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Predicting Hospital Patients' Admission to Reduce Emergency Department Boarding

Mohammadmahdi Moqri
University of Massachusetts Boston

PREDICTING HOSPITAL PATIENTS' ADMISSION TO REDUCE EMERGENCY DEPARTMENT BOARDING

A Thesis Presented

by

MOHAMMADMAHDI MOQRI

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PREDICTING HOSPITAL PATIENTS' ADMISSION TO

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Approved as to style and content by:

____

Davood Golmohammadi, Assistant Professor

Chairperson of the Committee

____

Peng Xu, Associate Professor

Committee Member

____

Ehsan Elahi, Assistant Professor

Committee Member

____

Philip L. Quaglieri, Dean

College of Management

____

Atreya Chakraborty, Associate Professor

Coordinator, Master's Thesis Program

ABSTRACT

PREDICTING HOSPITAL PATIENTS' ADMISSION TO REDUCE EMERGENCY DEPARTMENT BOARDING

August 2013

Mohammadmahdi Moqri, B.S.., Sharif University of Technology
M.S., Iran University of Science and Technology
MBA, University of Massachusetts Boston

Directed by Assistant Professor Davood Golmohammadi

Emergency Department (ED) boarding – the inability to transfer emergency patients to inpatient beds- is a key factor contributing to ED overcrowding. This paper presents a novel approach to improving hospital operational efficiency and, therefore, to decreasing ED boarding. Using the historic data of 15,000 patients, admission results and patient information are correlated in order to identify important admission predictor factors. For example, the type of radiology exams prescribed by the ED physician is identified as among the most important predictors of admission. Based on these factors, a real-time prediction model is developed which is able to correctly predict the admission result of four out of every five ED patients. The proposed admission model can be used by inpatient units to estimate the likelihood of ED patients' admission, and consequently, the number of incoming patients from ED in the near future. Using similar prediction models, hospitals can evaluate their short-time needs for inpatient care more accurately.

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CHAPTER 1

INTRODUCTION

Scholars have named Emergency Department (ED) crowding an “international crisis” and a “ticking time-bomb” because it is a universal problem with severe consequences (Hoot, 2008; Hodgins et al., 2011). Studies have reported ED overcrowding in almost every state in the United States (Olshaker, 2006). In a survey of 575 EDs in all 50 states, 91% of ED directors reported overcrowding as a problem, resulting in all ED beds occupied, full waiting rooms, and patients bedded in hallways (Derlet, 2001; Olshaker, 2006). ED crowding is associated with increased mortality, longer times to treatment, and higher patient frustration that can result in patients leaving without being seen (Olshaker, 2006; Bernstein, 2008; Liu, 2011).

Some of the factors contributing to ED overcrowding in recent years in the United States include downsizing in hospital capacity, the closure of a significant number of EDs, and increased ED visits (Olshaker, 2006). Studies show that ED boarding – the inability to transfer emergency patients to inpatient beds- is one of the most important factors (Bair, 2009; Hodgins et al., 2011) or the most important factor (Asplin, 2003; Olshaker, 2006) contributing to ED overcrowding.

Besides causing overcrowding, ED boarding has several other negative impacts. Boarding of inpatients is directly associated with ambulance diversion (Asplin, 2003;

Leegon, 2005; Leegon, 2006; Olshaker, 2006; Hoot, 2008). ED Boarding can also lead to higher mortality, increased wait time and length of stay in hospital, lower staff to patient ratios, lower patient satisfaction, increased risk of treatment error, and poorer treatment outcomes (Fatovich, 2005; Olshaker, 2006; Chalfin et al., 2007; Hoot, 2008; Pines, 2008; Hong et al., 2009; Liu, 2009; Forero, 2010; Forero, 2011). In addition, ED boarding can negatively affect other parts of the hospital such as medical/surgical wards, ICUs, operating rooms, and radiology and pathology units (Forero, 2011). In 2006, the Institute of Medicine (IOM) reported that ‘‘boarding not only compromises the patient’s hospital experience, but adds to an already stressful work environment, enhancing the potential for errors, delays in treatment, and diminished quality of care” (Liu, 2011). While research on the causes and consequences of ED boarding has been identified as the most important area for immediate research and operational change (Kellermann, 2000; Asplin, 2003; Fatovich, 2005; Olshaker, 2006), half of EDs in the United States continue to report extended boarding times for patients, and 22% of all ED patients are boarding at one time (Hoot, 2008).

Many factors contribute to ED boarding. Major increases in hospital admissions and ED presentations with no increase in the capacity of hospitals, a lack of inpatient beds, inadequate or inflexible nurse to patient staffing ratios, inefficient diagnostic services, delays in discharging hospitalized patients, and delays in cleaning rooms after patient discharge have been reported as possible sources of ED boarding (Asplin, 2003; Forero, 2010; Forero, 2011). Additionally, hospital operational inefficiency and lack of communication between inpatient units and ED is a major contributor to ED boarding

(Rabin, 2012). Common solutions proposed for ED boarding and crowding are as follows.

- Increasing inpatient capacity (Olshaker, 2006)
- Altering elective surgical schedules (Powell et al., 2010)
- Moving admitted ED boarded patients to inpatient hallways (Powell et al., 2010),
- Improving hospital operational efficiency (Rabin, 2012).

No single one of these solutions is always the best option. Increasing hospital capacity can mitigate the problem of overcrowding in most cases, but it is a strategic decision that requires significant time and investment. Altering elective surgical schedules can present a temporary solution that only provides more short-term surgical capacity and does not help patients in need of other critical care (such as ICU). Moving patients to hallways is a controversial solution. While some scholars and ED managers argue in favor of this solution (Young, 2007; Viccellio, 2009), others believe it may worsen the problem of ED boarding (Olshaker, 2006). I believe improving hospital operational efficiency is the key answer to ED boarding. Operational improvement can provide a quick, low-cost, practical solution to ED boarding. For example, Amarasingham et al. (2010)'s study shows that an improvement in the admissions protocol in a hospital in Dallas, Texas, saved around 28,000 hours in ED boarding times over the course of one year.

This study explores a scientific approach to improving hospital operational efficiency and, thus, to decreasing ED boarding. The goal is to develop a real-time prediction model capable of estimating the likelihood of admission of each ED patient to the hospital (as inpatient) with a high level of accuracy. These estimations of admission results can be used by inpatient units to estimate the number of incoming patients from the ED. Using the proposed prediction model, hospitals can more accurately evaluate their short-time needs for inpatient cares. Better estimation of required resources may improve hospital preparedness to provide care for patients arriving from EDs, quicken the process of inpatient bedding, and consequently help reduce ED boarding.

1-1- Research Questions

Quantitative analysis of ED patient information for the purpose of developing an admission prediction model is a novel research area. Few studies have investigated the relationship between patient information and the likelihood of admission in the literature. Based on the available records of patients' historic information, I try to answer three main research questions about these relations.

1. What are the important predictor factors of ED patients' admission to the hospital (as inpatient)? Based on the data, possible relationships between patient information and the likelihood of hospital admission for inpatient care are explored. Limited to the patients' data, I focus only on patients' demographic and clinical information available at the ED.

2. Is there any frequently observed pattern among the characteristics of admitted patients?" Possible patterns can be translated into rules of thumb for admitting new patients.

3. Can an admission prediction model based on demographic and clinical predictor factors accurately estimate the likelihood of patient admission?

By addressing these three research questions, I identify the important factors affecting patient admission result and use them to discover admission patterns and to develop an accurate admission prediction model.

1-2- Literature Review

Existing studies vary in target groups of patients, objectives, and methods. Some studies focus on a particular group of ED patients (Sadeghi et al., 2006; Considine et al., 2011), while others consider all ED encounters. Study objectives include identifying important factors in admission (Considine et al., 2011), identifying high-risk patients for admission (Ruger et al., 2007), developing hospital admission prediction models (Leegon et al., 2005; Leegon et al., 2006; Li and Guo, 2009), and estimating the total number of ED-to-inpatient-unit admissions (Peck et al., 2012). The most common methods used in these studies are Logistic Regression (Sadeghi et al., 2006; Ruger et al., 2007; Li and Guo, 2009; Sun et al., 2011; Considine et al., 2011) and Bayesian Networks (Leegon et al., 2005; Sadeghi et al., 2006; Li and Guo, 2009; Peck et al., 2012). A brief review of these studies, including their settings, methods, and results, are as follow.

Sadeghi et al. (2006) focus only on ED encounters with abdominal pain. They extract data such as age, gender, and symptoms from the charts of ninety patients with non-traumatic abdominal pain and develop a prediction model using the Bayesian network method. Their prediction model is able to predict the admission results of this patient group with an accuracy level comparable to emergency specialists. Although their model's accuracy level is promising, the targeted patient group (patients with abdominal pain) limits the applicability of their study. Considine et al.'s (2011) research is another example of studies with a specific target patient group. Focusing only on ED patients with chronic obstructive pulmonary disease, they develop an admission prediction model using binary Logistic Regression. They are able to predict the admission results of patients with 78.6% accuracy, and they identify age, oxygen use, and antibiotic administration as the most important factors associated with an increased likelihood of admission.

