and clustering results in Sections 3 and 4.

4.2.1 Experimental setup and evaluation metrics

The input variables are included for all of the attributes in Table 2 in Section 3, which also includes the disposition way. The target attribute here is the LOS attribute which has values of “low,” “medium,” and “high.” That is, we predict the users’ LOS based on the input variables. Table C of Appendix C is a coding sheet for the experiments. For example, if we do not differentiate all datasets based on the types of patients or triages of patients, we name the experiment “overall”. If we conducted an experiment based on patients’ behaviors without considering triage, we name it either “typical” or “exceptional.” If we conducted an experiment considering the triage of the patients with typical behaviors, we name it T_n_*Typical*. We adopt rule-based classification methods to build the model and then extract the rules for future predictions. Thus, *J48, CART,* and *JRip* are selected as methods for each experiment. In this research, we adopt five-fold cross validation using the Weka data mining tool. The tool help us divide the dataset into training and testing data and then run the evaluation five times to evaluate the accuracy of the prediction results.

We adopt accuracy to compare the overall performance among methods. We extend the concept of confusion table to evaluate the capacity of each method to predict the actual label, i.e., LOS short, medium, or long. Note that we only focus on patients with the shortest LOSs, due to this group’s higher correlation with data population as compared to a medium or long LOS. We infer that the group with the shortest LOS is one of the principal group causing ED overcrowding from previously analytical results.

4.2.2 Experiment 1: Typical and exceptional groups with shortest LOSs

Here, we compare the experimental results of the typical and exceptional visits.

Observation 1: The results show that the prediction accuracy is around 87% for each method for the overall population whereas the prediction accuracy is around 91% to 92% for the three decision tree methods for the typical A’ and B’ groups, as shown in Figure 2. That is, the decision tree methods can achieve better prediction results for the typical behavior patients compared to the total population for patients with short LOSs. This indicates that the variety of patients’ behaviors for medical treatment and treatment process for the total population is higher than that of the typical group. Overall, the J48 and CART methods achieve slightly better performance than the JRip method.

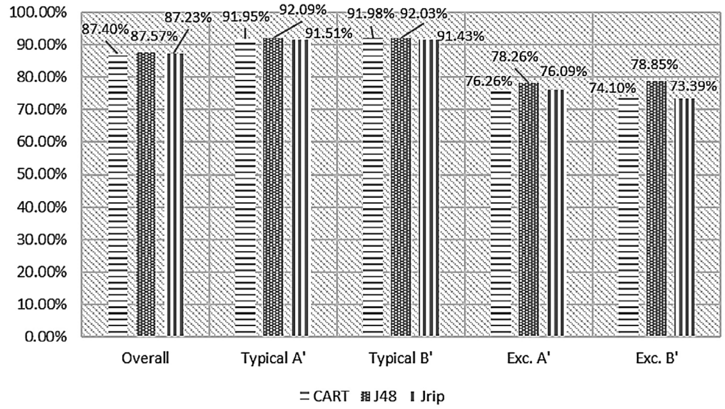

Figure 2. Prediction Accuracy of Overall Population Versus Typical and Exceptional Groups (Exceptional Denoted as Exc. herein)

Observation 2: The prediction accuracy of the two exceptional groups is slightly worse than that of the overall population, as shown in Figure 2. Thus, the prediction accuracy for exceptional groups is low compared to that of the overall population's behaviors. This indicates that the variety of patients' behaviors for medical treatment and treatment process in the exceptional group is higher than that of the typical group and of the total population. Accordingly, it is hard to predict their behaviors. In addition, the J48 method achieves much better performance than the other two methods for the exceptional group.

Observation 3: If we partition the data based on level of triage, we find that all methods achieve better prediction results for typical and exceptional ED visits who belong to Triage 5 (T5) or Triage 4 (T4) compared to patients with other conditions. Thus, non-urgent patients with short LOSs are easy to predict using the decision tree methods. Based on the results of the typical and exceptional groups, we confirm again that non-urgent patients who are frequent ED visitors cause ED overcrowding. The prediction results with and without considering triage for patients with typical and exceptional treatment behavior are shown in Figures 3 and 4.

4.2.3 Experiment 2: Comparisons between years

In this experiment, we compare the results of the two groups of users between the first half-years of 2009 and 2010 to verify the stability and robustness of the proposed approach.

