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Original Research

The application of braden scale and rough set theory for pressure injury risk in elderly male population

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Abstract

Background: The elderly with a limited body or bedridden are prone to pressure injury, and the Braden scale is often used as a risk assessment tool. However, few studies have explained the relationship between risk factors and risk levels using machine learning methods from Braden clinical observation data. Additionally, nearly half of the elderly over 75 years old in China are men.

Purpose: This study aimed to establish a pressure injury risk prediction model for elderly male patients using a machine learning method based on hospital clinical data. It further analyses the importance of risk factors and risk levels.

Methods: This study's Braden observation data were obtained from the electronic medical records of elderly male patients from 27 October 2019 to 1 November 2020 in the case hospital. Rough set theory was used to identify the perception patterns between risk factors and risk levels based on the data.

Results: The importance of rough set theory showed that sensory perception and nutrition are key risk factors for identifying elderly male inpatients. Therefore, nurses should pay special attention to the measurement scores of these two risk factors. Moreover, this method also revealed conditions/decision rules for different risk levels. Among elderly male inpatients at risk of severe pressure injury, 42% of the observation data showed that their physical condition is completely limited in sensory perception, possibly insufficient nutrition, friction and shearing problems, and bedridden activities.

Conclusion: This model can effectively identify the critical risk factors and decision rules for different risk levels for pressure injury in elderly male inpatients. This allows nurses to focus on patients at a high risk of possible pressure injury in the future without increasing their workload. This study also provides a way to solve the problem that the Braden scale shows insufficient predictive validity and poor accuracy in identifying patients with different pressure injury risk levels, so it cannot fully reflect patients' characteristics.

Keywords

Pressure injury risk; Braden scale; Predictive modeling; Data mining; Rough set theory

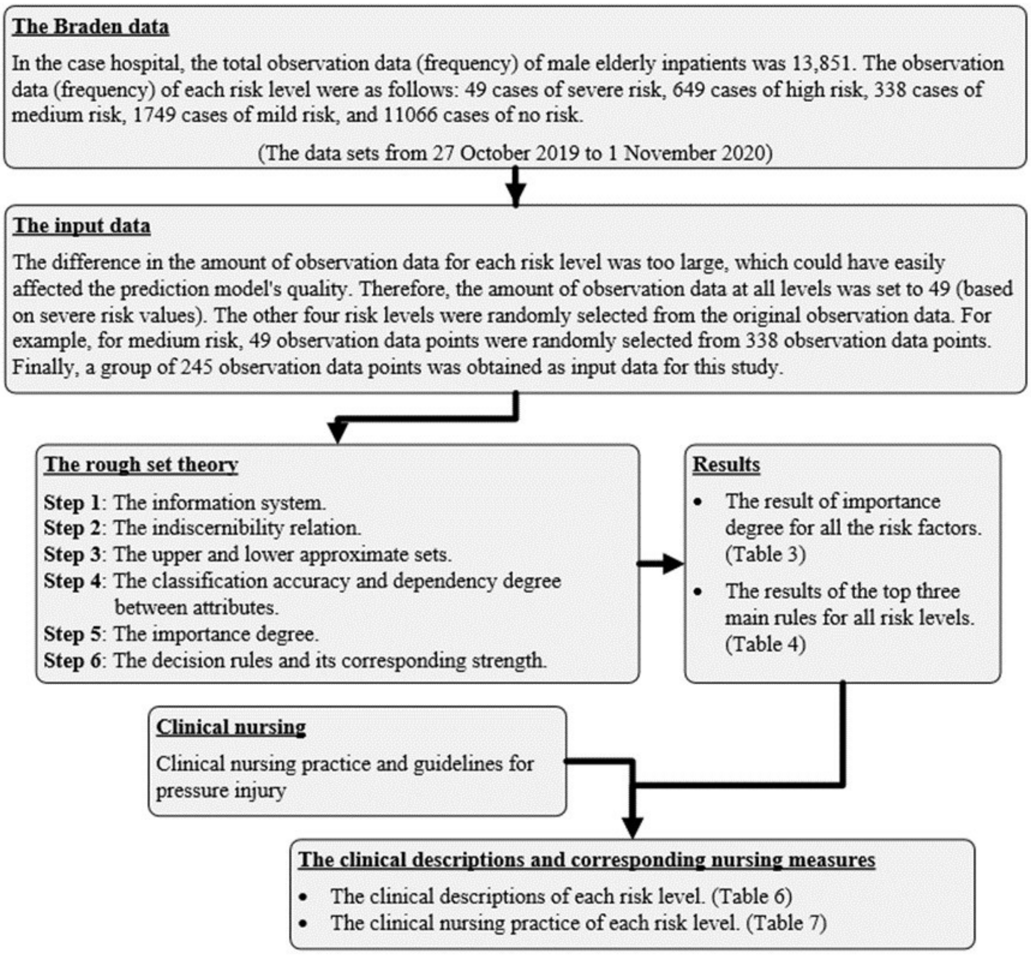

FIG. 1. Research flow of the rough set theory for Braden observation data.