Leegon et al. (2005)'s study is the first in the literature that predicts hospital admissions considering all encounter reasons. The authors use data from 16,900 ED encounters at Vanderbilt University Medical Center in Tennessee over a 4.5-month period in order to develop an admission prediction model. They consider nine predictor variables including age, arrival mode, chief complaint, and Emergency Severity Index (ESI) acuity level. They also consider the presence (or lack) of laboratory test, radiology test, and electrocardiogram exam as variables in their prediction model. Using a Bayesian Network, they develop a model capable of real-time admission prediction. In their later research, Leegon et al. (2006)'s study, the authors develop another prediction model, using an Artificial Neural Network, and validate their model against data from a 10-month period from the same hospital. Although these two articles can be considered pioneers in the area of ED patient admission prediction models, both of them are very brief (one page long), and neither explains their predictor variables, models or results in detail.

Sun et al. (2011) collected patient data from a larger ED in a Singapore hospital for a longer period of time. They develop a prediction model for admission using data from 317,581 ED patient visits over a 2-year period. In addition to patient age, gender, arrival mode, and acuity level, they consider ethnicity, past visits, and coexisting chronic diseases as predictor variables in their model.

In a recent study, Peck et al. (2012) develop similar admission prediction models for ED patients and compare them to triage nurse's admission predictions. Using data from 4,187

ED patient visits over a 2-month period, the authors develop two prediction models, one using Naïve Bayesian and the other using Logit-linear regression. They compare the performances of these models with the estimation of likelihood of admission given by the triage nurse, finding the results from both models to be significantly more accurate than the triage nurse's predictions. The proposed Logit-linear model was also able to predict total bed need roughly 3.5 hours before peak demand occurred, with an average estimation error of 0.19 beds per day.

A few studies have focused on increasing the accuracy of admission prediction models and on improving triage protocols. Ruger et al. (2007) show that the five-point patient acuity level commonly used in many EDs is not highly predictive of admission for patients in the middle triage group. They offer modifications to increase the accuracy of triage, especially for this group of patients. Li and Guo (2009) focus on another predictor variable, acuity level, to improve the accuracy of admission prediction. They include semantic information about chief complaints in their prediction model to capture the effect of related complaints (such as fever and vomiting). This novel approach has helped them develop an admission prediction model that outperforms benchmarks. Tables1 and 2 review these studies, as well as their predictor variables, model objectives, populations (number of patients), observation periods, and methods.

Table1. Studies on the relations between ED patients' information and admission result

Author, Year	Predictor Factors						
	Age	**Arrival Time**	**Gender**	**Chief Complaint**	**Arrival Mode**	**Acuity Level**	**Other Predictor Factors**
Leegon et al., 2005	Y	Y		ICD-9	Y	ESI	Presence of Exams
Leegon et al., 2006	Y		Y	ICD-9	Y	ESI	Presence of Exams
Sadeghi et al., 2006	Y		Y	Abdomina l Pain			Patient's Chart Information
Steele et al., 2006	Y			ICD-9			Patient's ED Record Information
Ruger et al., 2007	Y	Y	Y	ICD-9	Y	DRG	Medical Diagnosis, Payment Method
Li and Guo, 2009	Y	Y	Y	ICD-9		Y	Semantics Of Chief Complaints
Sun et al., 2011	Y		Y		Y	PAC	Ethnicity, Past Visits, Coexisting Chronic Diseases
Considine et al., 2011	Y		Y	ICD-10-AM related to pulmonar y disease	Y	Y	Physiological Status, ED Management Data
Peck et al., 2012	Y			Free Text Format	Y	ESI	Designation (ED or fast track), ED Provider

Table2. Studies' objectives, populations, observation periods, and methods

Author(s), Year	Objective of the Model	Population (Number of Patients)	Observation Period	Method(s)
Leegon et al., 2005	To predict ED patients' admission earlier and initiate admission processes earlier	16,900	4.5 Months	Bayesian Network
Leegon et al., 2006	To predict ED patients' admission earlier and initiate admission processes earlier	43,077	14.5 Months	Artificial Neural Network
Sadeghi et al., 2006	To act as an automated ED triage system for patients with abdominal pain	90	2 Months	Logistic Regression and Bayesian Network
Steele et al., 2006	To identify which injured ED patients require emergency operative intervention	8,289	7.5 Years	Classification and Regression Tree
Ruger et al., 2007	To identifying high-risk ED patients for triage and resource allocation	77,709	1 Year	Logistic Regression
Li and Guo, 2009	To help hospital estimate the ED patients to be admitted	2,784	1 Month	Logistic Regression, Naïve Bayes, Decision Tree, SVM
Sun et al., 2011	To assess whether a patient is likely to require inpatient admission at the time of ED triage	317,581	2 Years	Logistic Regression
Considine et al., 2011	To identify factors predictive of hospital admission in ED patients	321	1 Year	Binary Logistic Regression
Peck et al., 2012	To predict ED-to-IU patient volumes based on basic data gathered at triage.	4,187	2 Months	Logit-Linear Regression, Naive Bayesian

The review of the literature shows that predicting ED patient admission using demographic and clinical information (available at the ED) is a relatively new research area, with only a couple of admission predictor factors investigated so far. For example, to the best of my knowledge, no study yet investigates the relationship between type of radiology exams prescribed by the ED physician and the likelihood of a patient's admission.

CHAPTER 2

RESEARCH DESIGN

The analysis in this study is conducted using secondary data from a local hospital in the Boston area. The hospital ED has approximately 30,000 patient visits per year and about 20% of them result in admission for inpatient care. All patient visits at the ED from January 2012 to August 2012 are included in analysis.

The following section exclaims the methods employed in this study and introduces the tools used in the analysis of the data, namely C5.0 algorithm, Logistic Regression, and Artificial Neural Networks.

2-1- Methodology

In this study, eight candidate predictor factors were considered for possible inclusion in the model: age, gender, marital status, arrival mode, day and time of ED arrival, encounter reason (chief complaint), and type of radiology exam prescribed by the ED physician (if any). In the interest of analyzing the effect of these factors on the likelihood of the patient's admission to the hospital, the output (target) variable is defined with the two possible values of admission or discharge (rejection).

After cleaning the data and transforming it from unprocessed hospital reports to structured records and fields, the analysis was performed in four main steps:

Step1. Descriptive analysis of each predictor factor: each of the eight predictor factors for all the admitted and discharged patients undergoes an exploratory investigation. Two continuous variables corresponding to age and arrival time factors and six categorical variables for the other six predictor factors are defined. Then, using histograms and bar charts, the graphical distribution of each continuous and categorical variable is presented.

Step2. Determining the importance of each predictor factor (variable): each predictor variable is defined and described, after which a “test of significance” is performed. For each continuous variable, an F-test to compare the variable means for the admitted group and discharged group is used; for each categorical variable, a Chi-Square test to compare the frequency of admission in each category of the variable is used.

Step3. Finding relationships between independent variables and target variable in the form of admission rules: In the next step, a C5.0 rule induction algorithm is employed to find relationships between the predictor variables and the output variable, as well as to identify the predictor variables’ importance (the C5.0 algorithm is explained in the Analytical Tools section). Based on the data, a set of rules for the admission of a new patient are discovered. These rules estimate the likelihood of each patient’s admission based on his/her predictor variables.

Step4. Developing admission prediction models using independent variables to estimate the target variable: two prediction models based on all eight independent variables are developed, one using the Logistic Regression (LR) technique and the other using Artificial Neural Networks (ANN). The results of these two prediction models are then presented and compared.

The four steps of the analysis are shown as S1 to S4 in Figure1.

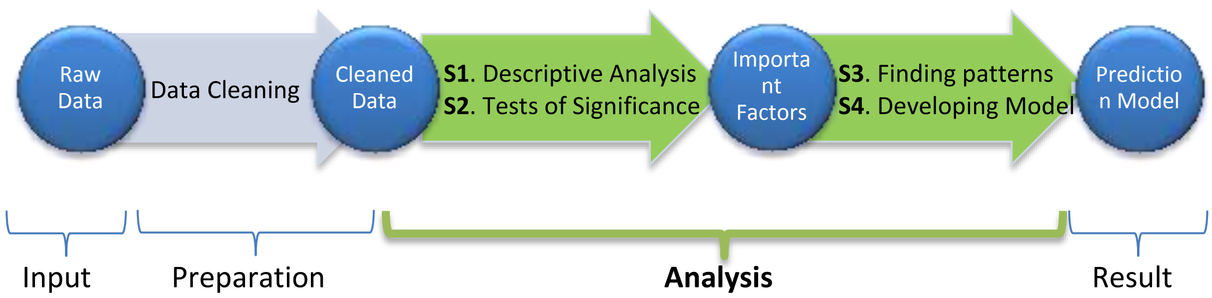

Figure1. Four main steps of the analysis

2-2- Analytical Tools

Three analytical techniques, namely C5.0 algorithm, Logistic Regression (LR), and Artificial Neural Networks (ANN), are used in this study. The following provides a brief introduction to these three methods.