Observations: The accuracy for the typical/exceptional A' and B' groups of the first half of 2009 is better than those of the first half of 2010 on average, as shown in Figure 5(a) and Figure 5(b). Overall, the JRip method achieves the worst results compared to the other two methods used in 2009 and 2010. This indicates that the JRip method is not suitable for the following rule generation process. Notably, the CART and J48 methods are worth investigating. Futhermoe, the typical user group still achives higher accuray than that of the exceptional group. Thus, in the following rule extraction and explanations section, we fouse on the tyipcal one. Overall, the results comfirm that our proposed model with the decision tree method can generate similar results and trends.

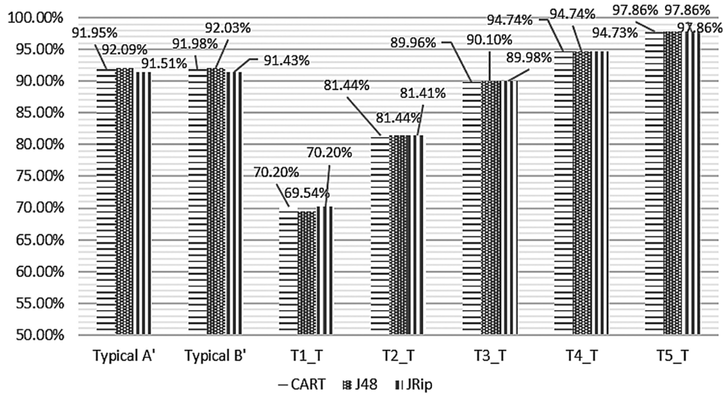

Figure 3. Prediction Accuracy with or without Considering Triage for Typical Groups

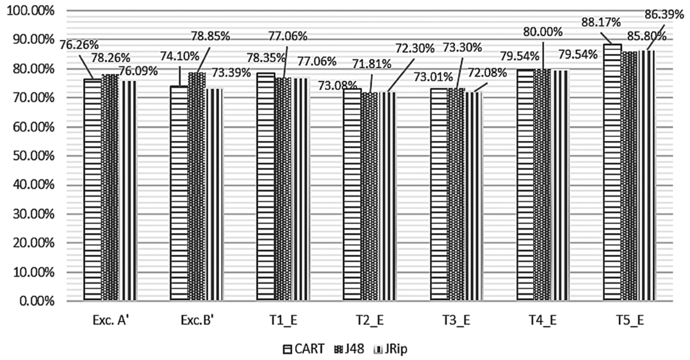

Figure 4. Prediction Accuracy with or without Considering Triage for Exceptional Groups

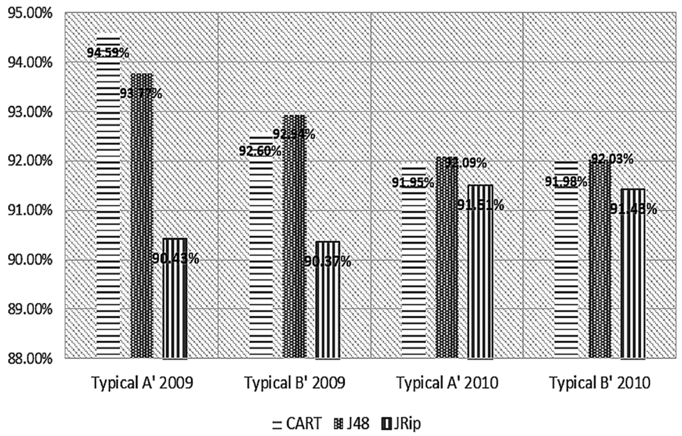

Figure 5(a). Prediction Accuracy between the Years Using the Three Methods for the Typical Groups

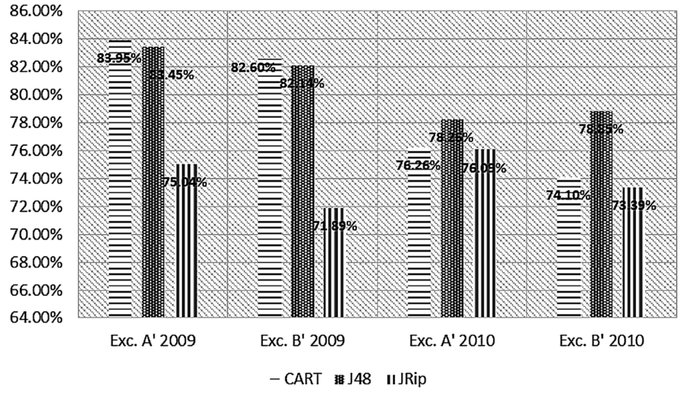

Figure 5(b). Prediction Accuracy between the Years Using the Three Methods for the Exceptional Group (Exceptional Denoted as Exc. herein)

5. Discussion

Herein, we focus on explaining rules extracted from typical group with the shortest LOSs, i.e. frequent and non-urgent group. We don't explain rules extracted from the exceptional group due to low accuracy based on the experimental results. In addition, we don't explain rules under each triage because the prediction results will depend on the triage levels. Triage is basically determined by physicians and ED nurses based on the severity of the patients' injury or illness. Thus, the triage methods could be over- or under-triage (Ashour & Okudan Kremer, 2016; Moll, 2010). We listed the top five typical behavior rules, which are extracted by the J48 method or CART method. We also compared the results of rules extracted from the datasets of the first half-years of 2009 and 2010.