1. Introduction

The Chinese population is aging dramatically [1]. In 2010, the percentage of the elderly population over 60 and 65 years old among the total population in China's official sixth census data was 13.32% and 8.92%, respectively [2]. Further, the percentage of China's population aged 60 years and above would increase by 28% (402 million) by 2040 [3]. This implies that China's population is rapidly aging.

Pressure injuries are a common health problem that often occur in elderly individuals who are physically limited or bedridden [4]. Pressure injuries may result in long-term chronic wounds for no reason and even death from ulcer complications [5]. Furthermore, the wound treatment of pressure injuries is a significant health care issue [6]. It is accompanied by the adverse effects of reducing the quality of life and increasing the treatment cost [7]. Fortunately, most pressure injuries can be avoided before they occur [8, 9]. Therefore, it is essential to use a reliable objective standard for evaluation and preventive measures [7].

The commonly used pressure injury risk scales are the Braden, Norton, and Waterloo scales [10, 11]. A study tested Braden's scale in a home care environment and concluded that it effectively identified the risk of pressure injuries, but its prediction ability was limited [12, 13]. A meta-analysis showed that all three scales had a moderate level of accuracy [4]. Another meta-analysis also showed that the Braden scale is not necessarily applicable to all patients, but it still has moderate predictive validity [14]. Therefore, the Braden scale is still often used in risk assessment and predicting pressure injuries in different populations [7, 15–21].

The Braden scale's risk level adds the scores of all risk factors and converts them into corresponding risk levels using a standard. The method is simple to operate, can reflect the overall risk degree or grade of patients, and can help in taking corresponding preventive nursing measures. However, due to changes in the clinical environment, the accuracy of any particular tool's prediction ability may decline [4]. Therefore, it is necessary to develop more accurate assessment tools to ensure that the objectives of evidence-based interventions can have the most significant impact [4].

Machine learning methods provide another way to overcome this limitation [22]. This type of study further identifies behaviour patterns from a group of patients' clinical data and establishes prediction models. For example, Cox and Schallom used regression analysis and decision tree (DT) to identify pressure injury risk in critically ill inpatients [15]. Moon and Lee applied the decision tree method to analyse pressure injury risk in residents of long-term care institutions [23]. Lahmann *et al.* used the chi-square automatic interaction detector (CHAID) method to explore pressure injuries in residents during long-term care [24]. Raju and Su used four machine learning methods: logistic regression, decision tree, random forest, and multivariate adaptive regression splines method, to discuss the risk factors for pressure injury [25]. Setoguchi and Ghaibeh used the alternating decision tree method to establish a pressure injury prediction model for operation duration, metastatic activity, and body mass index [26]. Casal-Guisande *et al.* proposed an integrated model of an expert system and image data to enrich further the prediction and interpretation of pressure injury treatment [27]. These studies show that data-driven decision-making is a new trend in pressure injury prediction.

There is a research gap in past studies on pressure injury risk prediction in the elderly. From a population perspective, few studies have explored male elderly inpatients as survey subjects. In China, 48% of the elderly (over 65 years old) are men, accounting for nearly half of the elderly population [2]. From the prediction model's perspective, these machine learning methods cannot further detail the behaviour patterns for each risk level of pressure injury. Rough set theory is a machine learning method with a proper interpretation function [28]. This method uses the decision rule form as the information expression for the behaviour patterns. Furthermore, it does not require any prior information and can objectively deal with uncertainty in the decision-making process [29–32].

This study uses rough theory to establish a prediction model from the Braden scale data of elderly male inpatients to fill the research gap. The model can further provide two pieces of information: (i) the importance of each risk factor for identifying the level of pressure injury, and (ii) the behavioural decisions for each risk level of pressure injury. The Braden scale survey data of male elderly inpatients over 65 years old were obtained from a third-class first-class general hospital in China.

