Journal of Clinical and Nursing Research, 2026, Volume 10, Issue 5
http://ojs.bbwpublisher.com/index.php/JCNR
Online ISSN: 2208-3693
Print ISSN: 2208-3685

A Scoping Review of Risk Prediction Models for Oral Mucosal Pressure Injury in ICU Patients with Oral Tracheal Intubation

Xuan Shen[1], Yingzi Yuan[1], Qianqian Guan[1], Ying Zhang[2]*

[1]School of Public Health and Nursing, Hangzhou Normal University, Hangzhou 311121, Zhejiang, China
[2]Affiliated Hospital of Hangzhou Normal University, Hangzhou 310015, Zhejiang, China

***Corresponding author:** Ying Zhang, youdianhz@163.com

Abstract: *Objective*: To conduct a comprehensive review of risk prediction models for oral mucosal pressure injury in ICU patients with oral tracheal intubation, aiming to provide a reference for the development and clinical application selection of risk prediction models in the future. *Methods*: Using the scope review methodology framework, this study searched PubMed, Web of Science, Embase, Cochrane Library, China Biomedical Literature Database, CNKI and Wanfang from database construction until December 31. Two researchers independently screened and extracted data for aggregated analysis. *Results*: Seven studies were finally included. The subjects were mainly ICU patients with oral tracheal intubation. Logistic regression model was used as the model construction method, and nomogram was used as the model presentation. The three most frequently occurring predictors were tracheal intubation indwelling time, APACHEII score, and dental pad usage. *Conclusion*: The included models had good overall predictive power. However, to establish models with a low risk of bias, good predictive performance, and strong operability, a high overall risk of bias needed to be addressed to provide some guidance for clinical practice.

Keywords: ICU; Pressure injury of oral mucosa; Predictive model; Risk assessment; Scope review

Online publication: May 31, 2026

1. Introduction

With the continuous development of critical care medicine and mechanical ventilation techniques in recent years, oral tracheal intubation has become the most commonly used and effective method for establishing artificial airways in critically ill patients in ICUs, accounting for more than 96% of all tracheal intubated patients [1]. While maintaining airway patency and providing life support, this also increases the risk of oral mucosal pressure injury (OMPI) to some extent. Studies have shown an increase in OMPI among patients with oral tracheal intubation in the ICU.

The incidence rate is as high as 31.3% to 55.6%, mostly occurring 2 to 13 days after intubation [2–6]. It is the most common device-related pressure injury and also the most common among all mucosal pressure injuries caused by invasive catheters [7]. Due to the critical condition and poor resistance of ICU patients, the occurrence of OMPI is not only difficult to heal spontaneously and prone to recurrence, but in severe cases, it may cause infection, ulceration, etc., increasing patients' pain, causing dysphagia, increasing medical expenses, prolonging the hospital stay, and may even result in doctor–patient disputes [2]. It is reported that about 20% of traditional site pressure injuries can be detected at stage 1, while only 5% of OMPI can be detected by medical staff in the early stage of injury [8]. Therefore, early identification of OMPI predictors and timely intervention are of great significance for reducing the incidence of OMPI, alleviating patients' pain, improving prognosis and enhancing patients' quality of life. Although there have been oral mucosal pressure injury risk prediction models at home and abroad in recent years, there is heterogeneity in the predictors and model performance of the prediction models in each study, and there is no review on the risk prediction models for oral mucosal pressure injury in ICU patients with oral tracheal intubation [4,9]. Therefore, this study provides a comprehensive review of the construction, application, performance, and influencing factors of predictive models in relevant domestic and international studies. It analyzes the problems and deficiencies in this research field, aiming to provide references for the development and application selection of models in the future, as well as for clinical nursing work and subsequent research.

2. Data and methods

2.1. Clarify the research question

(1) What are the existing models for predicting the risk of oral mucosal pressure injury in ICU patients with oral tracheal intubation, and what are the predictive factors involved?

(2) How is the performance of the existing models? Has internal or external validation been carried out?

(3) What are the shortcomings of the current research and what implications does it have for future research?