5.1 Examinations of the rules of patients' behaviors

We explain the results of the typical group and also make comparisons between the first half-years of 2009 and 2010 for each group of user.

Discussion 1: The results show that the J48 method has better prediction results on average compared to the CART method, whether in the first half-years of 2009 or 2010. The top rules of the first half-years of 2009 and 2010 are similar, as shown in Tables 9(a), 9(b), 10(a), and 10(b). For the J48 method, three of five rules are the same between the two years. To sum up the three rules, there are 22,573 and 22,152 records in the first half-years of 2009 or 2010, accounting for 55.26% and 46.71% of all data of the first half-years of 2009 or 2010, respectively. For the CART method, four of five rules are the same between the two years. The result shows with high accuracy that the rules are similar between the years. Thus, the results of each method are stable for the typical group. To sum up the three rules, there are 29,144 and 27,087 records in the first half-years of 2009 or 2010, accounting for 71.35% and 61.97% of all data of the first half-years of 2009 or 2010, respectively. This also indicates that the patients who cause ED crowding with similar characteristics and treatment behaviors between the years. According to the proportion of the records based on the rules, this could provide valuable information to explain ED behaviors related to short LOSs for medical management.

Discussion 2: For the J48 method, the rules of the treatment frequencies of X-rays, CT scans, or laboratory testing were equal to or less than two, as shown in Tables 9(a) and 10(a). That finding could indicate that, above all, patients did not linger in the ED when they did not receive any additional treatments, meaning that frequency of treatment is an important factor of LOS. Furthermore, among the major attributes of each rule were frequencies of each treatment, age and mode of arrival (e.g., "Walk-in" or "Escorted into the hospital").

Discussion 3: For the CART method, unlike the J48 method, the rules of the treatment frequencies of X-ray, CT scan, or Laboratory testing are more than one, as shown in Tables 9(b) and 10(b). Furthermore, the rules include a greater number of attributes compared to those of the J48 method. These attributes are frequencies of each treatment, mode of arrival, age, arrival time, arrival day, and level of triage.

Discussion 4: We found that there are no rules included in the value of "Referral from outpatient clinic" of the mode of arrival attribute. This

Table 9(a). Rules of the Typical Group Extracted by J48 from the First Half Year of 2010—(Cluster with the Shortest LOS)

Set	No.	Rule	Occurrence	Accuracy (%)
B'	(1)	Mode of Arrival = "Walk in/come" AND Age ≤ 21.0 AND Count of 0.0 < X-Ray ≤ 1.0 AND Count of CT = 0.0 AND Count of LAB is 0.0 < LAB ≤ 1.0	279	99.29
	(2)	**Count of CT = 0.0 AND Count of LAB = 0.0 AND Pattern = P (Low, Low, Low)**	13,045	99.16
	(3)	**Mode of Arrival = "Walk in/come" AND 21 < Age ≤ 45.0 AND Count of X-Ray = 1.0 AND Count of CT = 0.0 AND Count of LAB is 0.0 < LAB ≤ 1.0**	2,279	96.45
	(4)	**Mode of Arrival = "Escorted into the hospital" AND Age ≤ 40.0 AND Count of X-Ray = 0.0 AND Count of CT = 0.0 AND Count of LAB is 0.0 < LAB ≤ 1.0**	5,093	98.94
	(5)	Count of CT ≤ 0.0 AND Count of LAB ≤ 0.0 AND Pattern = P (Mid, Low, Low)	48	96.00

Table 9(b). Rules of the Typical Group Extracted by CART from the First Half Year of 2010—(Cluster with the Shortest LOS)