2. Methods

This section describes the Braden scale, observation data, and machine learning methods used in this study. First, the Braden scale was used as a risk assessment tool for pressure injuries. A provincial third-class first-class hospital provided clinical data of elderly male inpatients over 65 years of age. The clinical data were collated and used as the input observation data for data mining and analysis. Finally, each risk factor's importance and the decision rules for each risk level were obtained using rough set theory. The research framework and flowchart are presented in Fig. 1. This section can be divided into the following three subsections: (i) the Braden scale, (ii) study design and sample selection, and (iii) data mining and statistical analysis.

2.1 The Braden scale

The Braden scale was developed by Bergstrom *et al.* to evaluate pressure injury risk in 1987 [33, 34]. It is also the most commonly used pressure injury assessment scale in the United States and has been translated into many languages [34]. The five risk factors of the scale are sensory perception (C_1), mobility (C_2), nutrition (C_3), moisture (C_5), and activity (C_6). The score ranges of these risk factors are 1 to 4, which are the lowest and highest scores, respectively. Additionally, the score ranges of friction and shear (C_4) are 1 to 3. The six risk factors' scores are added to obtain the final Braden risk score, which ranges from 6 to 23. The Braden risk score is converted into the corresponding risk level through a standard, such as severe risk (score: less than or equal to 9), high risk (score: 10-12), moderate risk (score: 13-14), mild risk (score: 15-18), and no risk (score: greater than 18).

The six risk factors in the Braden scale are specific factors (called the condition attributes) that may develop into pressure injuries. The Braden risk score's risk level indicates the level of pressure injury risk (called the decision attribute). The Braden scale is shown in Table 1.

2.2 Study design and sample selection

This study was approved by the study hospital's Institutional Review Board (approval number: K20201234). Recruitment was conducted after permission was obtained from the study hospital. This study's subjects were elderly male inpatients (over 65 years old) from a medical centre in Zhejiang province, China. Braden data were obtained from the hospital's nursing electronic medical record system. We used a set of hospital nursing clinical data sets from 27 October 2019 to 1 November 2020. In the case hospital, the total observation data (frequency) of male elderly inpatients was 13,851. The observation data (frequency) of each risk level were as follows: 49 cases of severe risk, 649 cases of high risk, 338 cases of medium risk, 1749 cases of mild risk, and 11066 cases of no risk.

The difference in the amount of observation data for each risk level was too large, which could have easily affected the prediction model's quality. Therefore, the amount of observation data at all levels was set to 49 (based on severe risk values). The other four risk levels were randomly selected from the original observation data. For example, for medium risk, 49 observation data points were randomly selected from 338 observation data points. Finally, a group of 245 observation data points was obtained as input data for this study. The demographic characteristics of the study participants are shown in Table 2.

2.3 Data mining and statistical analysis

Pawlak invented the rough set theory in 1982 [28]. This method uses the classical set theory and equivalence relation as the basis of data space partition. The method then establishes the upper and lower approximation sets to approximate the classification boundary region for the objective through known information [35]. This approximation method can effectively deal with the potential fuzziness or uncertainty of the observation data's classification boundaries. The rough set theory can effectively establish the behavioural relationship between condition attributes and decision attributes and

TABLE 1. The Braden scale with its corresponding domain values

Attributes	Domain value
Condition attributes	
Sensory perception (C_1)	(1) Completely limited, (2) Very limited, (3) Slightly limited, (4) No impairment.
Mobility (C_2)	(1) Completely immobile, (2) Very limited, (3) Slightly limited, (4) No limitation.
Nutrition (C_3)	(1) Very poor, (2) Probably inadequate, (3) Adequate, (4) Excellent.
Friction and shear (C_4)	(1) Problem, (2) Potential problem, (3) No apparent problem.
Moisture (C_5)	(1) Constantly moist, (2) Very moist, (3) Occasionally moist, (4) Rarely moist.
Activity (C_6)	(1) Bedfast, (2) Chairfast, (3) Walks occasionally, (4) Walks frequently.
Decision attribute	
Overall risk level (D)	(1) Severe risk (Score: less than or equal to 9), (2) High risk (Score: 10-12), (3) Moderate risk (Score: 13-14), (4) Mild risk (Score: 15-18), (5) No risk (Score: greater than 18).

TABLE 2. The demographic characteristics of study subjects

Variables	frequency	%
Age		
65-69	41	17%
70-79	98	40%
80-89	76	31%
90 and above	30	12%
Unit in Contract		
Farmer	151	62%
Retirement	69	28%
Workers	5	2%
Other	20	8%

use the decision rule form as information expression. Nowadays, rough set theory has been applied to many different topics [36–38].

