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Risk Factors Affecting Death from Hospital-Acquired Infections in Trauma Patients: Association Rule Mining

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Abstract
Introduction: Trauma patients are potentially at high risk of acquiring infections in hospitals, which is the main cause of in-hospital mortality. The aim of this study was to identify the risk factors contributing to death from hospital-acquired infections in trauma patients by data mining techniques.
Methods: This is a cohort study. A total of 549 trauma patients with nosocomial infection who were admitted to Shiraz trauma hospital between 2017 and 2018 were studied. Sex, age, mechanism of injury, body region injured, injury severity score, length of stay, type of intervention, infection day after admission, microorganism cause of infections, and the outcomes were collected. Association rule mining techniques were applied to extract knowledge from the data set. The IBM SPSS Modeler data mining software version 18.0 was used as a tool for data mining of the trauma patients with hospital queried infections database.
Results: The age older than 65, surgical site infection skin, bloodstream infection, mechanism injury of car accident, invasive intervention of tracheal intubation, injury severity score higher than 16, and multiple injuries with higher than 71 percent confidence level were associated with in-hospital mortality. The relationship between those predicators and death among hospital-acquired infection was strong (Lift value >1).
Conclusion: Factors such as increasing age, tracheal intubation, mechanical ventilator, surgical site infection skin, upper respiratory infection are associated with death from hospital-acquired infections in trauma patients by data mining.
Keywords: Mortality, Hospital-acquired infections, Trauma, Association rule mining, Data mining.

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Introductions

Trauma is the second leading cause of death after heart diseases in Iran (1). Trauma patients are at potentially high risk of acquiring infections during hospitalization (2). Hospital-acquired infections are the main cause of mortality and morbidity (3). Death due to hospital infections is among the top five causes of death in the USA (4). Trauma patients with hospital-acquired infections significantly increase the risk of mortality, and have a longer length of hospital stay as well as higher medical care or service costs (5, 6). Hospital-acquired infections cause eighty percent of in-hospital mortalities (7). Age, motor vehicle accident, gunshot wound, stab wound, mechanical ventilation, number of invasive devices, number of surgeries, and severity of the injury increase the risk of hospital-acquired infections in trauma patients (8, 9). Invasive interventions due to patient morbidity, mortality, and excess costs increase the length of hospital stay and treat patient safety (10).

In the recent decade, data mining has been applied to find unexpected knowledge in the health domain. Data mining includes classification and descriptive techniques. It has been used extensively to analyze health datasets. Knowledge discovered in this way provides useful information for the control, survey, diagnosis, treatment, prognosis, management , and prevention of the disease. Matsuoka et al. carried out association rule mining to find the risk factors of bloodstream infection in the hospital information system. They found that lactobacillus, diarrhea, and catheters are important factors in preventing bloodstream infections (11). Khajehali and Alizadeh applied data mining to extract critical factors affecting the length of hospital stay for pneumonia patients. They found that patients under 15 years and the elderly between 74 and 88 years were hospitalized longer than the other age groups (12). Silva et al. demonstrated that data mining classification techniques support vector machines, and Naive Bayes can predict hospital-acquired infections with a sensitivity higher than 91.90 percent (13).

Data mining has different methods to mine significant knowledge from huge health care data (14). Association rule mining is one of the ruled-based machine learning methods in data mining used in health care data. It proceeds in two steps. First, it mines frequent items and then generates association rules. Indefinitely, association rule mined from health care data provides significant knowledge (15-19). These rules are useful information for disease prevention and management, and decrease complications (20). There are many algorithms used to associate rule mining from health care data (21). Among association rule mining algorithms, the Apriori algorithm is the most frequently used for mining frequent item sets for application of association rule mining in health care data (15, 22).

Data mining can be a reliable way to discover knowledge related to mortality that results in hospital-acquired infections form the hospital information database. Knowledge extracted from hospital information database might improve safety, and those patterns provide clinical data that could help to reduce mortality and morbidity resulting from hospital-acquired infections. Several researches were carried out to understand the risk factors for hospital-acquired infections in the hospitalized trauma patient. However, few researches have been done to identify the factors affecting death from hospital-acquired infections in trauma patients. To the best of our knowledge, our study is the first research that has discovered knowledge of death by hospital-acquired infections in Shiraz traumatic patients using hospital-acquired infections information database. However, the traditional method might not be able to find hidden knowledge related to death with hospital-acquired infections. Hence, the aim of this study was to discover the risk factors contributing to death from hospital-acquired infections in trauma patients by data mining.