- **C5.0 Algorithm**

A C5.0 algorithm is a classification technique based on C4.5 by Quinlan (1992). This method can be used to build decision trees and rule sets. A decision tree is a straightforward description of the splits found by the algorithm. In contrast, a rule set is a set of rules that tries to make predictions for individual records. The C5.0 algorithm divides the sample data based on the field that provides the "maximum information gain." Each division defined by the first split is then divided again and the process repeats until the subsamples cannot be divided further (SPSS Modeler users' guide, 2012). The C5.0 algorithm is also able to identify predictor variables' importance in predicting the target variable. The algorithm uses the same criteria ("maximum information gain") for identifying the importance of predictor variables.

- **Logistic Regression**

Logistic Regression (LR) is a statistical technique for data classification and prediction. In contrast to linear regression, the output variable in Logistic Regression is categorical. LR works by "building a set of equations that relate the predictor variables values to the probabilities associated with each of the output variable categories" (SPSS Modeler users' guide, 2012). After developing an LR model using available data, it can be used to estimate the value (category) of output variables for new entities. In order to estimate output value, LR calculates the probabilities of membership in every output category and assigns the output value (category) with the highest probability to that entity (Christensen, 1997; SPSS Modeler users' guide, 2012). Like linear regression, Logistic Regression provides a coefficient value and each predictor variable contribution to variations in the output variable (Menard, 2002).

- **Artificial Neural Networks**

An Artificial Neural Network (ANN) is a mathematical model that attempts to simulate the human brain by collecting and processing data for the purpose of "learning" (Golmohammadi, 2011). ANNs have different structures and processing algorithms. Figure2 shows a number of well-developed ANN structures. This study uses a Multiplayer Perceptron (MLP), one of the most common forms of ANNs.

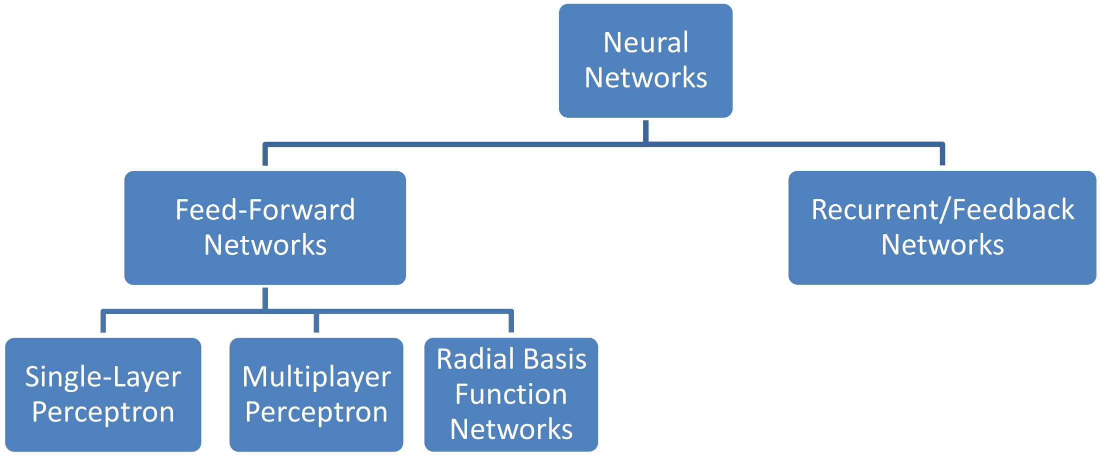

Figure2. A taxonomy of Neural Network architectures (after Gardner and Dorling, 1998)

Unlike many statistical techniques, the MLP makes no assumptions on the distribution of data, the linearity of the output function, or the type (measurement) of predictor and output variables (Gardner and Dorling, 1998; SPSS Modeler users' guide, 2012). An MLP consists of multiple parallel layers of nodes, which are connected by weighted links as shown in Figure3. The input layer contains the independent variables, the middle layers (hidden layers) contain the processing units, and the output layer contains the output variable(s).

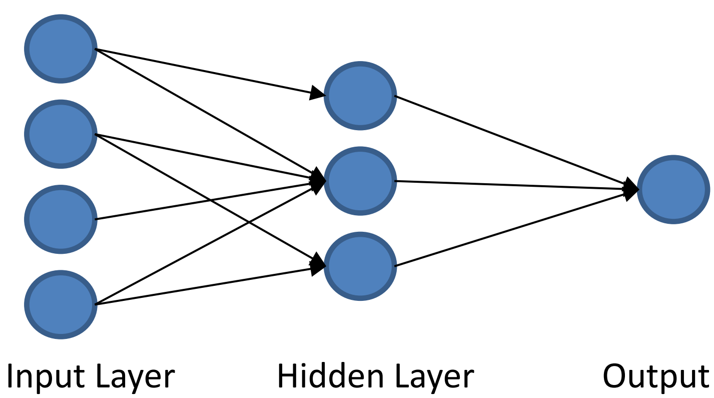

Figure3. The structure of the artificial neural networks

The process of finding the right weights in an ANN is called training. Training consists of two general phases of assigning weights and updating them to minimize the model's error (Golmohammadi et al., 2009; Golmohammadi, 2011). These phases are repeated until the performance of the network is satisfactory. In an MLP, the weights are usually estimated using Backpropagation (backward propagation of errors), a generalization of the Least Mean Squares algorithm (Gardner and Dorling, 1998).

CHAPTER 3

EMPIRICAL RESULTS

This section discusses the results of descriptive data analysis, statistical tests, discovered sets of rules, and prediction models.

3-1- Descriptive Data Analysis

From January 2012 to August 2012, a total of 15,050 visits were made to the ED and 2,528 (16.8%) of them resulted in an inpatient admission. The value of the eight predictor variables defined earlier (age, gender, marital status, arrival mode, day and time of arrival, chief complaint, and radiology exam) are explored for all visits. Then, based on the observed values of these variables, age and arrival time are classified into a continuous variable group and the other six variables are classified into a categorical variable group. Table3 lists mean, median, mode and other statistical information for the continuous variables and Table4 lists the number of categories and mode values for the categorical variables.

Table3. Continuous predictor variables

Variable	**Min**	**Max**	**Mean**	**Std. Dev.**	**Skewness**	**Median**	**Mode**
Age	0	102	42.79	23.32	0.27	42	49
Arrival Time	0	24	14.23	5.73	-0.47	14.46	18

Table4. Categorical predictor variables

Variable	**Categories**	**Mode**
Day of Arrival	7	Monday
Gender	2	Female
Marital Status	8	Single
Arrival Mode	9	Car
Encounter Reason	200+	Abdominal Pain
Radiology Exam	172	DX: Chest: Pa. & Lat. (2 Views)

The following presents the descriptive analysis of each of these eight variables.

Continuous Variables:

Based on the available data, two continuous independent variables are included in the final model: age and arrival time.

- **Age**

The range of patient ages observed was between 1 day and 120 years old with a mean of 42.8 years. The admission rate increased with an increase in patient age. Among 3563 patients 60 years or older, 1450 (41%) were admitted as inpatients, whereas from 2836 patients 20 years or younger, only 49 (less than 2%) were admitted. The mean (± standard deviation) age of the admitted patients was 63.3 (±20) years, compared to 38.5 (±21.6) years among those who were not admitted. Figure4 shows the distribution of patient ages and the admission result.

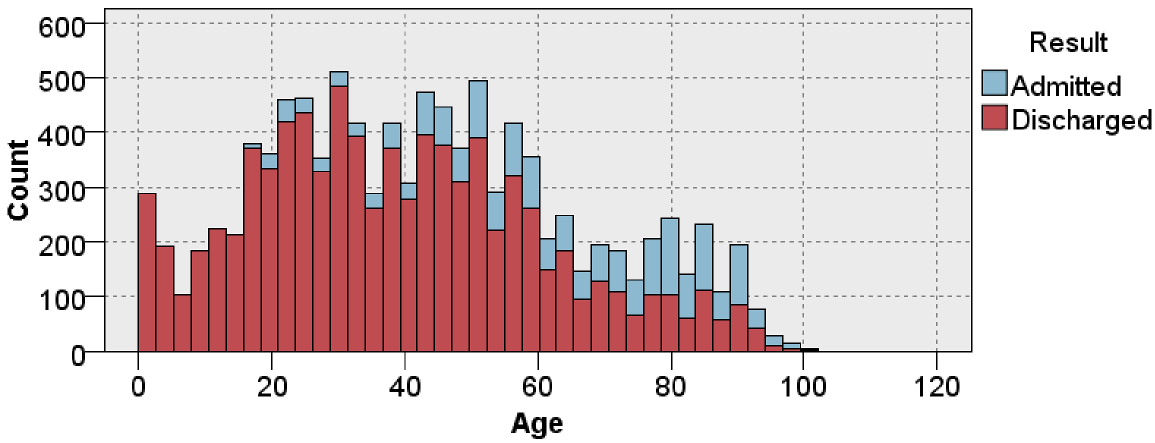

Figure4. Distribution of patient's age and the result of their admission

- **Arrival Time**

The studied ED accepted patients 24 hours a day. As expected, significantly fewer patients visited the ED between midnight and 8 AM. However, the rate of admission for these visits was slightly higher than average (366 admission from 2062 visits, or 17.8%). Around half of the visits occurred between 12 PM and 8 PM. Figure5 shows the distribution of patient arrival times and the admission result.