This method does not require any prior information (such as membership function and distribution form) and can objectively deal with and describe uncertain phenomena in observed data [29–32]. Nurses can easily understand different risk levels of pressure injury among elderly male patients and provide corresponding nursing measures. A brief description of the calculation for rough set theory is as follows [28, 38, 39].

The first step: the information

The observation data of the Braden scale can be defined as an information system S, which includes four main elements: (1) a non-empty and finite set of Braden clinical behaviours for male elderly inpatients U; (2) a non-empty set of finite attributes $A = C \cup D$, that is, items C and risk level D in the Braden scale; (3) the domain value of the attributes V; and (4) an information description function (representing all correspondence) f. The information system can be defined by Eqn. 1.

$$S = (U, A, V, f) \tag{1}$$

The second step: the indiscernibility relation

If the objects contain the same information on the same attribute, it will cause an indiscernibility relationship. The two objects are equivalent and belong to the intersection of the same classification. If the attribute set D is a non-empty subset of the attribute set A, the indiscernible relationship between the objects x_1 and x_2 can be defined by Eqn. 2.

$$(x_1, x_2) \in I_D \Leftrightarrow f(x_1, a_d) = f(x_2, a_d), \forall a_d \in D \tag{2}$$

The third step: the upper and lower approximate sets

The approximate space is composed of the equivalent relation between the universal set with n objects and the attribute set. In the equivalence relation of an attribute set, the equivalence class forms elementary sets. The rough set is the following two sets of lower and upper approximations that represent the data's uncertainty, as shown in Eqns. 3 and 5.

$$\underline{D}(X) = \{x \in U : I_D(x) \subseteq X\} \cup \{Y \in U \mid D : Y \subseteq X\} \tag{3}$$

$$\bar{D}(X) = \{x \in U : I_D(x) \cap X \neq \emptyset\} \cup \{Y \in U \mid D : Y \cap X \neq \emptyset\} \tag{4}$$

$$BN_D(X) = \bar{D}(X) - \underline{D}(X) \tag{5}$$

Moreover, the boundary region BN_D refers to the objects in the boundary region, which cannot be classified as belonging or not belonging to the set X under the current information.

If the elements of the universal U can completely determine the elements belonging to the set X, it is called a positive field pos_D. On the contrary, if it is uncertain, it is called a negative field neg_D. These fields are expressed in Eqns. 6 and 7, respectively:

$$pos_D(X) = \underline{D}(X) \tag{6}$$

$$neg_D(X) = U - \bar{D}(X) \tag{7}$$

The fourth step: the classification accuracy and dependency *degree between attributes*

The condition attribute set C corresponds to the degree of interpretation of the classification target, which can be defined by the ratio of the upper approximation set to the lower approximation set, as shown in Eqn. 8.

$$\gamma_D(C) = \frac{\sum card\, \underline{D}\ (X_i)}{card\, U} = \frac{pos_D\ (C)}{|U|} \tag{8}$$

where dependency degree $\gamma_D\ (C)$ means that under the equivalent relation information of the attribute set D, the objects of the universal set U can be correctly divided into a condition attribute set C.

The fifth step: the importance

According to the degree of dependency $\gamma_D\ (C)$ between attributes, the dependency degree change is further observed by deleting each condition attribute. The condition attribute C_1 is an example, and its strength is given by Eqn. 9.

$$\begin{aligned} \sigma_{(C,D)}\ (C_1) &= \frac{(\gamma_D(C) - \gamma_D\ (C - \{C_1\}))}{\gamma_D(C)} \\ &= 1\ -\ \frac{\gamma_D\ (C - \{C_1\})}{\gamma_D(C)} \end{aligned} \tag{9}$$

where $\sigma(C_1)$ is between 0 and 1, with a higher value indicating that condition attribute C_1 has a higher level of importance.

The seventh step: the decision rules and their corresponding strength

According to the degree of dependence between attributes, decision rules can be derived from the information system. This rule is also called the minimum coverage rule, and its expression is given by Eqn. 10.

$$\text{A decision rule: } \Theta \rightarrow \Gamma \text{ and it also read if } \Theta \text{ then } \Gamma \tag{10}$$

where Θ and Γ represent the condition attributes and decision attributes of the rules, respectively. The decision rules are 'if-then' statements related to the conditions and decision categories. It also expresses the relationship between condition attributes and decision attributes. The strength of the decision rules is given by Eqn. 11.

$$\eta_s\ (\Theta, \Gamma) = \frac{\sup_s\ (\Theta, \Gamma)}{card\ (U)} \tag{11}$$

where $\sup_s\ (\Theta, \Gamma)$ is the support of decision rule $\Theta \rightarrow \Gamma$ in $S \cdot card\ (U)$. is the cardinality of U.