Methods

This is a retrospective cross-sectional study of adult trauma patients who met the inclusion criteria of CDC protocol for hospital-acquired infections, admitted to a level 1 trauma center from 2017 to 2018.

The main source of information was the system of the hospital-acquired infections, which is registered by nosocomial infections supervisor and colleagues at Shiraz trauma hospital. This registered data is used to survey and control infections. Also, it was reported to the external regulatory body. Shiraz trauma hospital is a governmental trauma referral center in the city of Shiraz, which is the capital of Fars province located in the southwest of Iran with a generally hot semi-arid climate, with 1.7 million population. This study included 549 trauma patients with nosocomial infections who were admitted to this trauma hospital during the study period.

The data were collected based on Case Report Form (CRF) for hospital-acquired infection in trauma patients. Twelve features were extracted from nosocomial infection system including sex, age, mechanism of injury, body region injured, severity score, length of stay, type of intervention, infection day after admission, microorganism causes of infections, and the outcome. Feature and the type of feature are demonstrated in Table 1. This study on trauma patients with hospital-acquired infections database was used the data mining process including classifiers algorithms and association rule mining. The three main steps were:1) data preparation, 2) modeling, 3) evaluations and interpretation of the results.

The IBM SPSS Modeler data mining software version 18.0 was used as a tool for data mining the trauma patients with hospital-queried infections database.

Data Preparation

Data were extracted based on the inclusion criteria: all trauma patients with hospital-acquired infections above 15 years of age injured in a road traffic accident (car, motorcycle, and pedestrian accidents), falling, assaults, gunshots, and those who were struck by an object. On the other hand, we excluded the patients with hospital-acquired infection and the following features: admission for surgical procedure (elective), complications from previous trauma surgeries, patients with burn injuries, foreign object injuries, suicide, and sports injuries. Also, patients younger than 15 years old were excluded. Then, data were transformed into an appropriate format to be used for analysis by the IBM SPSS Modelers. The age value for each patient was divided into three groups: age 15-45, 46-64, and above 65 years. The target variable was survival status among trauma patients with hospital-acquired infections, divided into two categories of

Table 1: Association rule related to death with hospital-acquired infections among traumatic patients