Set	No.	Rule	Occurrence	Accuracy (%)
B'	(1)	Mode of Arrival = "Walk in/come, Referral from other hospitals, Medical referral 119, or Escorted to the hospital" AND Triage = "T1 or T5" AND Age < 32.5 AND Arrival Time = "Morning or Night" AND Arrival Day = "Weekday" AND Count of X-Ray is 1.5 ≤ X-Ray < 1.5 AND Count of LAB is 1.5 ≤ LAB < 2.5	14	100.00
	(2)	Count of LAB < 0.5	13,553	99.00
	(3)	Count of CT < 0.5 AND Count of LAB ≥ 0.5 AND Count of LAB < 1.5	13,386	94.75
	(4)	Mode of Arrival = "Walk in/come, Referral from other hospitals, Medical referral 119, or Escorted into the hospital" AND Triage = "T1 or T3 or T4 or T5" AND Age < 32.5 AND Arrival Time = "Morning or Night" AND Arrival Day = "Weekday" AND Count of X-Ray < 0.5 AND Count of LAB is 1.5 ≤ LAB < 2.5	134	89.33
	(5)	Age < 32.5 AND Arrival Time = "Afternoon" AND Count of X-Ray < 1.5 AND Count of LAB is 1.5 ≤ LAB < 2.5	270	88.82

Table 10(a). Rules of the Typical Group Extracted by J48 from the First Half Year of 2009—(Cluster with the Shortest LOS)

Set	No.	Rule	Occurrence	Accuracy (%)
B’	(1)	Mode of Arrival = “Walk in/come” AND Triage = T4 AND 45 < Age ≤ 47 AND Count of X-Ray ≤ 1.0 AND Count of CT ≤ 0.0 AND Count of LAB = 1.0	108	100.00
	(2)	Triage = T4 AND Age ≤ 32.0 AND Arrival Day = “Weekend” AND Count of X-Ray = 1.0 AND Count of CT = 0.0 AND ND Count of 1.0 < LAB ≤ 2.0 AND Pattern = P (Low, Low, Low)	327	100.00
	(3)	**Count of CT = 0.0 AND Count of LAB = 0.0 AND Pattern = P (Low, Low, Low)**	13,196	100.00
	(4)	**Mode of Arrival = “Walk in/come” AND 21 < Age ≤ 45.0 AND Count of X-Ray = 1.0 AND Count of CT = 0.0 AND Count of LAB is 0.0 < LAB ≤ 1.0**	2,121	99.17
	(5)	**Mode of Arrival = “Escorted into the hospital” AND Age ≤ 40.0 AND Count of X-Ray = 0.0 AND Count of CT = 0.0 AND Count of LAB is 0.0 < LAB ≤ 1.0**	7,256	98.79

Table 10(b). Rules of the Typical Group Extracted by CART from the First Half Year of 2009—(Cluster with the Shortest LOS)

Set	No.	Rules	Occurrence	Accuracy (%)
B’	(1)	Mode of Arrival = “Walk in/come, Referral from other hospitals, Medical referral 119, or Escorted into the hospital” AND Triage = “T1 or T5” AND Age < 32.5 AND Arrival Time = “Morning or Night” AND Arrival Day = “Weekday” AND Count of X-Ray is 0.5 ≤ X-Ray < 1.5 AND Count of LAB is 1.5 ≤ LAB < 2.5	332	100.00
	(2)	Triage = “T1 or T4 or T5” AND Age ≥ 76.5 AND Arrival Day = “Weekend” AND Count of X-Ray < 1.5 AND Count of CT < 0.5 AND Count of LAB is 1.5 ≤ LAB < 2.5	95	100.00
	(3)	Count of LAB < 0.5	13,895	97.32
	(4)	Count of CT < 0.5 AND Count of LAB is 0.5 ≤ LAB < 1.5	14,678	94.81
	(5)	Mode of Arrival = “Walk in/come, Referral from other hospitals, or Medical referral 119, or Escorted into the hospital” AND Triage = “T1 or T3 or T4 or T5” AND Age < 32.5 AND Arrival Time = “Morning or Night” AND Arrival Day = “Weekend” AND Count of X-Ray < 1.5 AND Count of LAB is 1.5 ≤ LAB < 2.5	239	89.05

indicates that the patients who are referrals from outpatient clinics do not cause ED overcrowding and are urgent patients.

We will check the *clinical value* (*CV*) and *clinical relatedness* (*CR*) in Section 5.2 to confirm the usefulness and accurcy of the rules.

5.2 Clinical implications of the rules

After discussion with the attending physicians, we adopt measurements for *clinical value* and *clinical relatedness* to evaluate the effectiveness of the rules. The *clinical value* (*CV*) specified whether the rule has clinical reference value; that is, the usefulness of the rules. If the rule does not have clinical reference value, the clinical status condition should be checked based on risk factors like smoking, age, heart rate, and so on. The *clinical relatedness* (*CR*) represents the correctness of the rule, as measured on a scale from 1 to 3, with a higher score indicating a more correct rule. Notably, a *CV* value of 1 means that the rule does not have referential value, while a *CR* value of 1 means that it is hard to determine the correctness of the rule based on its description. In this case, a greater number of clinical evidences are required to confirm the results. We summarize the results of the consultation with the attending physicians as follows. Noted that because the top ranked rules of the first half-years of 2009 and 2010 are nearly the same, we adopted the rules of 2010 to explain the results. In addition, most of the rules extracted from the exceptional group needed more medical resources but did not provide *CV*s according to the judgment of the attending physicians. Accordingly, this research focused on the explanations of rules belonging to the typical group.

