Using Nursing Information and Data Mining to Explore the Factors That Predict Pressure Injuries for Patients at the End of Life

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This study investigated the association between patient characteristics and the occurrence of pressure injuries for patients at the end of life. A retrospective study was conducted using data collected from 2062 patients at the end of life between January 2007 and October 2015. In addition to demographic data and pressure injury risk assessment scale scores, injury history, disease type, and length of hospitalization were revealed as the major independent variables for predicting the occurrence of pressure injuries. Both χ^2 tests and *t* tests were employed for binary variable analysis, and logistic regression was used to conduct multivariate analysis. Classification models were formulated through decision tree analysis, backpropagation neural network, and support vector machine algorithms. The rules obtained using the decision tree algorithm were analyzed and interpreted. The accuracy rate, sensitivity, and specificity of the decision tree, backpropagation neural network, and support vector machine algorithms were 77.15%, 79.54%, and 74.76%; 78.12%, 81.37%, and 74.85%; and 79.32%, 81.03%, and 78.75%, respectively. The predictive factors, ranked in order of importance, were history of pressure injuries, without cancer, excretion, activity/mobility, and skin condition/circulation. These were the primary shared risk factors among the four models used in this study.

KEY WORDS: Data mining, Nursing, Predictive factors, Pressure injuries

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Pressure injuries, also known as pressure sores and pressure ulcers, can occur in both acutely and chronically ill patients.[1,2] Pressure injuries place a heavy burden on medical institutions by increasing the hours worked by nurses as well as the overall costs of healthcare. Furthermore, such injuries increase the length of hospital stays and the risk of infection and mortality.[3] According to the Taiwan Clinical Performance Indicator Report,[4] the prevalence of pressure injury (incidence rates) for the period 2011 to 2016 in Taiwan general wards was 0.07% to 0.09%; medical intensive care units, 0.04% to 0.26%; and surgery intensive care units, 0.26% to 0.39%.

Multiple-organ dysfunction syndromes are a serious concern for nurses caring for patients at the end of life. End-of-life care focuses on maintaining vital signs and managing the subjective feelings of patients and staff.[5] Decreased hemodynamics and blood perfusion for patients at the end of life increases the risk of pressure injuries.[6] Lunney et al[7] reported that decreased bodily function is often accompanied by multiple-organ failure for patients at the end of life. Functional decline typically occurred 4 to 5 months before patients with cancer were deceased, and organ failure occurred approximately 3 to 4 months prior to the death of those patients. By contrast, functional decline in patients who were frail in long-term care facilities occurred 12 months prior to the end of life.[7] The chance of a pressure injury developing for patients at the end of life is 62.5% and 55.7% within 2 and 6 weeks of death, respectively.[8,9] The rapid course of pressure injuries often affects patients' physical and psychological well-being.[10] DiAgostino[11] and Langemo and Black,[10] have examined the causes of pressure injuries for patients at the end of life and noted that such patients have a higher probability of manifesting pressure injuries because they are bedridden and experience incontinence, skin fragility, physical decline, and malnutrition. However, the incidence of pressure injuries is multifactorial. During end-of-life care, although clinical care staff had conducted risk assessment of pressure injury and established relevant precautions, the occurrence of pressure injury was not prevented.[12,13] Consequently, pressure injuries among patients at the end of life may not be totally prevented.

For patients who may have pressure injuries, nurses should conduct palliative wound care.[14]

Medical institutions have assessed the occurrence of pressure injuries in high-risk groups through studies using assessment tools; these tools have been developed for clinical application.[15] As a result of advances in medicine and the widespread use of information technology, medical databases now store large amounts of clinical data.[16] Benoit and Mion[17] analyzed a clinical database and established a classification model for pressure injuries to improve the quality of clinical nursing care. Data-mining algorithms have also been widely used to compile databases, and they have produced excellent results in various fields, including medicine and nursing.[18–20] To date, it appears that only Raju et al[21] applied data mining algorithms in the context of pressure injuries in severely ill patients; however, they did not focus on patients at the end of life. Therefore, this study used a pressure injury risk assessment scale in a clinical setting to investigate the correlations between occurrence of pressure injuries for patients at the end of life and risk factors for pressure injuries in terms of patients' age, sex, history of pressure injuries, disease type, and length of hospitalization. A predictive model was then developed to explain the variables involved in the development of pressure injuries for patients at the end of life.