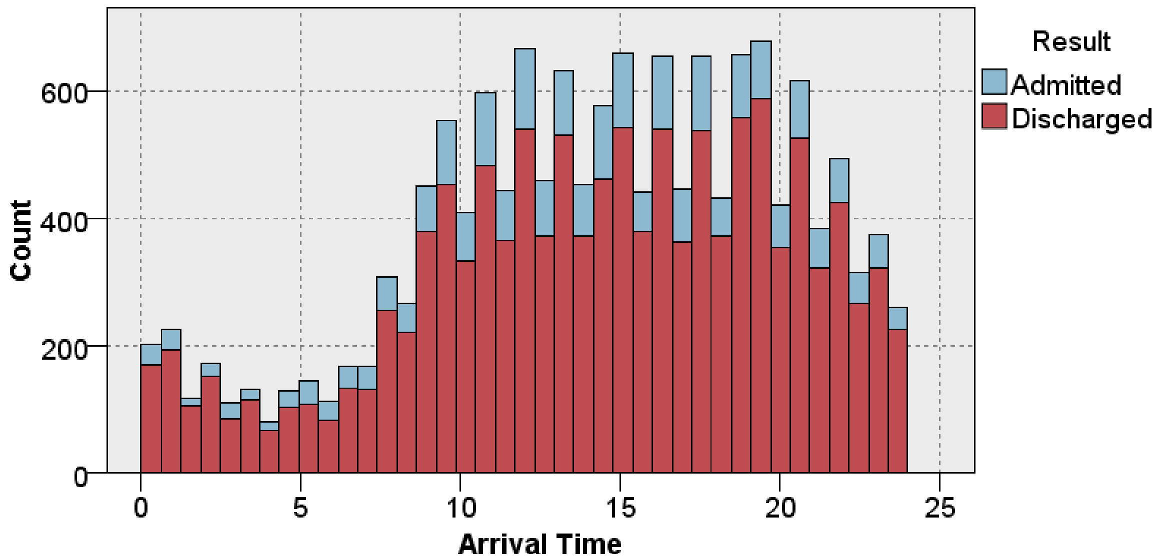

Figure5. Distribution of patients' arrival time and the result of their admission

Categorical Variables

Based on available data, six categorical independent variables are included in the final model: day of arrival, gender, marital status, arrival mode, encounter reason, and prescribed radiology exam.

- **Day of Arrival**

The ED accepted visits seven days a week. Categorizing visits based on the day of the week shows slightly more visits on Mondays than on other days of the week (16% of all visits), and a slightly higher admission rate on Fridays (19%). Figure6 and Table5 show the distribution of the visits and the admission rates by day.

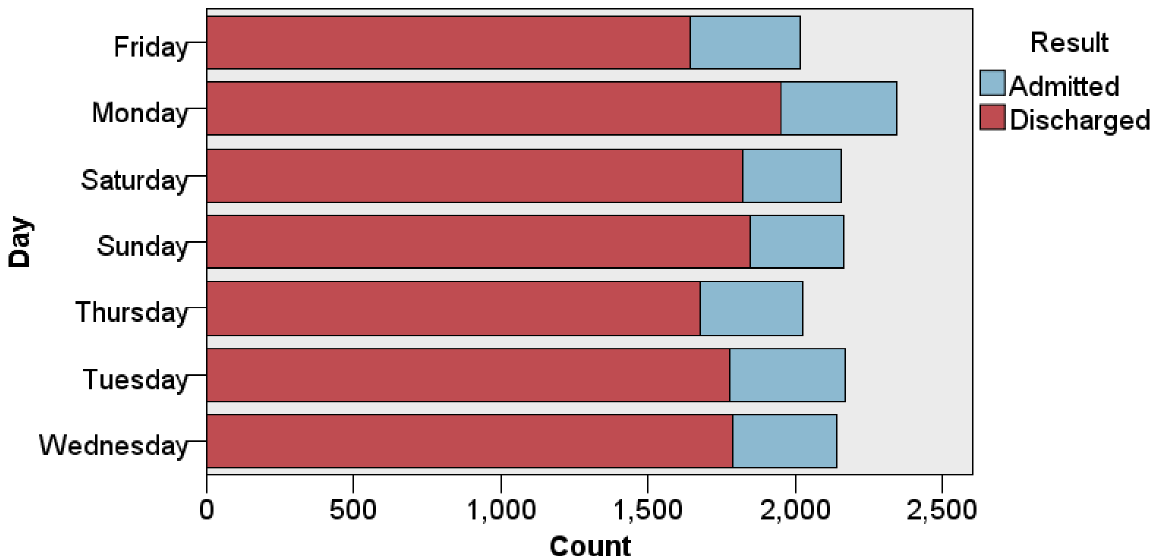

Figure6. Distribution of days of the visits to the ED

Table5. Visits frequency and the rates of admission in each day

Day		Discharged	Admit	Total	Day		Discharged	Admit	Total
Wednesday	Count	1791	354	2145	**Saturday**	Count	1827	332	2159
	Row %	83	17	100		Row %	85	15	100
	Column %	14	14	14		Column %	15	13	14
	Total %	12	2	14		Total %	12	2	14
Tuesday	Count	1778	396	2174	**Monday**	Count	1952	397	2349
	Row %	82	18	100		Row %	83	17	100
	Column %	14	16	14		Column %	16	16	16
	Total %	12	3	14		Total %	13	3	16
Thursday	Count	1680	352	2032	**Friday**	Count	1644	377	2021
	Row %	83	17	100		Row %	81	19	100
	Column %	13	14	14		Column %	13	15	13
	Total %	11	2	14		Total %	11	3	13
Sunday	Count	1850	320	2170	**Total**	Count	12522	2528	15050
	Row %	85	15	100		Row %	83	17	100
	Column %	15	13	14		Column %	100	100	100
	Total %	12	2	14		Total %	83	17	100

- **Gender**

Women were slightly more likely to visit the ED and to be admitted. From a total of 7837 female who visited the ED, 18% were admitted as inpatient, while from a total of 7213 visits by males, 16% were admitted. Figure7 and Table6 show the distribution of the visits and the admission rates for males and females.

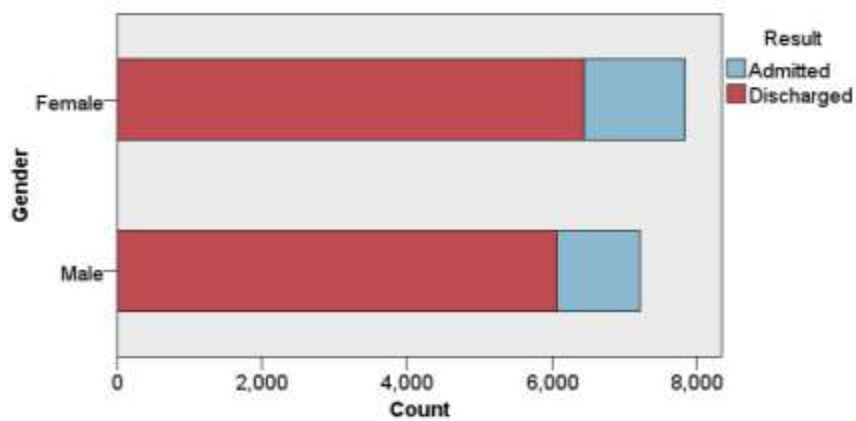

Figure7. Distribution of the ED patients' gender

Table6. Visits frequency and the rates of admission for males and females

Gender		Discharged	Admit	Total	Gender		Discharged	Admit	Total
Male	Count	6078	1135	7213	Female	Count	6444	1393	7837
	Row %	84	16	100		Row %	82	18	100
	Column %	49	45	48		Column %	51	55	52
	Total %	40	8	48		Total %	43	9	52
Total	Count	12522	2528	15050					
	Row %	83	17	100					
	Column %	100	100	100					
	Total %	83	17	100					

- **Marital Status**

The marital status of patients visiting the ED was recorded as: single (51%), married (32%), widowed (8%), divorced (8%), partner (less than 1%), and undeclared (less than 1%). The admission rate was highest among patients who were widowed (45% admission rate) and lowest among singles (10%). This may be because widowed patients were significantly older (average age of 79.7) and singles patients were significantly younger (average age of 29.3) than average; Figure8 and Table7 show the distribution of the visits and the admission rates among patients with different marital status.