Discussion 1: The attending physician's comparison of rules extracted by CART and the J48 method revealed that rules extracted by the J48 method can be correctly adopted at clinics. Based on those rules, we confirmed that treatment frequencies of laboratory testing, age, mode of arrival and day of arrival are important indicators to predict patients' LOSs. For instance, if the day of arrival was "Weekend" and the mode of arrival "Walk-in," then the LOS would be shorter.

Discussion 2 (J48): For Table 11, the attending physician pointed out that rules no. 1 and no. 2 in 2010 of the typical group can be attributed to defensive medical practices. For example, the rules show that the patients had the blood test or X-ray one time, which may have resulted from defensive medical practices. In addition, rules no. 1, no.2, no. 4 and no. 5 in 2009, and rules no. 3, no. 4, and no. 5 in 2010 have high referential values.

Discussion 3 (CART): For Table 11, the rules extracted by the CART method have lower *CV*s, that is, it is hard to determine the patients' conditions solely based on the rules. The patients' condition should be checked face-to-face, e.g., rules no. 1, no. 4, and no. 5. The attending physician also pointed out that it is not reliable to judge a patient's condition based on the level of triage. For example, rule no. 1 includes T1 and T5 triages. The huge difference between triage levels may be due to the patients' emotional instability or a clouding of consciousness. Thus, the doctors should determine the condition at a clinic but cannot infer it by the rule. In addition, triage is not a good attribute to judge the patient's LOS.

Table 11. Clinic Scores of Rules for the Typical Group-J48 and CART Methods

Evaluations of rules for the typical group-J48 method [a]							
2010 Set	No.	CV (1-3)	CR (1-3)	2009 Set	No.	CV (1-3)	CR (1-3)
B'	1	2	3	B'	1	3	3
	2	2	3		2	3	3
	3	3	3		3	2	3
	4	3	3		4	3	3
	5	3	3		5	3	3
Evaluations of rules for the typical group- CART method [b]							
2010 Set	No.	CV (1-3)	CR (1-3)	2009 Set	No.	CV (1-3)	CR (1-3)
B'	1	1	3	B'	1	1	3
	2	3	3		2	1	3
	3	3	3		3	3	3
	4	1	3		4	3	3
	5	1	3		5	1	3

[a]Rules are shown in Tables 9(a) and 10(a). [b]Rules are shown in Tables 9(b) and 10(b).

5.3 The views of the R-MDS visualization portal

We aim to build a decision support system (DSS) by visualizing the extracting rules and the statistical data in the proposed rule-based medical decision support (R-MDS) visualization portal. The doctors, and clinical staff can input patients' attributes, i.e., triage, age, treatment, etc., via the developed R-MDS dashboard application, which can graphically present the statistical results, rules, and the ED-related information for further interactions with the systems. The related patients' data and the rules extracted based on the proposed ED data mining process are stored in the ED rule-based knowledge base. We have built the visualization portal in this project using Silverlight. Thus, we can use web services via a Silverlight application to elicit the results from the ED rule-based knowledge repository and the ED database. We have built a front-end interface using Rich Interactive Application (RIA) services with Silverlight and using the C# and the .NET framework to implement the back-end services. Technically, user interfaces are declared in Extensible Application Markup Language (XAML), a declarative XML-based language, to manipulate the controllers easily and efficiently. In our preliminary design, there are three views (interfaces) provided in the developed portal, as follows: report view, diagnostic view, and maintenance view. We introduce the three views briefly in the following.

Report View: The interface shows the results based on the user's queries. There are three kinds of charts used, i.e., line, bar, and pie charts, to showing the descriptive statistical data of the ED.

Diagnostic View: Basically, users can append a new instance via the diagnostic view. In addition, the interface shows the matched inference rules based on the criteria set by users via the interface, as shown in Figure 6. The rules will be ranked based on their scores, i.e., to what degree they match the user's setting criteria. The user can also check the statistical data in the diagnostic interface or switch to the report view to conduct further explorations. We use *precision* and *recall* metrics to measure the types of retrieved (i.e., recommended) rules. The system allows the administrator to set the threshold that defines the high or low precision or recall.