2.2. Literature search strategies

A systematic search was conducted from database inception to 31 December 2025, across these databases: Web of Science, Cochrane Library, Embase, China Biomedical Literature Database, CNKI, VIP, Wanfang and other databases until Decdember 31, 2025, using a combination of subject terms and free terms. The English search terms included "Mouth Mucosa/Oral Mucosa/Buccal Mucosa", "Pressure Ulcer/Pressure Injuries/Pressure Sores", "predict/score/algorithm/equa/assess/calculate/identif*", "prognos/probabil/risk factors", and "ICU/Intensive Care Units". For example, in Chinese databases, the search formula is :(Mucosa + mucosal pressure injury + oral + oral mucosal pressure injury) AND (transoral tracheal intubation + ICU + critical care + critical patient + critical care unit + critical care) AND (risk prediction model + risk assessment + risk factor + influencing factor + nomogram + prediction + prevention). For the PubMed database, the search strategy is as follows:

#1 ("Mouth Mucosa"[Mesh]) OR (((Buccal Mucosa[Title/Abstract]) OR (Oral Mucosa[Title/Abstract])) OR (Mucosa, Mouth[Title/Abstract]))

#2 ("Pressure Ulcer"[Mesh]) OR ((Pressure Injuries[Title/Abstract]) OR (Pressure Sores[Title/Abstract]))

#3 ("predict"[Mesh]) OR ((algorithm[Title/Abstract]) OR (assess[Title/Abstract])OR(prognos [Title/Abstract]) OR (risk factors[Title/Abstract]))
#4 #1 AND #2AND #3

2.3. Criteria for literature inclusion and exclusion

2.3.1. Inclusion criteria

(1) Patients aged ≥ 18 years admitted to the ICU;
(2) The study type was original research, including cross-sectional studies, case-control studies, cohort studies, etc.
(3) The content of the study is to construct and (validate a risk prediction model for oral mucosal pressure injury in ICU patients with oral tracheal intubation.

2.3.2. Exclusion criteria

(1) Inability to obtain the full text, repeated publication, etc.;
(2) Secondary studies, such as reviews, systematic reviews, and master's theses;
(3) Failure to describe the content and methods of the prediction model;
(4) Not in Chinese or English

2.4. Literature screening and data extraction

The retrieved bibliographic records were imported into EndNote X9 software to remove duplicate references. Two researchers independently carried out the initial screening according to the inclusion criteria by reading the titles and abstracts. Then, they read the full text for re-screening. If there were differences of opinion during the screening process, a third researcher was consulted to resolve them. In this study, a standardized table for extracting data from risk prediction models, developed by Moons et al., was used [10]. The extracts included the author, publication year, country, type of study design, number of model builders and validators, incidence rate, model construction method, model predictor, model performance, etc.

2.5. Inclusion of literature risk of bias and suitability assessment

Two researchers used the Predictive Model Bias Risk Assessment tool (PROBAST) to assess the risk of bias and suitability of the included literature [11].

3. Results

3.1. Literature screening results and basic characteristics of the included literature

A preliminary search yielded 1,163 relevant literatures. After removing duplicate literatures, 1,032 literatures were obtained. After checking for duplicates, and in accordance with the literature inclusion and arrangement standards, as well as reading the titles, abstracts, and full texts, 7 literatures were finally included [4,9,12–16]. They were published between 2020 and 2025, including 6 from China and 1 from South Korea [4,9,12–16]. One retrospective case-control study[15], five prospective cohort studies, and one cross-sectional study; Two multicenter studies and six single-center studies [4,9,12–16].

3.2. Evaluation of literature quality

The risk of bias was evaluated based on PROBAST in terms of the study subjects, predictors, outcomes, and model analysis. The included models had a high risk of bias, which might be related to the study design, variable handling, variable selection, statistical analysis methods of predictors, improper handling of or non - mention of missing data, and validation methods. The suitability of the models' subjects, predictors, and outcomes was evaluated, and most of the models had good overall suitability. The specific evaluation results are shown in **Table 1**.