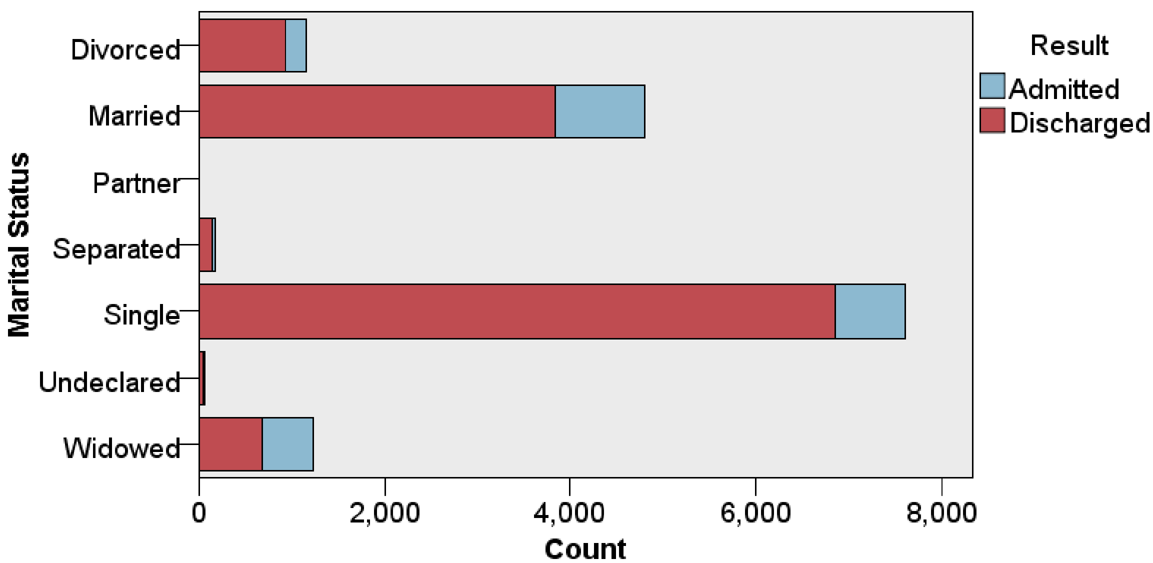

Figure8. Distribution of the ED patients' marital status

Table7. Visits frequency and the rates of admission for each marital status

Marital Status		Discharged	Admit	Total	Marital Status		Discharged	Admit	Total
Widowed	Count	676	556	1232	**Partner**	Count	3	0	3
	Row %	55	45	100		Row %	100	0	100
	Column %	5	22	8		Column %	0	0	0
	Total %	4	4	8		Total %	0	0	0
Undeclared	Count	48	13	61	**Married**	Count	3838	962	4800
	Row %	79	21	100		Row %	80	20	100
	Column %	0	1	0		Column %	31	38	32
	Total %	0	0	0		Total %	26	6	32
Single	Count	6860	746	7606	**Divorced**	Count	932	228	1160
	Row %	90	10	100		Row %	80	20	100
	Column %	55	30	51		Column %	7	9	8
	Total %	46	5	51		Total %	6	2	8
Separated	Count	150	22	172	**Total**	Count	12522	2528	15050
	Row %	87	13	100		Row %	83	17	100
	Column %	1	1	1		Column %	100	100	100
	Total %	1	0	1		Total %	83	17	100

- **Arrival Mode**

Most of the patients arrived at the ED by car (80%) or by ambulance (19.4%). Other patients' arrival modes (less than 1%) were recorded as "by foot", "by police", "by public transport", "other", and "unknown" and the arrival mode of patients who were dead on arrival were recorded as "DOE". 38% of the 2922 patients arriving by ambulance were admitted, while 12% of the 12047 patients arriving by car were admitted. Only 10 visits were observed for the arrival modes of "DOE", "by public transport”, and “other”, combined. Figure9 and Table8 show the distribution of the visits and the rates of admission among patients with different arrival modes.

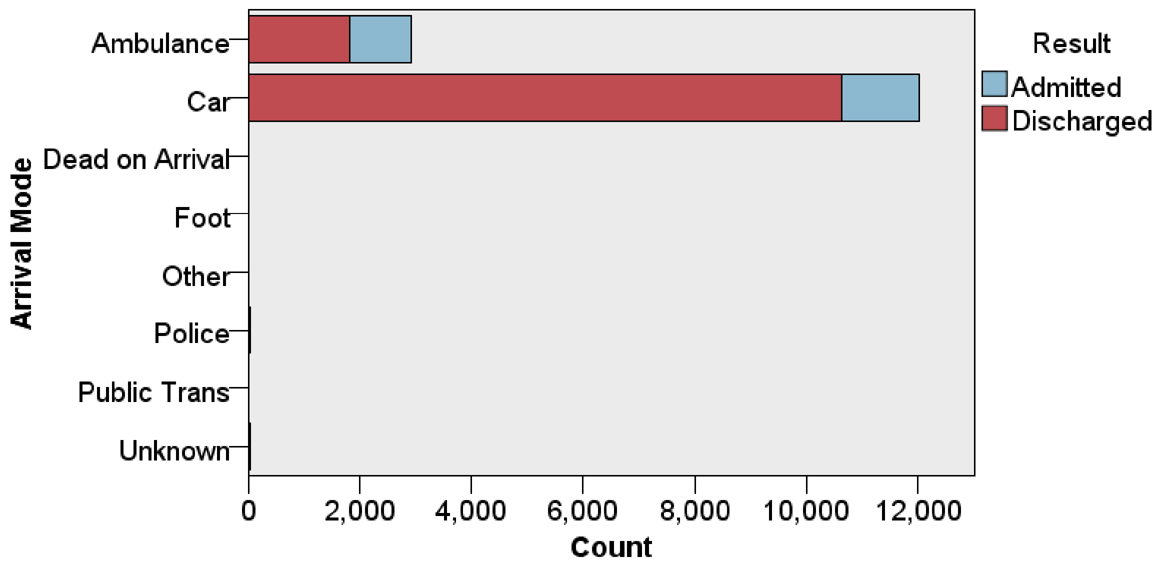

Figure9. Distribution of arrival modes to the ED

Table8. Visits frequency and the rates of admission for each arrival mode

Arrival Mode		Discharged	Admit	Total	Arrival Mode		Discharged	Admit	Total
Unknown	Count	21	5	26	**DOE**	Count	2	0	2
	Row %	80.8	19.2	100		Row %	100	0	100
	Column %	0.2	0.2	0.2		Column %	0	0	0
	Total %	0.1	0	0.2		Total %	0	0	0
Public Transport	Count	1	0	1	**Car**	Count	10651	1396	12047
	Row %	100	0	100		Row %	88.4	11.6	100
	Column %	0	0	0		Column %	85.1	55.2	80
	Total %	0	0	0		Total %	70.8	9.3	80
Police	Count	24	11	35	**Ambulance**	Count	1810	1112	2922
	Row %	68.6	31.4	100		Row %	61.9	38.1	100
	Column %	0.2	0.4	0.2		Column %	14.5	44	19.4
	Total %	0.2	0.1	0.2		Total %	12	7.4	19.4
Other	Count	5	2	7	**Foot**	Count	7	2	9
	Row %	71.4	28.6	100		Row %	77.8	22.2	100
	Column %	0	0.1	0		Column %	0.1	0.1	0.1
	Total %	0	0	0		Total %	0	0	0.1

- **Encounter Reasons**

More than 200 encounter reasons were recorded. Figure10 and Table9 show the ten most frequent encounter reasons observed among patients presenting at the ED, and patients with these ten encounter reasons constitute around one third of all visits. The most common encounter reasons were abdominal pain (6%), chest pain (3.5%), and shortness of breath (3%), and the highest rate of admission were observed among the group with shortness of breath as their main encounter reason (52%).

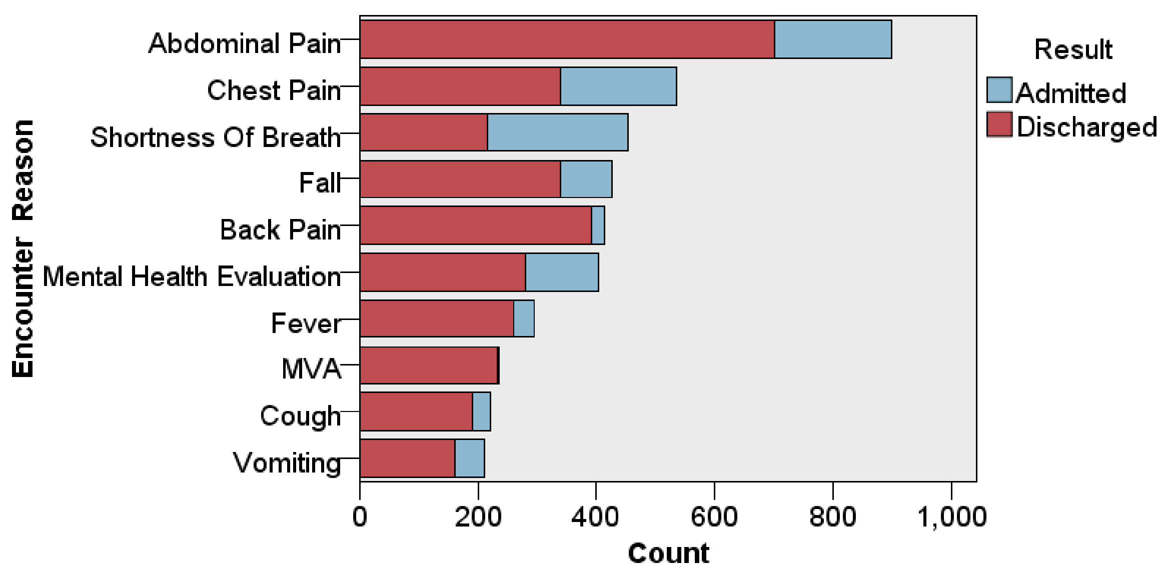

Figure10. Distribution of the patients' ten most frequent encounter reasons

Table9. Visits frequency for ten most frequent encounter reasons

Encounter Reason		Admit	Discharged	Total
Abdominal Pain	Count	198	700	898
	Row %	22.047	77.95	100
Back Pain	Count	23	391	414
	Row %	5.55	94.44	100
Chest Pain	Count	196	340	536
	Row %	36.56	63.43	100
Cough	Count	28	193	221
	Row %	12.66	87.33	100
Fall	Count	85	341	426
	Row %	19.95	80.04	100
Fever	Count	35	260	295
	Row %	11.86	88.13	100
Mental Health Evaluation	Count	124	280	404
	Row %	30.69	69.30	100
Motor Vehicle Accident	Count	3	233	236
	Row %	1.27	98.72	100
Shortness Of Breath	Count	235	217	452
	Row %	51.99	48.00	100

- **Radiology Exam:**

Among 172 types of radiology exams prescribed by the ED physician for presented patients at the ED, the most common tests were “Dx: Chest: Pa & Lat” (12%), “Dx: Chest: 1 Vw Ap Or Pa” (4%), and “Ct: Head Without Contrast” (3%). The highest admission rate were observed among the patients with the “Dx: Chest: 1 Vw Ap Or Pa” radiology exam (67%). Figure11 and Table10 show the ten most frequently prescribed radiology exams and their distributions.