For detailed calculation steps and the introduction of rough sets, please refer to Pawlak's studies [28, 40]. This study's rough sets were calculated using the Rough Set Data Explorer (Rose2) software [41].

3. Results

The rough set theory provided two results regarding each risk factor's importance and the decision rules for each risk level for pressure injury in elderly male inpatients. The former can help nurses identify the critical risk factors among the six risk factors; the latter can help nurses understand each risk level's behaviour rules/conditions. This information is helpful for nurses to understand patients' clinical behaviours better. The result of the 5-fold cross-validation for the model is given at the end.

3.1 The result of importance of each risk factor

First, a prediction model is established using rough set theory. Then, after each risk factor is excluded one by one, the prediction model's reduced accuracy is considered to be the importance degree of these factors. The results showed that the order of importance of all risk factors from high to low was: sensory perception (C_1), nutrition (C_3), activity (C_6), friction and shear (C_4), moisture (C_5), and mobility (C_2). Sensory perception (C_1) and nutrition (C_3) were the most prominent risk factors for elderly male patients. The degree of importance is obtained using Eqn. 9 in Step 5 of the rough set theory. The results for all the risk factors are shown in Table 3.

TABLE 3. The important degree for each risk factor

Risk factors	Important degree	Weight
Sensory perception (C_1)	0.388	0.257
Mobility (C_2)	0.127	0.084
Nutrition (C_3)	0.363	0.240
Friction and shear (C_4)	0.192	0.127
Moisture (C_5)	0.188	0.124
Activity (C_6)	0.253	0.167
Sum	1.511	1

3.2 The result of decision rules for each risk level

The rough set theory can further reveal the relationship between risk factors and risk levels in the original data and help in making decision rules through a minimum coverage rate. A total of 45 decision rules were derived from 245 observation data in this study through rough set theory. These rules include five rules for severe risk and 12 rules for high risk. Furthermore, 11 rules apply to moderate risk, 11 rules to mild risk, and six rules to no risk. To effectively understand each risk level's main behaviours, only the top three main rules are displayed for each risk level. They are also the main behavioural patterns representing this risk level. The top rule in the severe risk level is taken as an example. In male elderly patients with severe risk of pressure injury, 42% of the observation data showed that their condition was characterized by '(Sensory perception (C_1) = 1) & (Nutrition (C_3) = 2) & (Friction and shear (C_4) = 1) & (Activity (C_6) = 1)'. Moreover, when a male elderly inpatient meets this rule, he has a 42% possibility of serious risk of pressure injury. The result of each risk level's decision

TABLE 4. Minimal covering rules with top 3 for each risk level

No.	Conditions	Decision	Number of objects
1	(Sensory perception (C_1) = 1) & (Nutrition (C_3) = 2) & (Friction and shear (C_4) = 1) & (Activity (C_6) = 1)	Severe	42.86% [21/49]
2	(Mobility (C_2) = 1) & (Nutrition (C_3) = 1)	Severe	36.73% [18/49]
3	(Mobility (C_2) = 1) & (Nutrition (C_3) = 2) & (Moisture (C_5) = 2)	Severe	14.29% [7/49]
4	(Sensory perception (C_1) = 3) & (Nutrition (C_3) = 2) & (Moisture (C_5) = 3) & (Activity (C_6) = 1)	High	24.49% [12/49]
5	(Mobility (C_2) = 2) & (Nutrition (C_3) = 2) & (Moisture (C_5) = 2)	High	14.29% [7/49]
6	(Mobility (C_2) = 1) & (Nutrition (C_3) = 2) & (Friction and shear (C_4) = 2) & (Moisture (C_5) = 3)	High	10.20% [5/49]
7	(Sensory perception (C_1) = 2) & (Nutrition (C_3) = 3) & (Friction and shear (C_4) = 1) & (Activity (C_6) = 1)	High	10.20% [5/49]
8	(Sensory perception (C_1) = 4) & (Mobility (C_2) = 2) & (Nutrition (C_3) = 2)	Moderate	28.57% [14/49]
9	(Sensory perception (C_1) = 4) & (Mobility (C_2) = 2) & (Nutrition (C_3) = 2)	Moderate	26.53% [13/49]
10	(Sensory perception (C_1) = 3) & (Mobility (C_2) = 2) & (Nutrition (C_3) = 3)	Moderate	24.49% [12/49]
11	(Sensory perception (C_1) = 4) & (Mobility (C_2) = 3) & (Friction and shear (C_4) = 2) & (Activity (C_6) = 2)	Mild	42.86% [21/49]
12	(Mobility (C_2) = 3) & (Nutrition (C_3) = 2) & (Moisture (C_5) = 4)	Mild	18.37% [9/49]
13	(Sensory perception (C_1) = 4) & (Nutrition (C_3) = 3) & (Moisture (C_5)= 3) & (Activity (C_6) = 2)	Mild	16.33% [8/49]
14	(Friction and shear (C_4) = 3) & (Moisture (C_5) = 4)	No	75.51% [37/49]
15	(Sensory perception (C_1) = 4) & (Mobility (C_2) = 4) & (Activity (C_6) = 3)	No	40.82% [20/49]
16	(Activity (C_6) = 4)	No	40.82% [20/49]