Table 1. Evaluation of risk of bias and suitability of included models

Inclusion model	Risk of bias				Applicability			Overall	
	Subjects of Study	Predictors	Outcomes	Analysis	Research subjects	Predictors	Outcomes	Risk of bias	Appli cability
Choi, 2020 [4]	low	low	low	high	low	low	low	high	low
Gu, 2024 [9]	low	low	low	high	low	low	low	high	low
JIA, 2024 [12]	low	Not clear	low	high	low	low	low	high	low
Zhang, 2024 [13]	low	Not clear	low	high	low	low	low	high	low
Lee, 2024 [14]	low	low	low	high	low	low	low	high	low
Zhang, 2025 [15]	high	Not clear	high	high	high	low	low	high	low
Wang, 2024 [16]	low	low	Not clear	high	low	low	low	high	high

3.3. Construction and validation of a risk prediction model for oral mucosal pressure injury in ICU patients with oral tracheal intubation

3.3.1. Basic features included in the model

The study population of the model was mainly concentrated on ICU patients with oral tracheal intubation, including 2 multicenter studies and 5 single - center studies, with a total sample size ranging from 27 to 1521 cases.; The model construction methods can be divided into two categories. Five models were constructed using Logistic regression, one model using a machine learning algorithm, and one model using Cox regression [4,9,12–16]. Six models are presented as nomograms, and only one model is presented as an equation [4,9,12–16]. The model details are shown in **Table 2**.

Table 2. Model construction

Included studies	Publication Year (year)	Country	Research Design	Model construction number (Example)	Number of validators (example)	Incidence rate (%, model building/ validation)	Model-building methods
Choi [4]	2020	Korea	Prospective Cohort study	27	—	A: 32.5 B: 13.4	Logistic regression model Gaussian Bayes algorithm
Gu Tiantian [9]	2024	China	Prospective cohort study	335	143	14.03/16.78	Logistic regression model
Jia [12]	2024	China	Prospective cohort study	1037	484	41.7/25.9	Cox regression model
Zhang Shuguang [13]	2024	China	Prospective cohort study	373	160	19.3/19.38	Logistic regression model

Li Min [14]	2024	China	Prospective cohort study	400	152	17.2/19.7	Logistic regression model
Zhang Ying [15]	2025	China	Case-control studies	209	—	25.3	Logistic regression model
Wang [16]	2025	China	Cross-sectional study	640	275	44.7/41.8	Logistic regression model

Note: A: Lower oral mucosa; B: Upper oral mucosa

3.3.2. Predictors of the model

The number of predictors included in the study was 3 to 7. The majority of the model presentation methods were visual nomograms, and only one was a risk score formula constructed based on the regression coefficients of each factor. The model prediction content and presentation methods are shown in **Table 3**. For the subsequent analysis, the predictors were aggregated into six categories: general information, laboratory test indicators, tracheal intubation-related factors, drug factors, vital signs and scores, and other factors. Among them, the most frequently occurring factors were tracheal intubation indwelling time (n = 5), serum albumin (n = 4), and dental pad use (n = 3). The classification of predictors is shown in **Table 4**.

Table 3. Model prediction content and performance

Included in the study	Model predictors	Model presentation
Choi [4]	A: Dental pads/airway use, commercial ETT stent use, steroid use B: Commercial ETT stent use, vasopressors, hematocrit, serum albumin	The risk score formula was derived based on the regression coefficients of each factor
Gu [9]	Daily oral care frequency, tracheal intubation duration, tracheal tube material, whether dental pads are used, daily oral aspiration frequency, RASS score, history of diabetes	Nomogram
Jia [12]	Antibiotic use, duration of nutritional therapy, restlessness, hypotension, albumin levels	Nomogram
Zhang [13]	Gender, APACHEII score, hemoglobin, serum albumin, prone position ventilation, use of vasoconstrictor drugs, time of indwelling tracheal intubation	Nomogram
Li [14]	APACHEII score, RASS score, age, serum albumin level, dental pad + gauze + oropharyngeal tube, senior physician, artificial airway indwelling time	Nomogram
Zhang [15]	Prone position ventilation, application of vasoconstrictor drugs, inability to express chief complaint during catheterization, APACHEII score, indwelling time of tracheal intubation	Nomogram
Wang [16]	APACHEII score, modified Beck oral score, oxygenation index, sedation, prone ventilation, duration of tracheal catheter indwelling, frequency of tracheal catheter fixation	Nomogram

Table 4. Classification of risk predictors for the model unit: units

	Items	Number of models included		Project	Number of models included
General information	Age	1		Steroid use	1
	Gender	1		Antibiotic use	1
Laboratory test indicators	Serum albumin	4	Vital signs and scores	Use of sedative drugs	1
	Hematocrit	1		Hypotension	1