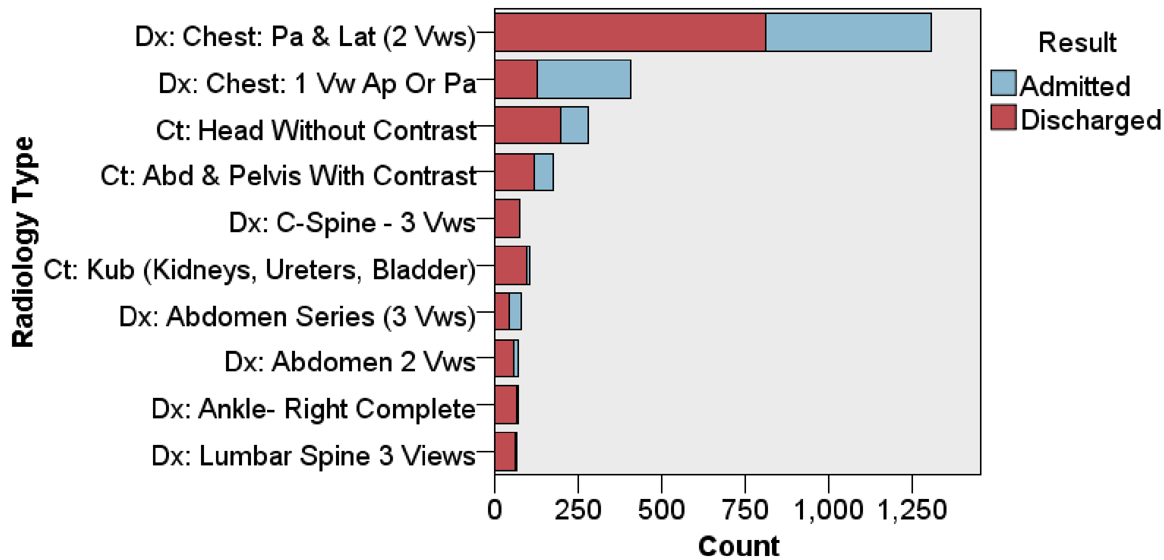

Figure11. Distribution of ten most frequent radiology exams

Table10. Visits frequency for most frequent radiology exams

Radiology Exam		Admit	Discharged	Radiology Exam		Admit	Discharged
Ct: Abd & Pelvis With Contrast	Count	59	118	**Dx: Ankle- Right Complete**	Count	2	66
	Row %	33.33	66.66		Row %	2.94	97.05
Ct: Head Without Contrast	Count	83	199	**Dx: C-Spine - 3 Vws**	Count	0	74
	Row %	29.43	70.56		Row %	0.0	100.0
Ct: Kub (Kidneys, Ureters, Bladder)	Count	9	96	**Dx: Chest: 1 Vw Ap Or Pa**	Count	283	125
	Row %	8.57	91.42		Row %	69.36	30.63
Dx: Abdomen 2 Vws	Count	15	56	**Dx: Chest: Pa & Lat (2 Vws)**	Count	495	813
	Row %	21.12	78.87		Row %	37.84	62.15

3-2- Importance of Predictor Factors

In order to determine the impact of these eight variables, a test of significance was performed for each. Statistical tests of significance show that both of the continuous variables are important factors in predicting the result of admissions with p-values less than 5%, and all six categorical variables are important predictors with p-values less than 1%. Table11 and Table12 summarize the results of these statistical tests, including their degrees of freedom and P-Values.

Table11. The result of tests of significance of difference for continuous variables

	F-Test	**DF**	**P-Value**	**Importance**
Age	2103.128	1, 10381	0	Important
Arrival Time	4.512	1, 10381	0.034	Important

Table12. The result of tests of significance of difference for categorical variables

Variable	**Chi Square**	**DF**	**P-Value**	**Importance**
Day	18.31	6	0.0055	Important
Gender	11.17	1	0.0006	Important
Marital Status	1021	7	0	Important
Arrival Mode	1185	8	0	Important
Encounter Reason	2171	180	0	Important
Radiology Exam	1614	171	0	Important

The results of these tests answer my first research question about important predictors of patients' admission, showing all eight independent variables to be important predictors of the admission result.

3-3- Rule Sets:

Using IMB SPSS Modeler (V15.0)'s C5.0 algorithm with a target variable of the admission result and the eight predictor variables defined above, I searched through the data to find admission rules with high frequency and high probabilities. These rules can be used by hospitals to identify ED patients with a high likelihood of admission as inpatients.

More than ten rules were discovered from the data, but I included only the rules which covered at least 500 visits. Table13 shows the five rules discovered for admitting a new patient meeting this requirement. For each rule, the cover number shows the number of visits to which the rule applied, frequency is the number of visits the rule predicted correctly, and probability is the ratio of these two measures.

Table13. Discovered rules for admitting a new patient based on historic data

Rule number	Rule	Cover (n)	Frequency	Probability
1	Age > 79 years and Arrival Mode = Ambulance	592	363	61.32%
2	Age > 48 years and Radiology Exam= "Dx: Chest: Pa & Lat (2 Vws)"	646	316	48.92%
3	Age between 48 and 79 years and Arrival Mode = Ambulance	721	289	40.08%
4	Age > 63 years	842	261	31.00%
5	Age > between 55 and 63 years	548	109	19.89%

The C5.0 algorithm was also able to estimate and rank the importance of the eight predictor variables, identifying age, radiology tests, and encounter reason as the most important predictor factors. Figure11 show the complete ranking of all important factors according to the C5.0 algorithm.

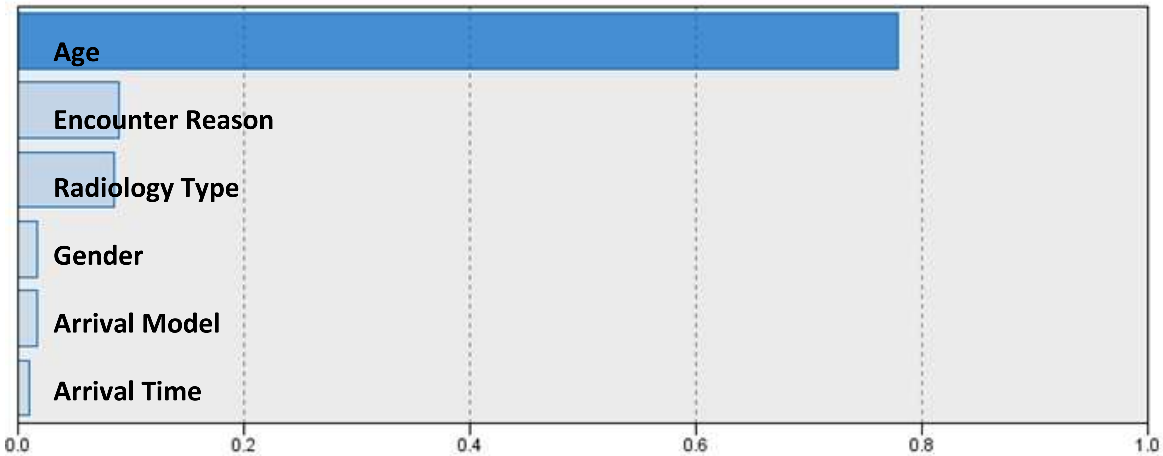

Figure12. Predictors' importance according to the C5.0 algorithm

These results answered my second research question about patterns among admitted patients. The discovered rules are clear indicators of patterns and can be used as rules of thumb for admitting new patients.

3-4- Prediction models

In order to answer the third research question, two prediction models based on all eight predictor variables were developed, one using LR and the other using the ANN method. Then, the performances of these prediction models on the historic data were calculated and compared.

Before developing the models, some modification to data were required. The major modification was related to missing information for some observations. After eliminating the observations with missing data, the total number of 10380 visits remained as input data for the LR prediction model.