Rule ID	Antecedent	Consequent	Support%	Confidence%	Lift
1	Age=above 65 and Hospital-acquired infection=Bloodstream Infection and Mechanism of Injury=car accident	Survival status=dead	1.257	85.7	5.52
2	Age=above 65 and Hospital-acquired infection=Bloodstream Infection and Mechanism of Injury=car accident and infect in less than 21 day	Survival status=dead	1.257	85.7	5.52
3	Type of invasive intervention=Trachea intubation and Age=above 65	Survival status=dead	1.09	83.33	5.38
4	Type of invasive intervention=Trachea intubation and Age=above 65 and infect in less than 21 day	Survival status=dead	1.09	83.33	5.38
5	Microorganisms=Enterobacter and Age=above 65 and Mechanism of Injury=car accident	Survival status=dead	1.09	83.33	5.83
6	Microorganisms=Enterobacter and Age=above 65 and Mechanism of Injury=car and infect in less than 21 day	Survival status=dead	1.09	83.33	5.83
7	Age=above 65 and Hospital-acquired infection=Bloodstream Infection and Mechanism of Injury=car and length of stay=between 8 and 30 day	Survival status=dead	1.09	83.33	5.83
8	Age=above 65 and Hospital-acquired infection=Bloodstream Infection and Mechanism of Injury=car and length of stay=between 8 and 30 day and infect in less than 21 day	Survival status=dead	1.09	83.33	5.83
9	Microorganisms=Escherichia coli and age=older than 65 and Hospital-acquired infection=upper respiratory infection	Survival status=dead	1.45	75.00	4.84
10	Mechanism of Injury=Falling down and body region injured=Multiple Injuries and length of stay=between 8 and 30 day	Survival status=dead	1.45	75.00	4.84
11	Microorganisms=Escherichia coli and age=older than 65 and Hospital-acquired infection=upper respiratory infection and infect in less than 21 day	Survival status=dead	1.45	75.00	4.84
12	Mechanism of Injury=Falling down and age=older than 65 and Mechanism of Injury=acinetobacter and length of stay between 8 and 30 day	Survival status=dead	1.45	75.00	4.84
13	Mechanism of Injury=Falling down and body region injured=Multiple Injuries and length of stay=between 8 and 30 and infect in less than 21 day	Survival status=dead	1.45	75.00	4.84
14	Microorganisms=Enterobacter and age=older than 65	Survival status=dead	2.00	72.72	4.69
15	Microorganisms=Pseudomonas aeruginosa and Mechanism of Injury=falling down and Microorganisms=acinetobacter	Survival status=dead	1.27	71.43	4.61
16	Age=older than 65 and injury severity score=higher than 16 and type of invasive intervention=mechanical ventilator	Survival status=dead	1.27	71.43	4.61
17	Microorganisms=Bloodstream Infection and type of invasive intervention=mechanical ventilator=y and length of stay=between 8 and 30	Survival status=dead	1.27	71.43	4.61
18	Age=older than 65 and body region injured=Multiple Injuries and Microorganisms= acinetobacter and hospital-acquired infections upper respiratory infection	Survival status=dead	1.27	71.43	4.61
19	Age=between 46 and 64 and hospital-acquired infection=surgical site infection skin=and Microorganisms=Acinetobacter and length of stay=between 8 and 30 day	Survival status=dead	1.27	71.43	4.61
20	Hospital-acquired infection=Bloodstream Infection and type of invasive intervention=type of medical ventilator and length of stay=between 8 and 30 day and infect in less than 21 day	Survival status=dead	1.27	71.43	4.61
21	Mechanism of Injury=Falling down and age=older than 65 and Microorganisms= acinetobacter and length of stay=between 8 and 30 day and infect in less than 21 day	Survival status=dead	1.27	71.43	4.61
22	Age=older than 65 and body region injured=Multiple Injuries and Microorganisms Microorganisms=acinetoactor and hospital-acquired infection=upper respiratory infection and infect in day less than 21	Survival status=dead	1.27	71.43	4.61
23	Age=between 46and 64 and hospital-acquired infection=surgical site infection skin and Microorganisms=acinetobacter and length of stay=between 8and30 and infect in less than 21 day	Survival status=dead	1.27	71.43	4.61

dead or alive. Finally, duplicated and records with missing values were omitted. Also, all features were converted to binary format in order to associate the rule mining predefined requirement.

Modeling

In this study, CRISP-DM (Cross-Industry standard process for data mining) methodology was used as the data mining process for association rule mining in death with hospital-acquired infections among trauma patients. CRISP-DM methodology consists of six steps (identify the problem, data understanding, data preparation, modeling, evaluation, and deployment). All features of hospital-acquired infections among trauma patient's databases were done by descriptive analysis. There were a total of 549 hospital-acquired infections among trauma patients studied with a mean age of 42.24 years (SD 19.68).

Association Rule Mining

A priori algorithm was used to extract the information associated with death by hospital acquired infections among trauma patients. A priori is processed in two steps. At first, it determines frequent items in the data set, and then it creates rules from the table of frequent items. In this study, the minimum confidence was considered 70%, while the minimum support was assigned as 1%. Traumatology specialists were consulted to generate an association rule.

Result

This is a cross-sectional study of discovering knowledge from hospital acquired infection among trauma patients using association rule mining techniques. Among them, 82.1% were male and the remaining 17.9% were female. The majority of patients were 15-45 years old (64.5%). Data set of the study is summarized in Table 2.

Association Rule Related to Death with Hospital-acquired Infections among Trauma Patients

Reliable rule related to death with hospital-acquired infections among trauma patients and the association rules generated when the minimum confidence threshold were more than 70 percent, and the Lift value was more than one. Then, the association rule was only generated with antecedent equal survival status. Therefore, 23 reliable rules related to death were generated. Table 1 represents support values, confidence values, and Lift vales of the rules associated with death by hospital-acquired infections among traumatic patients, which was sorted by confidence values. All rules are displayed in Table 1 and can be interpreted in the following way.