METHODS

This study used logistic regression and three data mining algorithms (decision tree, backpropagation neural network, and support vector machine) to elucidate how predictive variables for patients at the end of life determine whether the occurrence of pressure injuries is indicative of a potential skin-failure phenomenon.

Figure 1 illustrates the process through which statistical inference (logistic regression) and the three data mining algorithms were applied to construct the classification models.

The Windows edition of IBM SPSS Statistics v. 20.0 (IBM, Armonk, NY) was used for descriptive statistical analysis. The decision tree, backpropagation neural network, and support vector machine algorithms in Waikato Environment for Knowledge Analysis 3.8 (University of Waikato, Hamilton, Waikato, New Zealand) were used to construct the classification models, and the rules obtained using the decision trees were analyzed and interpreted.

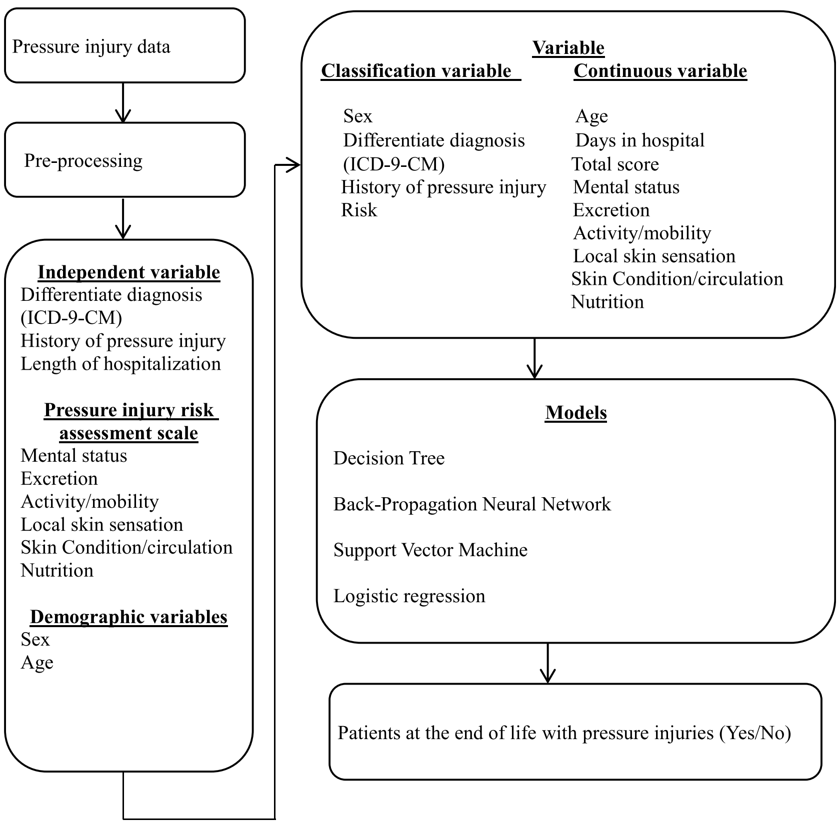

FIGURE 1. Flowchart of data analysis for patients at the end of life with pressure injuries.

Data Collection and Preprocessing

The research project proposal was submitted to the institutional review board of the En Chu Kong Hospital in Taiwan, which reviewed and approved the ethical aspects of this study (ECKIRB1041203). All stages of the study were conducted in accordance with the required guidelines and regulations. Informed consent was obtained from all participants. The pressure injury risk assessment used in the present study was generated following a literature review of evaluation tools for high-risk groups available in Taiwan.[22] For the correlation coefficient of the Chinese-language scale, $P < .05$ was considered statistically significant. The Cronbach's α for the scale was .7317 (>.71).[22] Factors examined in the pressure injury risk assessment included participant mental status, excretion, activity/mobility, local skin sensation, skin condition/circulation, and nutrition. Each factor was given a risk level, scored from 1 to 4. The higher the score, the better the patient's body condition. The highest possible score was 24 points (4 points $\times$ 6 factors). The higher the total score, the higher the possibility of the occurrence of a pressure injury. Total scores were further stratified as low, 6 to 9; mild, 10 to 14; moderate, 15 to 19; and 20 to 24, high risk for pressure injuries.