- **LR Prediction Model**

Using SPSS Modeler (V15.0)'s Logistic Regression tool, an LR model with Binominal output was developed (since the target variable, admission result, has only two possible values). Three common LR methods, "Enter," "Forwards," and "Backwards," were tested and the highest level of accuracy was obtained using the "Enter" method.

Two of the predictor categorical variables, encounter reason and radiology exam, include almost 200 categories each. Therefore, the generated LR function (to estimate the target) is extremely large. However, the Modeler software enabled us to perform a sensitivity analysis of the LR model and to calculate the weights assigned to each predictor variable. These weights show the effect of each predictor variable in estimating the target variable and can be translated as the predictor variable's importance in predicting the target variable (admission result). Figure12 shows the importance of all eight predictor factors according to the LR model.

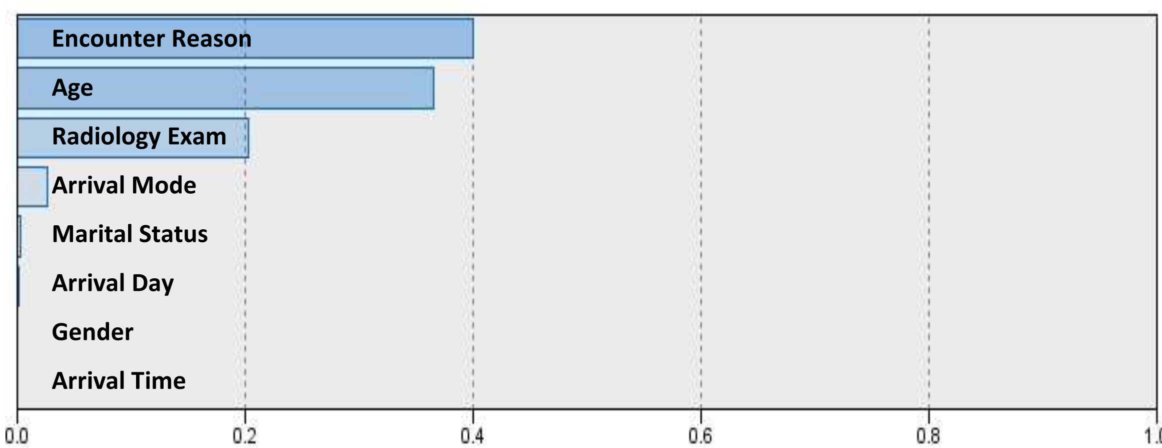

Figure13. Predictors' importance according to the LR

The data were divided into two sets for training and testing. The training set, which included 70% of data, was used to generate the LR model, while the testing set, comprising the remaining 30% of the data, was used for evaluating the LR model and comparing it to the ANN model. The LR model correctly predicted 85% of admission results and 80% of discharge results in the training data set and 86% of admission results and 78% of discharge results in the testing data set. The overall accuracy of this model was 82.54% on all visits on the training set and 81.98% on the testing set. Table14 and Table15 show the performance of the LR model on the training and testing data sets.

Table14. The performance result of the LR model on training data set

Training Data Set		**Predicted**		
		Result		**Percentage Correct**
		Admitted	**Discharged**	
Observed Result	**Admitted**	5,103	884	85.23%
	Discharged	1,188	4693	79.80%
Overall Percentage				82.54%

Table15. The performance result of the LR model on testing data set

Testing Data Set		**Predicted**		
		Result		**Percentage Correct**
		Admitted	**Discharged**	
Observed Result	**Admitted**	2,143	342	86.24%
	Discharged	569	2,002	77.87%
Overall Percentage				81.98%

- **ANN Prediction Model**

I took advantage of ANN to develop the second prediction model. In developing an ANN, the number of hidden layers (or nodes) and initial weights need to be set. In addition, I needed to decide what portion of data to use for training, choose a learning algorithm, and define a stopping rule for the training procedure. Using SPSS Modeler (V15.0)'s ANN method, several different structures with different numbers of hidden nodes (in one and two hidden layers) were tried. The results, then, were compared to the SPSS Modeler's recommended ANN structure. The highest level of accuracy for ANNs developed based on the predictor variables and available data was achieved with a model with 14 hidden nodes in one layer, as shown in Figure14.

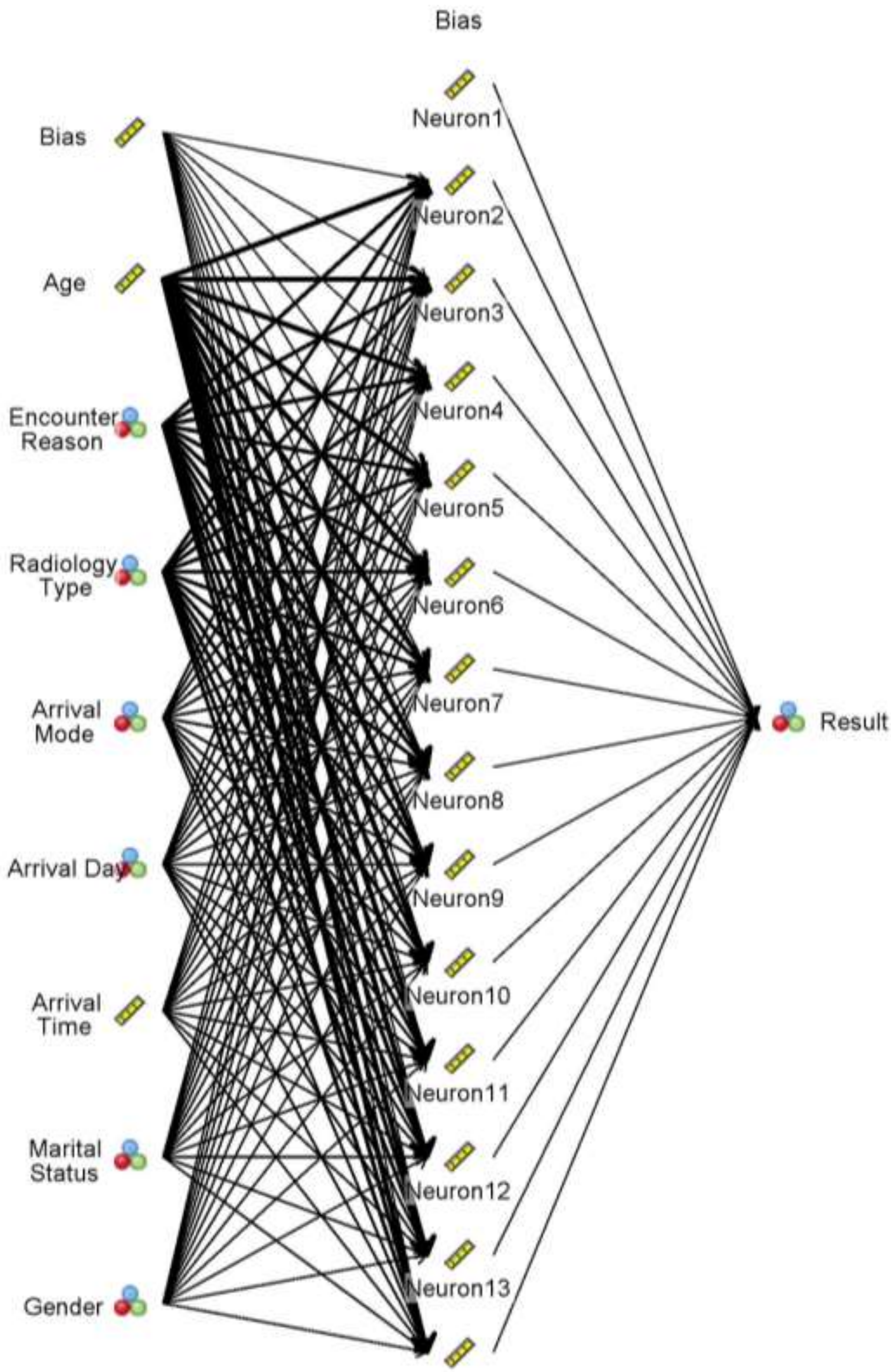

Figure14. The structure of the ANN prediction model with highest performance level

In the proposed ANN model, the initial weights are set randomly and Backpropagation is used as the learning algorithm. In addition, in order to prevent over-fitting of the ANNs, 70% of the data is used for training the model and the other 30% for testing it. A stopping rule is also defined in the form of maximum training time. Because the number of variables in the model is relatively small, and also the accuracy of the model rarely increased after the first ten minutes, I decided to set the maximum training time as fifteen minutes.

Based on the weights assigned to predictor variables, ANN can estimate each predictor variable's importance in predicting the target variable (admission result). Figure15 shows the importance of the eight predictor factors according to the ANN model.