The equations of *precision* and *recall* are:

$$precision = \frac{Number\ of\ attributes\ of\ the\ retrived\ rule\ matched\ with\ the\ user's\ query}{Number\ of\ attributes\ of\ the\ retrived\ rule} \quad (1)$$

$$recall = \frac{Number\ of\ attributes\ of\ the\ retrived\ rule\ matched\ with\ the\ user's\ query}{Number\ of\ input\ attributes\ (user's\ query)} \quad (2)$$

Table 12 shows the three types of retrieved (i.e., recommended) rules defined in the research: perfect rules, specific rules, and broad rules. First, when the retrieved rule has both higher *recall* and *precision* than the setting threshold, the rule is a perfect rule for matching the user's query. Second, any specific rule denotes that the value of each attribute of the retrieved rule can match most of the value of each attribute of the user's query, although the retrieved rule might contain some attributes not included in the user's query. Accordingly, a retrieved rule with high *recall* but

Figure 6. Snapshot of the Diagnostic Interface

Table 12. Types of Retrieved Rules based on Precision and Recall

	High recall	Low recall
High Precision	Perfect rules	Specific rules
Low precision	Broad rules	Non relevant rules

low *precision* is a broad rule. Third, by contrast, if a user's query contains too many attributes, then the *recall* of the retrieved rule might be low, meaning that fewer attributes in the retrieved rule might not match the user's query. A rule with high *precision* but low *recall* is a specific rule. Both board and specific rules belong to a partial match of the user's query. As Figure 7 illustrates, the system displays the types of rules with associated *precision* and *recall* to help the user to check the value of each rule. The system does not recommend rules with low *precision* and *recall*.

Maintenance View: The maintenance view includes the rule authority management, user management, global message management, and rule management. It helps system administrators conduct basic but important system management tasks. Figure 8 shows the rule management interface of this view.

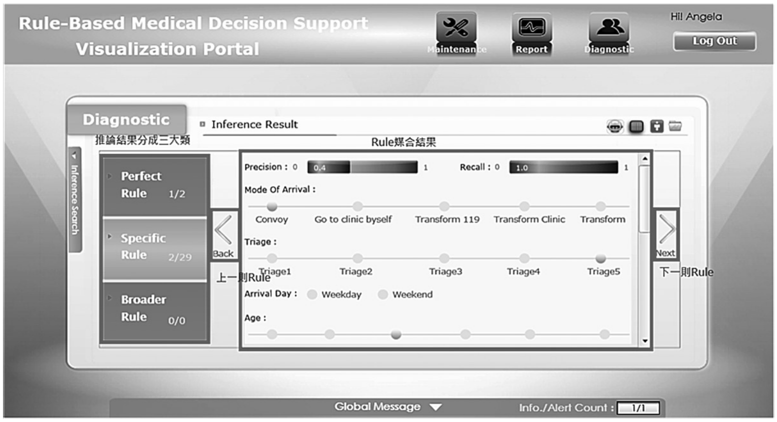

Figure 7. Snapshot of Types of Rules

Figure 8. Snapshot of the Rule Management Interfaces

6. Conclusion

In this work, we propose a novel approach and framework for mining ED patient behavior in terms of different LOSs: a rule-based data mining and analytical approach for ED decision support. The major contributions of this research are threefold.

- *The proposed approach for mining two types of ED visits:* LOS variants of ED patients are diverse; thus, collecting numerous patient records to conduct an empirical study is a challenging task. We integrate data mining and domain knowledge to conduct this research, leveraging the benefits of both perspectives for application in the context of medical informatics. Accordingly, we propose a hybrid analytical approach and build a predictive model with explanatory capability to assist a hospital ED to better understand its overcrowding conditions. We confirm the stability of the each phase of the proposed approach for analyzing ED visits by applying it to datasets with information from 2009 and 2010. Our cooperating hospital is the second-largest ED, and a representative institute in the capital of our country. That is, it is not a local hospital. Thus, the research results explain the characteristics of ED visits and offer a reference approach for research on overcrowding in EDs in Taiwan. To our knowledge, no similar-scale empirical study has been published for non-urgent ED patient behavior in Taiwan EDs. Technically, our proposed framework and approach can help researchers conduct more effective feature selection for further data mining or patients' flow-simulation tasks.
- *The accuracy of the proposed approach for typical ED visits:* We confirm the accuracy of the rules for the patients with minor signs of diseases and short LOSs as the primary group causing ED overcrowding. Our evaluation reveal that typical patients in the semi- or non-urgent groups positively correlated with ED crowding. As mentioned earlier, in our cooperating hospital, approximately 87 percent of patients remain in the ED for less than two hours. We highlight that this does not represent a special case in our country but rather a special condition in comparison to other countries. First, our country has used National Health Insurance models since the mid-1990s. Moreover, our country's EDs cannot reject any patient who visits the ED, and there are no clear regulations regarding the use of ED resources by the public. Accordingly, even non-urgent patients use EDs as a way to see a physician in Taiwan. Thus, understanding the characteristics and treatment information for the majority of ED visits group is an important and emergent task in our country in order to resolve ED overcrowding by developing strategies or establishing practice policies.
- *The clinical and practitioner implications of rules:* We present results with attending physicians to confirm the clinical value and relatedness of the extracted rules. Since patients with short LOSs demonstrated similar treatment information and behaviors in visiting EDs, we identify important attributes such as laboratory testing, age, arrival day and mode of arrival as good indicators for predicting patients' LOSs. Interestingly, most of the key attributes belong to the patients' behaviors to the ED. That finding indicates that patients' individual behaviors—for instance, using EDs as a way to