This study used data from patients at the end of life, with or without pressure injuries, in the final 6 months before death. Data from pressure injury risk assessments, end-of-life registration files, and skin pressure injury notification outcomes were obtained from a medical teaching hospital; these data covered the period between January 2007 and October 2015. Of the 2062 records obtained, 1026 and 1039 patients were with and without pressure injuries, respectively. Only patients 20 years or older were enrolled in this study. The input fields contained data on sex, age, differential diagnosis (ICD-9-CM), history of pressure injuries, length of hospitalization, mental status, excretion, activity/mobility, local skin sensation, skin condition/circulation, nutrition, and risk. The input fields were classified into categorical and numerical variables, and the occurrence of pressure injuries was the target variable for prediction.

Performance Measure of Algorithms Used

Both χ^2 tests and t tests were employed to examine whether statistical differences existed in the continuous and categorical predictor variables of the participants with and without pressure injuries. Logistic regression was performed to identify the relevant risk factors that lead to pressure injury development during the end-of-life period, including pressure injury disease history, disease type, length of hospitalization, pressure injury risk assessment scale, and personal attributes. Standardized regression estimates were used to evaluate the importance of influential factors. The predictive power of the model was assessed by the area under the receiver operating characteristic curve. The adequacy of the model was evaluated by deviance, Pearson's χ^2 statistics, and Hosmer and Lemeshow statistics.[23]

The K-fold cross-validation method[24] was used to evaluate the performance of the classification models. The data were divided into K parts; the data from the $K - 1$ parts were used as training data, and the data from the remainder were used as testing data. After the classification models were constructed according to various parameter combinations, accuracy rate, sensitivity, and specificity were used to evaluate their performance. Accuracy rate was calculated by dividing the number of correct classifications (true positives and true negatives) by the total number of classifications. For patients with pressure injuries, sensitivity was defined as the proportion of patients who tested positive (ie, had pressure injuries), and for patients with no pressure injuries, specificity was represented by the proportion of patients who tested negative (ie, had no pressure injuries).

Data Mining Algorithms

Many studies have used traditional statistical methods for constructing classification models. However, these methods must satisfy the assumptions. If the data do not satisfy the assumptions, the traditional statistical methods may not be applicable.[25] Data mining algorithms do not need to satisfy the assumptions of traditional statistical methods; therefore, they can overcome compound problems and process large data rapidly.[26]

Decision Tree

Decision trees form a part of machine learning, which is an important area of artificial intelligence.[27,28] Decision trees are similar to the mathematically or symbolically valued target functions that are robust even with "noisy" data and are capable of learning disjunctive expressions. Because of its inherent characteristics, a decision tree implements a top-down divide-and-conquer method that recursively partitions a dataset into smaller subdivisions. These procedures are the basis of a set of tests defined at each branch in the tree. The tree-like structure is composed of a root node (created from the entire set of data) and a set of internal (splits) and terminal (leaves) nodes.[33]

Backpropagation Neural Network

The backpropagation neural network is a standard neural network algorithm with multilayer perceptron architecture. The learning process for a backpropagation neural network consists of initialization, forward, and reverse phases. In the initialization phase, the weights and biases in the network are initialized to small random numbers (eg, ranging from 0.0 to 1.0). In the forward phase, the data are fed into the input layer of the network. Then, the net input and output of each neuron in the hidden and output layers are calculated. To calculate the net input of the neuron, each input connected to the neuron is multiplied by its corresponding weight and summed; the net input is then updated by adding the bias of the neuron. The net output of each neuron is calculated in a similar way. In the reverse phase, the error is propagated backward by modifying the weights and biases to reflect the propagated errors.[29]