Factors related to tracheal intubation	Hemoglobin	1	Other factors	Oxygenation index	1
	Tracheal intubation indwelling time	5		APACHEII score	4
	Pad use	3		Modified beck oral score	1
	For commercial tracheal intubation use	2		RASS score	1
	Number of oral aspirations per day	1		Duration of nutritional therapy	1
	Number of oral care sessions per day	1		Prone position ventilation	2
	Tracheal tube fixation frequency	1		Restlessness	1
	Inability to express the chief complaint during catheterization	1		History of diabetes	1
Drug factors	Vasoconstrictor drug use	2		Tracheal intubation operator	1

3.3.3. Model performance and validation

All seven models were validated [12–14,16]. Four of them had both internal and external validation, while three had only internal validation [4,9,15]. In terms of model performance, all seven studies reported area under the receiver operating characteristic curve (AUC) ranging from 0.680 to 0.918, with six of them having an AUC of 0.7 or above, indicating good model discrimination [4,9,12–16]. Five studies reported calibration metrics using the Hosmer-Lemeshow goodness-of-fit test, all with $p > 0.05$, suggesting good calibration ability of the model. The model details are shown in **Table 5**.

Table 5. Validation and performance of the model

Included studies	Validation methods	Validation Results	Model performance			
			Degree of discrimination	**Calibration degree**	**Specificity**	**Sensitivity**
Choi [4]	Inside	A: AUC = 0.60 B: the AUC = 0.85	A: AUC = 0.68 B: the AUC = 0.82	A: Hosmer-Lemeshow goodness-of-fit test $p = 0.130$ B: Hosmer-Lemeshow goodness of fit test $p = 0.399$	A: 0.76. B: 0.89	A: 0.85, B: 0.6
Gu [9]	“Internal	AUC = 0 .908	AUC = 0.93	Hosmer-Lemeshow goodness-of-fit test $p = 0.164$	0.894	0.833
Jia [12]	Inside, outside	C index = 0.77	The C index = 0.77	—	—	—
Zhang [13]	Inside, outside	AUC = 0.875	AUC = 0.87	Hosmer-Lemeshow goodness-of-fit test $p = 0.651$	0.738	0.875
Min [14]	Inside, outside	AUC = 0.956	AUC = 0.913	Hosmer-Lemeshow goodness-of-fit test $p = 0.427$	0.841	0.888
Zhang [15]	Inside	—	AUC = 0.881	—	—	—
Wang [16]	Inside, outside	AUC = 0.936	AUC = 0.918	Hosmer-Lemeshow goodness-of-fit test $p = 0.795$	0.861	0.829

4. Discussion

4.1.1. Focusing on the predictors of oral mucosal pressure injury (OMPI) in ICU patients with oral tracheal intubation can provide reference for improving the prognosis of ICU patients

This study summarized the risk prediction models of oral mucosal pressure injury in ICU patients with orotracheal intubation at home and abroad. It was found that the common risk predictors were the indwelling time of tracheal intubation, APACHEII score, serum albumin value, pad usage, vasoconstrictor drug use, etc. Due to the different materials and types of dental pads, the effects of using dental pads on oral mucosal pressure injury in patients vary. Two studies have shown that the use of dental pads is a risk factor for oral mucosal pressure injury, which is consistent with most previous studies [4,14,17–19]. Other studies have shown that the use of dental pads is a protective factor [9]. This suggests that healthcare workers should exercise caution when choosing the type of dental pad and determining whether to use it for patients based on their dental and oral conditions. The higher the patient's APACHE II score, the higher the risk of oral MMPI. Four studies have shown that a high APACHE II score is a risk factor for OMPI [13–16]. This is because the higher the APACHE II score, the more severe the patient's condition, with insufficient tissue perfusion, hemodynamic instability, and increased hypoxia. All of these can lead to increased hypoxia, dryness, and fragility of the oral mucosa. Nursing staff should pay more attention to the APACHE II score of patients. For those with a higher score, the mucosal tissue at the compression site should be closely evaluated during the indwelling of the artificial airway, and preventive protective measures should be implemented.

Patients with oral tracheal intubation may suffer from varying degrees of malnutrition because of their critical condition and inability to eat orally [20]. For example, low serum albumin levels can alter osmotic pressure, leading to tissue edema, perfusion impairment, and a decline in the body's tissue repair ability [21]. For such patients, admission screening and assessment should be carried out, and continuous monitoring should be conducted. For patients with low serum albumin levels who undergo oral tracheal intubation, effective nutritional intervention should be given in a timely manner.