Note: The value in the parentheses refers to the total number of data that meet this rule within this level.

rules is obtained by Eqns. 10 and 11 in Step 6 of the rough set theory. The results of the top three main rules for all risk levels are presented in Table 4.

3.3 The 5-fold cross-validation

The rough set theory results come from actual clinical data, which reveal the behaviour rules of different risk levels of pressure injury among elderly male patients in the case hospital. To determine these decision rules' robustness, we carried out a 5-fold cross-validation on the same data set through several well-known data-mining analysis methods from previous studies. These include random forest, backpropagation artificial neural network, and support vector machine [25, 42].

All data-mining analysis methods cross-validated the same dataset based on a 5-fold cross-validation sampling method to ensure that each observation appears at least once in the training and test data. First, the entire dataset is divided into five datasets using the average method, of which four are the training data set, and the rest are the testing data set. The training dataset was used as the basis for establishing the prediction model. Further, the test dataset was used as the source to verify the accuracy of the model. Then, all methods built prediction models based on these datasets and obtained the correct classification rates. This operation was performed five times. Finally, all processes got the correct classification rate and average rate, as shown in Table 5. The results in Table 5 show that the average accurate classification rates for all methods: rough set theory (90.61%), random forest (89.55%), backpropagation artificial neural network (88.98%), and support vector machine (91.02%).

4. Discussion

4.1 Clinical nursing implications from importance for each risk factor

From the importance perspective (as shown in Table 3), 'Sensory perception (C_1)' and 'Nutrition (C_3)' are the most significant risk factors for identifying the risk of pressure injuries in the elderly male population, and they are also the critical risk factors for preventive measures. The main reason for this is that the self-protection and mobility of elderly male patients are reduced or lost due to the disease itself or physiological function decline. This decreases the skin's sensitivity to destructive compression and causes excessive long-term compression of the skin in some parts of the body, thus leading to the occurrence of pressure injuries. Clinically, patients are often in a coma or bedridden state due to complete loss of perception and mobility. Therefore, patients do not feel pain stimulation caused by excessive compression. Further, they do not eat autonomously, which leads to insufficient nutrition intake. Often showing a state of inadequate nutrition or even gradual emaciation, the local bone protuberance pressure increases significantly, leading to a significant increase in pressure injury risk levels. Furthermore, elderly patients often remain in passive positions due to reduced or complete loss of self-protection and mobility caused by the disease itself or by physiological hypofunction. This may cause their skin to become sensitive to damaging compression decreases, which can cause excessive long-term compression of the skin on some parts of the body, thus leading to pressure injury.

4.2 Clinical nursing implications and practice from decision rules for each risk level

From the perspective of decision rules (as shown in Table 4), nurses can further understand the possible clinical conditions (i.e., clinical behaviour rules) of male elderly inpatients at each risk level. Then, according to different clinical conditions, nurses can provide the corresponding nursing mea-

TABLE 5. Average correct rates for 5-fold cross-validation

No.	Rough set theory	Random forest	Backpropagation artificial neural network	Support vector machine
1	98.75%	88.98%	85.71%	89.80%
2	84.52%	89.39%	95.92%	93.88%
3	85.81%	90.20%	89.80%	87.76%
4	83.09%	89.80%	85.71%	93.88%
5	100%	89.39%	87.76%	89.80%
Average correct classification (%)	90.61%	89.55%	88.98%	91.02%