see a physician—are important factors of ED overcrowding. We examined the condition from the perspectives of ED visits and hospitals. We would advise the patients with minor signs or illness can utilize self-diagnostic platforms to confirm the necessity of going to an ED or instead looking for a suitable clinic. In addition, patients can check the ED's condition using an app offered by the hospital to decide if they should go to the ED immediately or register online before going to the hospital. For example, the National Health Insurance Administration Ministry of Health and Welfare launched an app to provide public inquiries with information about the number of ED visits, ED crowding conditions, and so on at all levels of first-aid duty hospitals in Taiwan. In addition, educating the public to value limited medical resources, use them appropriately, and leave ED visits for those who are truly in need of them remains a critical and important task. Hospitals can implement several policies to help alleviate ED overcrowding caused by non-urgent patients. One of the applied policies is to differentiate ED visits based on urgent and non-urgent patient groups in order to determine the priority of care and the location of treatment. That is, triage levels 1 and 2 can have treatment with higher priority. Furthermore, hospitals can have clinics that are designed to respond specifically to patients with non-urgent medical needs and hospitals can consider opening clinics on holidays, e.g., Chinese New Year, to avoid the ED to be packed with patients. For patients in need of urgent medical attention, a hospital's ED could have temporary wards to avoid too many patients waiting in the ED for hospital admission. However, these strategies should be examined carefully in order to develop a comprehensive policy in the near future. In general, the process in the ED involves a waiting period, triage, ED treatment, boarding, and IU treatment. The ED medical staff will evaluate the patient's condition in this phase of ED treatment to determine whether it is necessary to admit the patient to the hospital or discharge the patient. To shorten the boarding time and alleviate ED overcrowding, we will continue to research the key factors of inpatient and discharged ED visits for predicting whether a patient will be admitted to the hospital in the triage phase, i.e., the early stage of the ED process. In the future, given the importance of grouping and prioritizing ED patients (Ashour & Okudan Kremer, 2016) related to shortcomings in the current triage system, we plan to apply our results to investigate grouping and prioritizing levels of ED patients beyond the current triage method in order to improve ED care.

We deploy R-MDS (i.e., a rule-based medical decision support visualization portal), which graphically presents statistical results, rules, and other ED-related information. Aligned with that research, we evaluate the effectiveness of the visual-based interface to help domain experts to validate results and use feedback from results to refine rules. Wilk et al. (2013) develop clinical-decision support systems (CDSSs) for use in the ED that assist physicians in making decisions at the point-of-care. The research use the O-MaSE (Organization-based Multi-agent System Engineering) method to map each task from the task-based emergency workflow to a specific system goal, and then to associate each of these goals with architectural components (agents). The research provides us with a reference to improve our system based on the task-based support architecture with the backbone of task-based emergency workflow for decision support. Finally, the ultimate objective of this long-term research is to help the ED better understand ED overcrowding in our country, build a precise prediction model, and develop an interactive DSS for Mackay Memorial Hospital to help doctors, nurses, and clerks make better, more informed decisions.

Protection of Human and Animal Subjects

Human and / or animal subjects were not included in the project. We have passed the review from the institutional review board approval of clinical trial of Mackay Memorial Hospital in Taiwan.