Support Vector Machines

Support vector machines have a sound theoretical foundation and are considered one of the most powerful and accurate methods of machine learning.[30] Support vector machines can map input vectors into a high-dimensional feature space by using nonlinear mapping functions and can determine a computationally efficient method to search a separate hyperplane in the space. Support vector machines mainly create an optimal hyperplane as a basis for classification decisions, thereby reducing training and test errors simultaneously.[31,32]

RESULTS

Exploratory Analysis of Sample Data

Table 1 lists the distributions of study participant characteristics. A total of 2062 records were selected, with dates ranging from January 2007 to October 2015. The number of patients at the end of life with and without pressure injuries was 1026 and 1039 patients, respectively (approximately a 1:1 ratio). The mean age was 75.5 years, with a standard deviation of 14.4 years for all patients at the end of life. The average number of days in hospital was 12.0, with a standard deviation of 15.2 days, for all patients at the end of life. The development of pressure injuries occurred in various places, including patients' homes, long-term care facilities, and hospitals. The risk score comprised six variables, each with a severity score ranging from 1 (lowest) to 4 (highest); thus, the possible total score ranged from 6 to 24. The risk category was then determined on the basis of the total severity scores; scores of 6 to 9, 10 to 14, 15 to 19, and 20 to 24 were classified as low, mild, moderate, and high levels of risk, respectively. The moderate risk category had the largest number of patients (n = 874, 44.2%).

Table 2 presents the bivariate analysis results of the participant characteristics and their pressure injury status at the end of life. The prevalence of pressure injuries was highest in the groups aged 81 to 90 years (n = 414, 58.2%) and 91 years or older (n = 131, 59.3%); 346 (77.9%) patients at the end of life had a history of pressure injuries, and 570 (65.0%) had not been diagnosed with cancer. The patients without pressure injuries most commonly scored in the low (n = 163, 86.7%) and mild (n = 330, 67.8%) risk categories. For patients with pressure injuries, the most common categories were moderate (n = 453, 51.8%) and high (n = 391, 76.1%) risk.

This study compared participants with and without pressure injuries to determine whether statistical differences existed in characteristics, assessment scale scores, and end-of-life pressure injury status. The results revealed statistically significant differences for age, length of hospitalization, risk score, mental status, excretion, activity/mobility, local skin sensation, skin condition/circulation, and nutrition.

Table 1. Distributions of the Research Participants' Characteristics

Classification Variable (Items)	n	%
Total	2062	100
Sex		
Male	1125	54.6
Female	937	45.4
Age (years)		
21–30	5	0.3
31–40	38	1.9
41–50	106	5.1
51–60	172	8.3
61–70	247	12.0
71–80	563	27.3
81–90	710	34.4
≥91	221	10.7
Pressure injures for patients at the end of life		
Yes	1026	49.8
No	1036	50.2
History of pressure injury		
Yes	444	21.5
No	1618	78.5
Differentiate diagnosis (ICD-9-CM)		
Advanced disease	903	43.8
With cancer	282	13.7
Without cancer	877	42.5
Risk		
Low (6–9)	188	9.1
Mild (10–14)	487	23.6
Moderate (15–19)	874	42.4
Higher (20–24)	513	24.9
Continuous Variable (Items)	**Mean**	**SD**
Age, y	75.5	14.4
Length of hospitalization	12.0	15.2
Total score	16.1	4.3
Mental status	2.9	1.3
Excretion	2.1	1.4
Activity/mobility	3.5	1.0
Local skin sensation	2.6	1.1
Skin condition/circulation	2.6	1.0
Nutrition	2.4	1.1

Table 2. Characteristics of the End-of-Life Research Participants and Their Pressure Injury Statuses