TABLE 6. The clinical descriptions of each risk level

Risk level	Clinical descriptions
Severe risk	The severity grade rules showed that male elderly patients of this grade are usually wholly unconscious and mobile and are usually unconscious or bedridden. Most of these patients are suffering from severe neurological diseases, respiratory and circulatory failure of important organs, critical/severe diseases, and chronic or end-stage diseases. Their clinical manifestations are consciousness disorder or coma, which leads to loss of sensation. The patient does not feel the pain stimulation of excessive compression. Moreover, due to the inability to eat independently, which leads to insufficient nutrition intake, these patients often present with a state of insufficient nutrition and even gradual emaciation. The pressure at the local bone protuberance increases significantly and the risk of a pressure injury increases significantly.
High risk	The symptoms of such male elderly patients are many, including faecal or urinary incontinence (i.e., moisture), severe malnutrition, moderate or above anaemia (i.e., nutrition), and the long-term use of medical devices (i.e., slight limitation of perception). Patients also include those with nervous system diseases (i.e., the weakening and disappearance of sensation and mobility abilities); tissue trauma (i.e., burns, and scalds); and elderly patients with a history of use of sedatives or toxic drugs. These patients usually have a variety of risk factors for pressure injury.
Moderate risk	This group of male elderly patients includes patients who use medical equipment (such as plaster fixation, traction, indwelling tube, mask, cuffs, oxygen saturation, elastic socks, etc.). Patients with weakened mobility and motor strength (slightly limited perception), patients with severely limited walking ability or no walking ability, and patients who must use wheelchairs to move, such as some orthopaedic patients, amputees, etc.
Mild risk	This risk level is common in some elderly male patients after surgery, such as patients who have undergone orthopaedic hip replacement, and is characterized by slightly limited mobility.
No risk	These kinds of patients are generally male elderly patients who can walk or turn over independently and have a fair ability to take care of themselves. It is common in some patients recovering from diseases or are about to be discharged from hospital. It is sufficient to regularly evaluate and urge appropriate activities according to the disease condition under normal circumstances.

sures. A mild risk level is taken as an example. The mild risk level is common in some elderly male inpatients after surgery, and their mobility is slightly limited, such as in inpatients after orthopaedic hip replacement. Nursing measures for elderly male patients with mild risks include urging and assisting them in turning over frequently to minimise local pressure. If the patient needs to use a wheelchair, it can be matched with chair surface decompression equipment. The clinical descriptions and corresponding nursing measures are summarised in Tables 6 and 7, respectively.

4.3 Features and contributions of the rough set theory model

From the 5-fold cross-validation results, the average classification accuracy of the four models was found to be between 88.98% and 91.02% (as shown in Table 5). The results showed no significant difference in classification accuracy among the four methods based on the same data. Therefore, these models have good prediction reliability. However, the advantage of rough set theory is that it can further explain the model using condition attributes (i.e., risk factors) and decision attributes (i.e., risk levels) through rule expression (i.e., IF-THEN). This expression can help nurses understand the behaviour pattern (i.e., occurrence characteristics) of each pressure injury risk level and take nursing measures accordingly. Three well-known methods (i.e., random forest, backpropagation artificial neural network, and support vector machine methods) have been applied to pressure injury studies [24, 42]. However, these methods belong to the category of the black-box algorithms [43]. They cannot provide further information on decision-making rules for clinical nurses. Therefore, compared with previous related studies (Table 8), this study's rough set theory can further highlight the importance of each risk factor and the decision rules for different risk levels. Simultaneously, it also makes up for the research gap caused by using the Braden scale in a data-driven decision-making environment.

4.4 Methodological considerations

Several limitations should be considered when interpreting the results of this study. First, we evaluated only some units, who might have characteristics that differ from those of the general population; that is, the generalisation and external validity of the results should be discussed further. Second, since the results of this study are based on Braden scale observation data (frequency) of 245 male elderly hospitalised patients in the hospital in the past year and do not consider other relevant clinical or physical factors of the