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Appendix A
Parameter Testing of Data Partition Using Apriori Algorithm

Here, we explain how we use the Apriori algorithm to tune the parameters for data set partitioning. In Table A, the "#Rule" column denotes the number of rules and the "Coverage" column denotes the percentage of data sampled based on the rules. In addition, the Pearson (R) column denotes the Pearson's correlation coefficient between typical ED visits and the data population, whereas the Pearson (E) column denotes the Pearson's correlation coefficient between those with exceptional characteristics and the data population. To determine the sets of indicators by which to partition the data set, we first remove those sets in which Pearson (R) or Pearson (E) are negative values, as this denotes that data selected by the rules is negatively correlated with the data population. As it would be improper to use these sample data, sets A and D are removed. Next, we select those sets in which Pearson (R) is above 0.8 and then select that set with the highest coverage. As shown in the Table A., this is set F, which has the highest number of rules compared to the other sets. Then, we select the set with the second highest coverage but fewer rules as compared to set F. Thus, we select set H, which has only 1,311 rules but yields 77.36% coverage. Finally, Sets F and H are used to extract rules for sampling the data.

Table A. Sets of the Indicators to Extract Rules

NO.	Support	Confidence	#Rules	Coverage	Pearson (R)	Pearson (E)
A	0.0100	0.8500	7,345	62.26%	0.8708	-0.0658
B	0.0100	0.7000	12,175	77.36%	0.9249	0.1708
C	0.0100	0.6000	14,136	77.36%	0.9249	0.1708
D	0.0010	0.8500	20,554	62.26%	0.8708	-0.0658
E	0.0010	0.7000	32,709	77.89%	0.9319	0.1980
F(A')	0.0010	0.6000	38,716	80.28%	0.9469	0.2469
G	0.1000	0.8500	358	54.82%	0.8637	0.5005
H(B')	0.1000	0.7000	1,311	77.36%	0.9249	0.1708
I	0.1000	0.6000	1,327	77.36%	0.9249	0.1708

Appendix B
Correlation Analysis of Patients with Different LOSs

Table B. Correlation Analysis of Patients with Different LOSs With Total Population in the First Half-Years of 2009 and 2010

Year	Sets	Cluster 0	Cluster 1	Cluster 2
Typical				
2009	A’	0.9239	-0.0430	0.1385
	B’	0.9197	0.1069	0.2197
2010	A’	0.8699	-0.0227	0.0853
	B’	0.8650	0.0965	0.1746
Exceptional				
2009	A’	0.3736	-0.1953	-0.0015
	B’	0.3735	-0.2527	0.0321
2010	A’	0.3458	-0.1830	0.1180
	B’	0.3213	-0.2226	0.0990

Appendix C
Coding Sheet for Experiments

Table C. Coding Sheet for Experiments

	Codes	Descriptions
(1) Level of Triage	Overall	Data Population
	T1	Resuscitation
	T2	Emergency
	T3	Urgent
	T4	Semi-Urgent
	T5	Nonurgent
(2) Treatment Behaviors	Overall	Data Population
	Exceptional	Exceptional group
	Typical	Typical group
(3) Prediction Models	J48	Decision Tree-J48
	CART	Decision Tree-CART
	JRip	Decision Tree-Jrip
(4) Evaluation Method	C	10 fold cross-validation
(5) Prediction Label	Cluster 0	Short Length of Stay
	Cluster 1	Medium Length of Stay
	Cluster 2	Long Length of Stay

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基於混合式資料探勘方法歸納急診室壅塞之病患特徵

A Hybrid Data Mining Approach for Generalizing Characteristics of Emergency Department Visits Causing Overcrowding

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摘　要

醫院急診室壅塞將增加病患等待時間，因此若能了解病患就診行為將可減緩急診室壅塞問題。本研究試圖以決策數歸納分析方式瞭解與解釋病患就診行為，故提出混合式資料探勘方法以預測病患的滯留時間（length of stay, LOS）與解釋不同LOS下病患的相關就診行為，其中就診頻繁的非緊急且LOS短暫的病患為本研究重要分析目標。本研究取得合作醫院「臺北馬偕紀念醫院」2009與2010年急診室病歷，分別為40,849與43,708筆資料以進行實證研究，兩組獨立的資料有助於研究驗證所提方法之穩定性與強健性。研究基於病患個人特徵與診治行為，以決策數歸納並確認非緊急且LOS短暫的病患為造成急診室壅塞之重要族群，研究並分別透過實驗正確率、臨床價值性與相關性，萃取出高參考價值的病患行為規則。研究發現LOS短暫的病患具有相似的行為；此外，研究歸納抽血（Lab）次數、年紀與入院方式為預測病患滯留時間重要指標。研究主要由病患特徵以歸納與釐清造成臺灣急診室壅塞之原因，並提供具備相似背景之急診研究進行臨床支援決策的參考模型。

關鍵字：臨床醫療決策、急診室壅塞、混合式資料探勘、滯留時間、病患特徵

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