Variable (Items)	Without Pressure Injury (No) (n = 1036)		With Pressure Injury (Yes) (n = 1026)		X^2	P
	n	%	n	%		
Sex						
Male	599	53.2	526	46.8	8.924	.003
Female	437	46.6	500	53.4		
Age, y						
21–30	4	80.0	1	20.0	78.200	<.001
31–40	29	76.3	9	23.4		
41–50	73	68.9	33	31.1		
51–60	115	66.9	57	33.1		
61–70	140	56.7	107	43.3		
71–80	288	51.2	274	48.8		
81–90	297	41.8	414	58.2		
≥91	90	40.7	131	59.3		
History of pressure injury						
Yes	98	22.1	346	77.9	179.618	<.001
No	938	58.0	680	42.0		
Differentiate diagnosis (ICD-9-CM)						
Advanced disease	562	62.2	341	37.8	142.501	<.001
With cancer	167	59.2	115	40.8		
Without cancer	307	35.0	570	65.0		
Risk						
Low (6–9)	163	86.7	25	13.3	304.939	<.001
Mild (10–14)	330	67.8	157	32.2		
Moderate (15–19)	421	48.2	453	51.8		
Higher (20–24)	122	23.8	391	76.2		

Application of Logistic Regression and Its Result

Age, history of pressure injuries, cancer status (with/without cancer), length of hospitalization, excretion, activity/mobility, local skin sensation, skin condition/circulation, and nutrition were significantly associated with the probability of developing pressure injuries. By contrast, mental status was negatively associated with the probability of developing pressure injuries. According to the standardized coefficient estimates, local skin sensation, skin condition/circulation, history of pressure injuries, type of disease, and activity/mobility were the most significant predictors of the development of pressure injuries (Table 3).

The odds of developing pressure injuries increased by 2% for every year of age. Patients with a history of pressure injuries were 3.08 times more likely to develop pressure injuries. As compared to other advanced-type diseases, patients with and without cancer were 2.60 and 1.29 times more likely to develop pressure injuries, respectively. The odds of developing pressure injuries increased by 2% for an additional day of hospital stay. Furthermore, the odds of developing pressure injuries increased for every unit increase in excretion status (33%), activity/mobility (57%), local skin sensation (23%), skin condition/circulation (108%), and nutrition (18%), respectively. However, for every one-unit increase in mental status, the odds of developing pressure injuries declined by 15%.

The area under the receiver operating characteristic curve of the logistic regression was 0.828. When a cutoff value of 0.5 was chosen, the sensitivity and specificity were 73.88% and 74.71%, respectively. The model of fit was assessed through Pearson χ^2 statistics, deviance statistics, and Hosmer-Lemeshow statistics, and the corresponding P values were .25, .79, and .803 respectively.

Application of the Backpropagation Neural Network Algorithm

The backpropagation neural network algorithm established the importance rank of predictors; the size of vertical bars corresponded to the importance. We ran this algorithm for 200 trials with different random seeds. Correct classification, sensitivity, and specificity ranged from 74.68% to 78.12%, 76.74% to 82.34%, and 70.66% to 75.34%, respectively.

The factors that best predicted the development of pressure injuries were age, history of pressure injuries,

Table 3. Prediction Results of Logistic Regression Regarding the Presence of Pressure Injuries in the End-of-Life Stage

Variable (Reference group)	*B*	SE	Wald	*P*	Odds Ratio	95% Confidence Interval	
Sex (female)							
Male	−0.02	0.11	0.05	.83	0.98	0.79	1.21
Age	0.01	0.00	13.92	<.001	1.02	1.01	1.02
History of pressure injury (no)							
Yes	1.13	0.14	63.40	<.001	3.08	2.34	4.06
Differentiate diagnosis (advanced disease)			67.97	<.001			
With cancer	0.25	0.17	2.21	.14	1.29	0.92	1.80
Without cancer	0.95	0.12	65.66	<.001	2.60	2.06	3.27
Length of hospitalization	0.02	0.00	31.56	<.001	1.02	1.02	1.03
Mental status	−0.16	0.07	5.50	.02	0.85	0.74	0.97
Excretion	0.29	0.04	44.83	<.001	1.33	1.23	1.45
Activity/mobility	0.45	0.08	33.56	<.001	1.57	1.35	1.83
Local skin sensation	0.21	0.07	7.53	.01	1.23	1.06	1.42
Skin condition/circulation	0.73	0.07	125.89	<.001	2.08	1.83	2.36
Nutrition	0.17	0.05	10.16	<.001	1.18	1.07	1.31
Constant	−6.68	0.45	216.07	<.001	0.00		

absence of cancer, excretion, activity/mobility, skin condition/circulation, pressure injury assessment assay, nutrition, and length of hospitalization. Patients' sex and local skin sensation were not important predictive factors.