Interpretation of Association Rule Mining Results

Traumatic patients with hospital-acquired infections who were older than 65 acquired bloodstream infection, and mechanism of injury type was a car accident would die with 85 percent confidence, 1,25 percent support Also, there was a positive correlation between antecedent and consequence of the first rule, in which the Lift values were equal to 5.52. The second rule was: if each case was older than 65, acquired bloodstream infection, the mechanism of injury type was a car accident, and acquired infection in less than 21 days in the hospital with 85 percent confidence, he/she might die and had a positive correlation (lift=5.52). The third rule was: traumatic patient with hospital-acquired infections who had Tracheal intubation, and was older than 65 with 83.33 percent confidence level would die with positive correlation (lift=5.38). Details of each rule are shown in Table 1.

Table 2: Descriptive hospital-acquired infection data set

Variable	n (%)
Gender	
Female	98 (17.90%)
Male	451 (82.10%)
Total	549 (100%)
Age	
15-45	354 (64.50%)
46-64	103 (18.80%)
>=65	92 (16.80%)
Total	549 (100%)
Mechanism of injury	
Car accident	218 (39.70%)
Motorcycle Accident	132 (240%)
Pedestrian	74 (13.50%)
Gunshot	12 (2.20%)
Falling	87 (15.80%)
Assault	13 (2.40%)
Struck by objects	13 (2.40%)
Total	549 (100%)
Injured Body Region	
Head and Neck	216 (39.30%)
Face	21 (3.80%)
Thorax	64 (11.70%)
Abdomen	17 (3.10%)
Extremities	121 (22%)
Multiple Injuries	110 (20%)
Total	549 (100%)
Injury Severity Score (n=492)	
1-8	176 (35.80%)
9-15	206 (41.90%)
>=16	110 (22.40%)
Total	492 (100%)
Length of Stay	
=<7day	75 (13.70%)
8-30days	293 (53.40%)
>31days	181 (330%)
total	549 (100%)
Outcome	
Survived	464 (84.50%)
Died	85 (15.50%)
Total	549 (100%)

Discussion

Knowledge extracted from databases might improve safety, and the patterns provided from empirical data can be helpful to reduce mortality and morbidity resulting from hospital-acquired infections. In this study, increased age was associated with death in hospital-acquired infections. Many researches have demonstrated that acquired hospital infection might be associated with increased age (23-25). Car accidents and falling had a positive correlation with death since car accidents and fallings were the reasons for most of the admissions. Glance et al. showed that vehicle accidents were related to hospital-acquired infections (6). Invasive interventions, such as tracheal intubation and mechanical ventilator, were associated with death by hospital-acquired infections. This is consistent with Artiga's studies that indicated invasive intervention was associated with hospital-acquired infections (5, 26). In this study, surgical site infection and upper respiratory infection of trauma patients was associated with death. Another study demonstrated that Bloodstream Infection (27) and surgical site infection skin were associated with death (2, 9). Enterobacter, Escherichia coli, Pseudomonas aeruginosa, and acinetobacter were associated with death with hospital-acquired infection in the trauma patient. Hosseini and Ranjbar reported that Pseudomonas aeruginosa and acinetobacter were observed in multiple trauma patients (28). Interesting patterns were found among those who were infected less than 21 days with a positive correlation with death in hospital-acquired infection among trauma patients.

Limitations, Strengths and Future Directions

Past medical history and environmental hygiene data were not collected, but are essential determinants in the outcome. However, all the important features of injured patients were covered. This study might provide the initial framework to survey and control hospital-acquired infections in trauma patients by the business intelligence system. Future studies will be the replication of the data mining study with other data mining techniques and other features such as antibacterial, physiology on hospital admission, and past medical history. Also, future studies will develop a business intelligence platform to control and survey hospital-acquired infections in this trauma hospital.

Conclusion

Association rule mining might be the best approach for identifying the factors affecting death with hospital-acquired infections in trauma patients. Factors such as increasing age, tracheal intubation, and mechanical ventilator, surgical site infection skin, and upper respiratory infection are the most critical risk factors contributing to death from hospital-acquired infections in trauma patients by data mining.

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Authors' Contribution

MK contributed to the design, data collection, analysis, or interpretation of data, drafting, and final approval of the version to be published. MN contributed to the acquisition, analysis and interpretation of data; drafted the manuscript, and final approval of the version to be published. MY contributed to the design, collection of data, and revision of the manuscript critically for important intellectual content and final approval of the version to be published. MZ contributed to the acquisition, analysis and interpretation of data; revised the manuscript, and finally approved the version to be published.

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