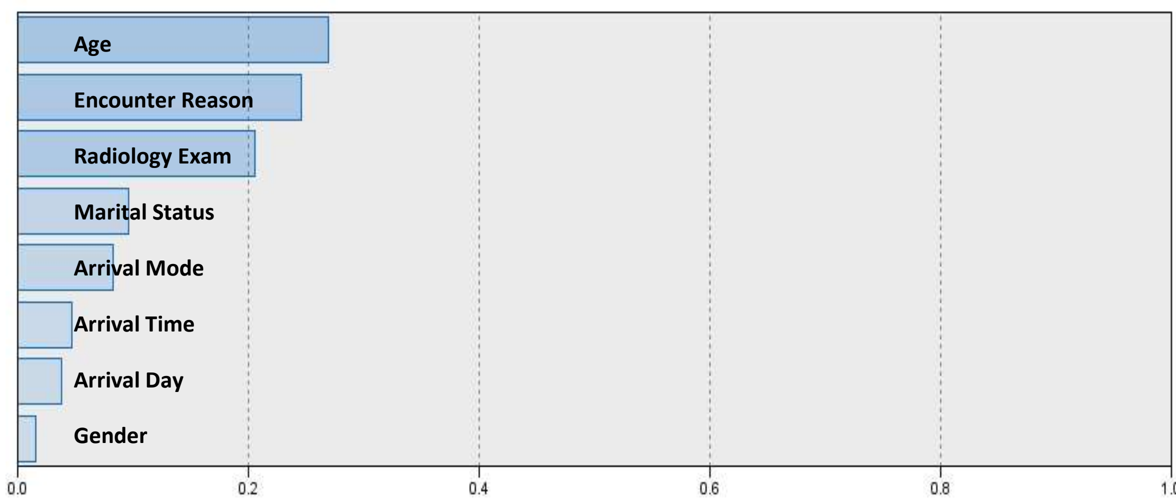

Figure15. Predictors' importance according to the ANN

The ANN model correctly predicted 88% of admission results and 78% of discharge results in the training data set and 87% of admission results and 75% of discharge results in the testing data set. The overall accuracy of this model was 82.97% on all visits on the training set and 82.10% on the testing set. Table16 and Table17 show the performance of the ANN model on the training and testing data sets.

Table16. The performance result of the ANN model on training data set

Training Data Set		Predicted		
		Result		Percentage Correct
		Admitted	Discharged	
Observed Result	Admitted	5,233	701	88.19%
	Discharged	1,316	4,594	77.73%
Overall Percentage				82.97%

Table17. The performance result of the ANN model on testing data set

Testing Data Set		Predicted		
		Result		Percentage Correct
		Admitted	Discharged	
Observed Result	Admitted	2,317	296	88.67%
	Discharged	623	1,897	75.28%
Overall Percentage				82.10%

The accuracy of the ANN model is slightly higher than the LR model. This increase in accuracy can be attributed to the capability of ANNs to handle complex non-linear relations between predictor and target variables. The results of the LR and ANN prediction models answer my third research question about the possibility of developing an accurate admission prediction model. The 82% percent overall accuracy of the prediction models means that these models can correctly predict the admission result of four out of every five ED visits.

CHAPTER 4

DISCUSSION, IMPLICATIONS, AND CONCLUSION

This section discusses more details on the results and managerial implications of the results. A summary of the findings and conclusion is also provided at the end of this chapter.

4-1- Discussion

Using the available data of patients, I was able to discover patterns between patients' characteristics, identify the important factors in patients' admission to hospital, and develop an admission prediction model. Here, I further discuss two issues related to the model input and output, one a conceptual issue about the relationship between the input and the output, and the other, a technical issue about the output.

The first issue arises from the difference between causal and correlational relationship between predictor factors and the result. The discovered patterns and developed models in this study are all based on the correlational relationships between the predictor factors and the admission results. Although some factors, such as encounter reason, may have a causal effect on the admission result, the predictor factors discovered in this study should be considered as correlational factors. The purpose of the models in this study is to serve as a real time predictor of the admission results for new patients, not to find the causes of their admissions.

The second issue is related to destinations of the patients. Given the limitation of the available data, the result of the developed models is patients' admissions or discharges. Although this information provides great insight for the ED and hospital, it only can drive an estimation of the total demand for all inpatient units. This information can be communicated to all inpatient units, such as ICU and operating rooms, as an estimation of their combined demand, but it cannot determine the demand for each unit. I acknowledge that having the demand for each unit can contribute to the decrease in ED boarding and ED overcrowding more than the combined demand, in most cases. This study provides a foundation for developing extended models with more detailed outputs, when the required data is available.

4-2- Managerial Implications

This study suggests that in order to decrease ED overcrowding and boarding, hospital and ED managers should focus more on operational efficiency and communication. I believe hospital units, including ED, need to become more "connected". Instead of focusing on each unit's output, managers need to see hospital as a whole system and focus on increasing the system's output.

By estimating the real time inpatients demands (from ED) and communicating them to inpatient units, the proposed prediction models provide unit managers with an extra piece of information about their units' demands. Managers can incorporate this information in their real time decision makings process, and over time, they will be able to make more informed and accurate decisions about their resource utilization and allocation.

The implementation of this study in an ED requires an integrated information sharing system, for communicating the estimates of demands, from the ED to inpatient units. In addition, a user interface for inputting new patients' information into the system and a simple processor machine (or a desktop computer) for running the model in required.

4-3- Summery and Conclusion

The main purpose of this study was to find an effective and efficient operational solution to the problem of patient boarding in emergency departments. One of the main causes of ED boarding is that inpatient units do not have an accurate and timely estimation of the number of near-future incoming ED patients. I tried to find a solution to estimate the number of ED patients in need of inpatient cares earlier and more accurately. This goal was achieved by developing real-time admission prediction models capable of estimating the likelihood of admission for each ED patient using the patient's information. These estimations then can be used by inpatient units to create a better estimate of their incoming patients in near-future.

Based on the historic data of 15,000 ED patients from a local hospital in the Boston area, eight important predictor factors of the admission result were identified: patient age, arrival time at ED, marital status, gender, arrival mode, day of arrival, encounter reason, and radiology test prescribed by the ED physician. After exploring each of these factors, age, encounter reason, and radiology exams were identified as the most important predictor factors of patients' admission to the hospital. To the best of my knowledge, this research is the first work to study the effect of different types of radiology exams prescribed by the ED physician on the patients' admission results.

Based on these eight predictor factors, a set of admission rules was identified. Using a C.5 rule induction algorithm, I searched through the data and discovered five admission rules with a high level of accuracy and high coverage (frequency). These discovered patterns in the data can be used by hospitals as rules of thumb for identifying ED patients with a high likelihood of admission as inpatients.

In the next step, two admission prediction models were developed. With the help of IBM SPSS Modeler software, I took advantage of two of the most frequently used prediction models in the healthcare literature, Logistic Regression and Artificial Neural Networks. I tried three common Logistic Regression methods, "Enter," "Forwards," and "Backwards," and achieved the highest level of accuracy using the "Enter" method. I also developed an ANN based on Multiplayer Perceptron, a feed-forward method, and Backpropagation (backward propagation of errors) as the training function. After trying different ANN structures, the highest level of accuracy was achieved, with a structure including 14 hidden nodes in one layer. Evaluation of the LR and ANN models was performed using 30% of the data which was not included in developing these models.

The overall accuracy of both models was above 80% and the ANN model slightly outperformed the LR model (82.10% compared to 81.98% on the testing data sets). With this level of accuracy, hospitals can predict the admission results of four out of every five ED patients. By implementing similar real-time prediction models, hospital will be able to accurately estimate the likelihood of admission for all ED patients, and therefore have a better and earlier estimation of the total number of near-future ED patients in need of inpatient care.

The main limitations of this study arise from the limitation of available data. First, the patient information available includes only a portion of prediction factors. Specifically, I believe other prescribed exams by ED physicians such as laboratory exams and blood test are important predictor factors of ED patients' admission. Second, the encounter reasons in the database were recorded as free text format by the ED physicians. Although I used some statistical techniques to handle these texts for modeling, the unclassified structure of this information reduced the accuracy of the models.

Much remains to be done in this area, and two promising research directions for future studies include: 1- modifying the proposed model to predict the destination of each ED patient (an inpatient unit receiving the patient), rather than just a prediction of the admission result; 2- extending the prediction model to a more comprehensive model calculating the total number of ED patients to be admitted in the near future. Such future research can further help hospitals to improve their estimation of required resources, their preparedness to provide care for patients arriving from EDs, and their process of inpatient bedding, which would consequently reduce emergency department boarding.

APPENDIX A

LIST OF SIMILAR STUDIES IN THE LITERATURE

Authors	**Publication Year**	**Article Title**
Leegon et al.	2005	Predicting Hospital Admission for Emergency Department Patients using a Bayesian Network
Leegon et al	2006	Predicting Hospital Admission in a Pediatric Emergency Department using an Artificial Neural Network
Sadeghi et al.	2006	A Bayesian model for triage decision support
Steele et al.	2006	Clinical Decision Rules for Secondary Trauma Triage: Predictors of Emergency Operative Management
Ruger et al.	2007	Identifying high-risk patients for triage and resource allocation in the ED
Li and Guo	2009	Hospital Admission Prediction Using Pre-hospital Variables
Sun et al.	2011	Predicting Hospital Admissions at Emergency Department Triage Using Routine Administrative Data
Considine et al.	2011	Early predictors of hospital admission in emergency department patients with chronic obstructive pulmonary disease
Peck et al.	2012	Predicting Emergency Department Inpatient Admissions to Improve Same-day Patient Flow

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