Application of Support Vector Machine Algorithms

The application of support vector machine algorithms established the rank of predictors; the size of vertical bars corresponded to the importance. We ran the support vector machine algorithms for 200 trials with different random seeds. Correct classification, sensitivity, and specificity ranged from 78.12% to 79.92%, 78.67% to 82.53%, and 75.24% to 82.24%, respectively.

The factors that best predicted the development of pressure injuries were history of pressure injuries, absence of cancer, excretion, activity/mobility, skin condition/circulation, risk, length of hospitalization, age, mental state, and sex. Patients' local skin sensation and nutrition were not important predictive factors.

Comparison of the Three Data Mining Algorithms

We ran each of the classification algorithms for 200 trials with different random seeds. The accuracy, sensitivity, and specificity rates were 77.15%, 79.54%, and 74.76% for the decision tree algorithm; 78.12%, 81.37%, and 74.85% for the backpropagation neural network; and 79.32%, 81.03%, and 78.75% for the support vector machine, respectively.

The support vector machine algorithm had the highest classification actual rates, followed by the backpropagation neural network and decision tree algorithms. Although the accuracy rate of the decision tree was the lowest, it produced rules that were easy to interpret.

DISCUSSION

This study investigated the risk factors for pressure injuries among patients at the end of life. Predictions were made by employing four models using demographic data, a pressure injury risk assessment scale developed from the literature, and independent variables. The results revealed that history of pressure injuries, noncancer diagnosis, excretion, activity/mobility, and skin condition/circulation were the shared key risk factors among the four models for predicting the development of pressure injuries.[34–36]

The demographic data revealed that men were 0.98 times more likely to develop pressure injuries than women were; this finding was identical to that of a previous report.[37] Further analysis revealed that sex did not generate statistically significant differences in the occurrence of pressure injuries. For age, the ratio of patients with pressure injuries to patients without pressure injuries was 58.2% in patients aged 81 to 90 years (n = 414) and 59.3% in patients 91 years or older (n = 131). Patients aged 81 to 90 years developed the most pressure injuries of all the age groups. These results indicate that the potential risk of pressure injury development increases with age.[38] Older adults are frequently hospitalized due to age-related issues and decline in physical function. Pressure injuries in older patients can lead to further complications. Patients at the end of life are often more likely to develop pressure injuries because they often have activity/

mobility restrictions and excess excretion. The results confirmed previous findings that patient age influences the occurrence of pressure injuries and revealed a statistically significant correlation between age and pressure injuries for patients at the end of life.

Differentiating patients at the end of life with pressure injuries by diagnosis revealed that 65.0% were noncancer diagnoses (n = 570). Patients without cancer were significantly more likely to develop pressure injuries than those with advanced diseases. The patients were grouped into those with advanced diseases, those with cancer, and those without cancer according to ICD-9-CM. The results of the present study regarding diagnosis and pressure injury occurrence are inconsistent with those obtained in another study,[39] in which patients with cancer (n = 115, 40.8%) were more likely to develop pressure injuries than were those without cancer. One explanation for this is that patients without cancer often have more limited activity and mobility, which fosters the development of pressure injuries.

Logistic regression analysis revealed statistically significant differences between patients with and without pressure injuries and days in hospital (n = 346, 77.9%). This result is consistent with the findings of a previous study.[38] In the present study, the average number of days in hospital for patients with pressure injuries (14.12 ± 17.7 days) was higher than the average for patients without pressure injuries (10.00 ± 11.76 days). This indicated a higher probability of pressure injury occurrence when patients were hospitalized for longer periods or were close to the end of life.