4.1.2. The risk prediction model for oral mucosal pressure injury needs to be further optimized

The seven risk prediction models included in this study performed well overall, but the overall risk of bias was high. The main reasons are as follows:

(1) In terms of predictive factors, healthcare workers responsible for collecting and evaluating these factors lacked unified training. Moreover, predictive factors like scale score assessment were prone to interference and bias

(2) In terms of sample size calculation, only one model met the model construction criterion that the number of cases of clinical outcome events divided by the number of candidate predictive factors is greater than or equal to 20. The remaining models all had insufficient sample sizes and may have had bias.

(3) In statistical analysis, there is a lack of detailed handling reports on some complex data issues (such as deletion, competition risk, controlled sampling, etc.), which increases the risk of biasMost models use univariate analysis to screen predictors, converting continuous variables into categorical variables in the early stages of model construction.In addition, most predictive models have incomplete performance evaluations and are single - center studies.

Based on the shortcomings of existing models, it is suggested that future studies focus on the following aspects for optimization and improvement:

(1) Existing studies do not evaluate predictors well. In the future, more factors can be included, such as edema, types of oral care fluid, and oral bacterial culture conditions, etc. This can enable more comprehensive predictions and provide guidance for clinical practice.

(2) Most of the existing OMPI risk prediction models use traditional logistic analysis methods. In contrast, machine learning can better define the complex relationship between predictors and outcomes through a large number of mathematical operations. This approach aligns with the comprehensive and complex characteristics of actual clinical work and holds a significant advantage in disease prediction [22]. Therefore, in the future, the utilization of machine learning algorithms to enhance the accuracy of model predictions will be considered.

(3) Most existing models do not separately study the upper and lower regions of the OMPI. Further detailed studies can be conducted in the future to achieve better regional prevention in clinical practice.

(4) In future model development and validation, try to expand sample sources and quantities as much as possible, enhance large-sample multi-center validation, and promote better clinical promotion and application of risk prediction models.

5. Summary

Currently, an increasing number of scholars are focusing on and identifying the risk of oral mucosal pressure injury in patients with orotracheal intubation in the ICU. This study analyzed the seven included models, summarized their basic characteristics, and examined the aspects of the current research that can still be further optimized and improved. It is suggested that future researchers could further conduct large-sample, multi-center validation on the basis of the existing model, promote and apply it after clinical practice, improve the accuracy of the model, and enable medical staff to identify the high-risk population of oral mucosal pressure injury in the ICU at an early stage and intervene. At the same time, artificial intelligence technology could be considered in future research. For example, machine learning algorithms can be used to build models and present them visually. In this way, medical staff can estimate risks more intuitively and reduce their workload.

Funding

Zhejiang Provincial Medical and Health Science and Technology Project (Project No.: 2023KY956); Hangzhou Biomedicine and Health Industry Development Support Science and Technology Special Project (6th Phase) (Project No.: 2022WJC025); 2025 Hangzhou Normal University Teaching Construction and Reform Project, Construction of Digital-Enabled Clinical Teaching Case Database for Rehabilitation Nursing (Project No.: JG2025320)

Disclosure statement

The authors declare no conflict of interest.

References

[1] Feng Y, Shi D, Huang J, 2012, Research Progress on Different Fixation Methods in Transoral Tracheal Intubation. China Practical Nursing Journal, 28(z2): 143.

[2] Amrani G, Gefen A, 2020, Which Endotracheal Tube Location Minimises the Device-Related Pressure Ulcer Risk: The Centre or a Corner of the Mouth? International Wound Journal, 17(2): 268–276.

[3] Kim S, Nah H, Kim J, et al., 2021, Relationships Between Oral-Mucosal Pressure Ulcers, Mechanical Conditions, and Individual Susceptibility in Intubated Patients Under Intensive Care: A PCR-Based Observational Study. Biological Research for Nursing, 23(4): 557–567.

[4] Choi B, Kim M, Kim S, 2020, Risk Prediction Models for the Development of Oral-Mucosal Pressure Injuries in Intubated Patients in Intensive Care Units: A Prospective Observational Study. J Tissue Viability, 29(4): 252–257.

[5] Wang B, Jiang X, Shi G, et al., 2024, Analysis of Characteristics and Influencing Factors of Oral Mucosal Pressure Injury in Elderly ICU Patients with Tracheal Intubation. Chinese Journal of Geriatric Stomatology, 22(04): 200–204 + 229.