TABLE 7. The clinical nursing practice of each risk level

Risk level	Clinical nursing practice
Severe risk	Nursing measures for male elderly patients with severe risk include: (1) actively treat primary diseases and various symptoms and signs caused by them. Nursing measures such as restoring the function of essential organs, correcting hemodynamic disorders, correcting the anoxic state of the body, and improving the body's circulation can fundamentally prevent pressure injury. (2) Maintaining appropriate ward temperature, keeping the skin clean and dry, turning over frequently, reducing skin friction, properly carrying out a local massage on the back, and keeping the bed unit clean, dry, and free of slag. (3) Based on an air cushion bed application, hydrocolloid or soft silica gel dressings need to be pasted on the bone bulge of patients to promote local skin blood circulation to enhance the skin's pressure resistance. Changing the patient's body position (lying on the side at 30 degrees) for a fixed time can effectively relieve the pressure on the bone bulge, thus improving the effect of preventing pressure injury. Simultaneously, in the sacrococcygeal and heel parts where pressure injury is most likely to occur, a polymer posture pad is added between the decompression dressing and the air cushion bed to buffer gravity compression further. (4) To improve the nutrition of patients, high protein, high vitamin diet, total parenteral nutrition, and other nursing measures should be given according to the disease condition to improve the patients' immunity.
High risk	Nursing measures for male elderly patients with high risk include (1) Comprehensive evaluation of patients and careful screening of patients with high risk of pressure injuries. (2) Correct use of tools to prevent pressure damage (such as a bed or chair surface decompression equipment and wedge sponge pad) to reduce tissue pressure. (3) Ensure the frequency of turning over and strengthen nursing measures such as systemic nutrition.
Moderate risk	Nursing measures for male elderly patients with moderate risk are divided into three parts: First, the nurse conducts a comprehensive evaluation of the patient's physical condition. Next, the patient's body is turned over at regular intervals to reduce the time for all compressed parts, such as sacrococcygeal or heel. Additionally, the patient can use wedge sponge pads to ensure that the body is in a 30-degree lateral position. Finally, the patient need to keep his skin dry and pay attention to whole body nutrition.
Mild risk	Nursing measures for elderly male patients with mild risks are to urge and assist them in turning over frequently to minimise local pressure. If the patient needs to use a wheelchair, it can be matched with chair surface decompression equipment.
No risk	Elderly male patients who are not at risk do not need to take any nursing measures.

TABLE 8. Research on pressure injury by machine learning methods

Authors	Descriptions	Methods
Cox and Schallom [15]	Identifying risk factors for pressure injury in adult critical care patients	Regression analysis Decision tree analysis
Moon and Lee [23]	Applying of decision tree analysis to risk factors associated with pressure injuries in long-term care facilities	Decision tree analysis
Raju and Su [25]	Exploring factors associated with pressure injuries: a data mining approach	Logistic regression Decision tree
Lahmann *et al.* [24]	Friction and shear highly associated with pressure injuries of residents in long-term care - classification tree analysis (CHAID) of Braden items	Random forest Multivariate adaptive regression splines
Setoguchi and Ghaibeh [26]	Predictability of pressure injuries based on operation duration, transfer activity, and body mass index through the use of an alternating decision tree	Alternating decision tree

patients themselves, the findings of this study are limited. In particular, the limitations of patient data collection and unidentified variables that lead to pressure injuries may have been missed in this analysis. Finally, this study only included subjects from one hospital in China as the target population. The results of this study should not be extrapolated to hospitals in other regions of China. Additionally, the rough set theory is based on set theory and is a formal modelling method. It has limitations similar to those of most data-mining methods. For example, owning and using correct data is a necessary prerequisite. However, compared with the black-box algorithms (e.g., random forest, backpropagation artificial neural network, and support vector machine), it is more sensitive to the results [44]. For example, the amount of data will affect the number of decision rules. The levels of attributes will affect the scope of decision rule coverage, and the lack of attributes and data will also limit the technology.

4.5 Future research direction and work

Future studies can include other relevant clinical data of patients themselves, physical health records, and family members' attitudes and knowledge, thus providing more accurate and personalised comprehensive nursing measures. This study uses the rough set theory to identify the critical risk factors and decision rules for each risk level. In the future, the dominance-based set rough set method, fuzzy rough set method, and other data-mining methods can also be used to determine the predictive factors of pressure injury. Moreover, the research object can also consider the Braden Scale data of pressure injury patients from different departments.

5. Conclusions

In this study, rough set theory was used to identify the critical factors of pressure injury in elderly male inpatients and decision rules under different risk levels. This model provides excellent prediction results, and our model offers greater interpretation power than the Braden scale or other black-box algorithm models. This model can be integrated into clinical nursing practice, making it easier for hospitals to guide prioritized preventive nursing to the most critical male elderly hospitalised patients. Nurses can focus on high-risk patients who may suffer from pressure injuries without increasing their workload.

Author contributions

Fengmin Cheng and Yanjun Jin conducted the study and drafted the manuscript. Yanjun Jin and Yen-Ching Chuang analyzed the data and used the ROSE2 software. Fengmin Cheng, Tao-Hsin Tung, and Ching-Wen Chien conceived the study, and participated in its design and coordination. All of the authors read and approved the final manuscript.

Ethics approval and consent to participate

All procedures were performed in accordance with the guidelines of our Institutional. Review Board of Taizhou Hospital of Zhejiang Province affiliated to Wenzhou Medical University (approval number: K20201234) and adhered to the tenets of the Declaration of Helsinki. All patients' information was anonymous.

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Conflict of interest

The authors declare no conflict of interest.

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