Table 3 presents the logistic regression prediction results regarding the chance that pressure injuries will develop during the end-of-life stage. An analysis of correlations among the six risk factors revealed that except for mental status ($P = .02$; odds ratio, 0.85) and local skin sensation ($P = .01$; odds ratio, 1.23), all factors attained statistical significance ($P < .001$). In terms of the correlation between key risk factors and pressure injuries, the following factors exhibited statistical significance: age, medical history of pressure injuries, absence of cancer, length of hospitalization, excretion, activity/mobility, skin condition/circulation, and nutrition ($P < .05$).

This study examined whether significant differences ($P = .005$) existed between total scores on the pressure injury risk assessment scale for patients with and without pressure injuries. Those with pressure injuries scored 15 to 19 (n = 453, 51.8%) and 20 to 24 (n = 391, 76.2%), exhibiting moderate and high risk for developing pressure injuries. Therefore, health professionals should carefully monitor the probability of pressure injury development for patients at the end of life whose total risk-level score on the pressure injury risk assessment scale is equal to or greater than 17. Special care is required to actively prevent the development or mitigate the deterioration of pressure injuries in these patients and to prevent related infections.

In this study, three data mining algorithms were used to construct classification models and identify the factors that best predicted the occurrence of pressure injuries. Among the chosen algorithms, the decision tree is capable of generating rules that can be used to determine whether patients at the end of life have a high risk of pressure injuries. These rules can assist nurses in screening to assess the likelihood that pressure injuries will develop and administer appropriate care measures to each patient. This is especially critical with pressure injuries, which benefit considerably from early prevention or mitigation measures and a care plan focused on preventing infection.

Palliative wound care should be provided for patients with pressure injuries to improve quality of life and relieve the pain of chronic wounds. The purpose and priority of wound care depends on the patient's health condition. Therefore, implementing such care should be considered from the following perspectives: (1) facilitating effective communication, (2) stabilizing a wound and preventing or hindering it from deteriorating, (3) minimizing the infection rate, and (4) managing patient and family member concerns.[14]

Limitations and Future Research Directions

Several limitations of this study should be acknowledged. First, the sample size was limited. We did not determine whether a pressure injury occurred before or after the patients were admitted. Another limitation is the wide timeframe of the study; it encompassed 8 years, during which many changes to care practices occurred. Using different scales to determine the risk of pressure injuries might have affected the results and requires further analysis. Finally, this was a cross-sectional study, which restricted the collection of research data; therefore, other predictive factors for pressure injuries could not be evaluated. Nevertheless, the results remain useful in that they serve as internal evidence to help nurses with no clinical experience in making correct clinical decisions.

In this study, a trial-and-error method was employed to determine the parameter values of three data mining algorithms. In the future, heuristic algorithms could be combined with these three algorithms to overcome the problem of parameter setting. Other data mining algorithms could also be used to determine predictive factors for pressure injuries for patients at the end of life.

The pressure injury risk assessment scale used in this study is common in Taiwan. However, numerous pressure injury risk assessment scales are capable of detecting susceptibility to pressure injuries. Therefore, the results obtained using different pressure injury risk assessment scales (eg, Braden score) may be a worthwhile topic for future research.

CONCLUSIONS

This study used logistic regression and three data mining algorithms to identify effective predictors for pressure injuries for patients at the end of life. Data mining algorithms can be used to gather valuable and relevant information from any large medical database. We obtained a total of 2062 records from a medical teaching hospital; the dates of the records ranged between January 2007 and October 2015; hospitalized patients provided information regarding the Pressure Injury Assessment Assay, automatic discharge, and death. The results of this study revealed that the logistic regression and the decision tree algorithm provided the most interpretable models. This study employed the decision tree algorithm and logistic regression to obtain valid and consistent results. The predictive factors obtained were, in order of importance, history of pressure injuries, non-cancer diagnosis, excretion, activity/mobility, and skin condition/circulation.

This study helps nurses to predict the occurrence of pressure injuries, communicate with care staff and patients at the end of life, and develop care objectives. All of these tasks can be done in a timely fashion with the assistance of statistical modeling. Understanding the issue of pressure injuries for patients at the end of life will help improve care plans and prevent the development or mitigate the deterioration of pressure injuries, prevent infections, and assist patients to experience a good death.

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