[6] Coyer F, Stotts N, Blackman V, 2014, A Prospective Window into Medical Device-Related Pressure Ulcers in Intensive Care. International Wound Journal, 11(6): 656–664.

[7] Barakat-Johnson M, Barnett C, Wand T, et al., 2017, Medical Device-Related Pressure Injuries: An Exploratory Descriptive Study in an Acute Tertiary Hospital in Australia. J Tissue Viability, 26(4): 246–253.

[8] Nan R, Pei J, Zhang Y, et al., 2020, Research Progress on Nursing Care for Mucosal Pressure Injuries. Journal of PLA Nursing, 37(12): 62–64.

[9] Gu T, Huang G, Zhang P, et al., 2024, Construction and Validation of a Risk Prediction Model for Oral Mucosal Pressure Injury in Patients with Orotracheal Intubation. Journal of Nursing, 39(20): 64–68.

[10] Moons K, de Groot J, Bouwmeester W, et al., 2014, Critical Appraisal and Data Extraction for Systematic Reviews of Prediction Modelling Studies: The CHARMS Checklist. PLoS Medicine, 11(10): e1001744.

[11] Chen X, Zhang Y, Zhuang Y, et al., 2020, PROBAST: Assessment of Bias Risk in Diagnostic or Prognostic Multivariate Predictive Model Studies. China Journal of Evidence-Based Medicine, 20(06): 737–744.

[12] Jia L, Deng Y, Xu Y, et al., 2024, Development and Validation of a Nomogram for Oral Mucosal Membrane Pressure Injuries in ICU Patients: A Prospective Cohort Study. Journal of Clinical Nursing, 33(10): 4112–4123.

[13] Zhang S, Jiang H, Hou J, et al., 2024, Construction of a Risk Prediction Model for Oral Mucosal Pressure Injury in Elderly Patients Undergoing Endotracheal Intubation via the Mouth in the ICU. Nursing Research, 38(20): 3592–3597.

[14] Li M, Tang L, Yao Q, et al., 2024, Construction and Validation of a Predictive Model for Oral Mucosal Pressure Injury Risk in Patients Undergoing Endotracheal Intubation via the Mouth. Nursing and Rehabilitation, 23(06): 1–8.

[15] Zhang Y, Pan Y, Huang Y, et al., 2025, Risk Factor Analysis and Risk Prediction Model Construction for Oral Mucosal Pressure Injury in Patients Undergoing Endotracheal Intubation via the Mouth in the Emergency Intensive Care Unit. Journal of Practical Clinical Medicine, 29(3): 75–79 + 83.

[16] Wang Z, He X, Tao Z, et al., 2024, Construction of a Line Graph Model for the Risk of Oral Mucosal Pressure Injury in ICU Patients with Tracheal Intubation. Chinese Journal of Modern Nursing, 30(13): 1764–1770.

[17] Kim C, Kim M, Kang M, et al., 2019, Oral Mucosa Pressure Ulcers in Intensive Care Unit Patients: A Preliminary Observational Study of Incidence and Risk Factors. J Tissue Viability, 28(1): 27–34.

[18] Hampson J, Green C, Stewart J, et al., 2018, Impact of the Introduction of an Endotracheal Tube Attachment Device on the Incidence and Severity of Oral Pressure Injuries in the Intensive Care Unit: A Retrospective

Observational Study. BMC Nursing, 17: 4.

[19] Zhang Q, Song C, Zou Q, et al., 2020, Observation on the Efficacy of Modified Transoral Tracheal Intubation Fixation Method for Instrument-Induced Pressure Injuries of the Oral and Facial Neck in ICU Patients. Chinese General Practice, 18(08): 1421–1424.

[20] Ren X, Chen J, 2019, Prevention and Nursing Care of Tongue Pressure Ulcers in Patients Undergoing Transoral Endotracheal Intubation. General Nursing, 17(15): 1841–1843.

[21] Serra R, Caroleo S, Buffone G, et al., 2014, Low Serum Albumin Level as an Independent Risk Factor for the Onset of Pressure Ulcers in Intensive Care Unit Patients. International Wound Journal, 11(5): 550–553.

[22] Liu Y, Yang X, Li L, 2021, Advances in the Application of Machine Learning for Disease Prediction. Journal of Nursing Science, 28(07): 30–34.