scientific reports

Check for updates

OPEN

Explainable SHAP-XGBoost models for pressure injuries among patients requiring with mechanical ventilation in intensive care unit

Li Zheng[1,3], Yu-juan Xue[2,3], Zhen-nan Yuan[1,4]✉ & Xue-zhong Xing[1,4]✉

pressure injuries are significant concern for ICU patients on mechanical ventilation. Early prediction is crucial for enhancing patient outcomes and reducing healthcare costs. This study aims to develop a predictive model using machine learning techniques, specifically XGBoost combined with SHAP, to identify key risk factors of pressure ulcers in this population. Utilizing the MIMIC-IV 2.2 database, we included a cohort of 29,448 mechanically ventilated patients in ICU intensive unit. These patients were divided into a training set (20,614 patients, 70%) and an internal validation set (8,834 patients, 30%). Of these, 2,052 patients developed pressure injuries. We applied the XGBoost algorithm to build the predictive model and used SHAP analysis to identify the top ten factors influencing pressure ulcer development: 'sepsis', 'age', 'the count of platelet', 'length of ICU stay', 'PaO2/FiO2 ratio', 'hemoglobin concentration', 'admission type', 'renal disease', 'albumin concentration', and 'ethnicity'. The predictive model achieved an area under the ROC curve (AUC) of 0.797 (95% CI: 0.786–0.808) in the training set and 0.739 (95% CI: 0.721–0.758) in the validation set. Calibration curves demonstrated good fit, and the decision curve analysis indicated clinical utility. This study successfully developed a machine learning model that accurately predicts the risk of pressure ulcers in ICU patients with mechanical ventilation. This model could serve as a useful tool for guiding early interventions, ultimately reducing the incidence of pressure injuries in this vulnerable population. The integration of SHAP analysis offers insights into the most critical factors.

Keywords Pressure ulcer, Mechanical ventilation, XGBoost

Background

Pressure injuries, also known as bedsores, represent a significant clinical challenge, particularly among critically ill patients in the intensive care unit (ICU) who are on mechanical ventilation. These patients are at heightened risk due to prolonged immobility, impaired skin integrity, and other complex comorbidities. Pressure ulcers not only lead to increased morbidity and prolonged hospital stays but also impose substantial economic burdens on healthcare systems[1–3]. Early identification of patients at risk for pressure injuries is crucial to prevent their occurrence and improve patient outcomes.The traditional risk assessment tools often lack predictive accuracy and fail to capture the multifactorial nature of pressure injury development in ICU patients. The Norton and Braden scales are widely used tools for assessing the risk of pressure ulcers in general hospitalized populations. However, mechanically ventilated patients represent a unique subset of critically ill individuals who often require sedation and analgesia, making it difficult to accurately evaluate certain criteria such as mental status, activity level, mobility, sensory perception, and continence. Machine learning is a type of artificial intelligence that can be used to build predictive models, but it is rarely used in research on pressure injuries[4]. The advent of machine learning, particularly models such as XGBoost, offers a promising avenue for developing more accurate

[1]Department of Intensive Care Unit, National Clinical Research Center for Cancer/Cancer Hospital, National Cancer Center, Chinese Academy of Medical Sciences & Peking Union Medical College, Beijing 100021, China. [2]Department of Pediatrics, Peking University People's Hospital, Peking University, Beijing, China. [3]Li Zheng and Yu-juan Xue contributed equally to this work and share first authorship. [4]Xue-zhong Xing and Zhen-nan Yuan contributed equally to this work and share corresponding authorship. ✉email: yuanzhennan02@163.com; xxzncc@163.com

predictive models. Furthermore, SHAP (SHapley Additive exPlanations) analysis enables the identification of key variables driving model predictions[5], offering deeper insights into the risk factors associated with pressure injury development. This study aims to leverage machine learning and SHAP analysis to build a robust predictive model for pressure injuries in mechanically ventilated ICU patients, utilizing the large-scale MIMIC-IV database.

Patients and methods

Database and study population

A flowchart of the patient selection process is shown in Fig. 1. This study was conducted using data from the Medical Information Mart for Intensive Care IV (MIMIC-IV, version 2.2), a publicly available database containing detailed information on ICU admissions at the Beth Israel Deaconess Medical Center in Boston, MA, from 2008 to 2019. The dataset includes over 76,000 ICU admissions and provides comprehensive data, including demographics, laboratory results, vital signs, treatments, and outcomes. The study was exempt from institutional review board approval as it utilized a publicly available de-identified database, and access was granted after completing the Collaborative Institutional Training Initiative (CITI) program (Record ID: 36067767).

For this study, we included ICU patients who were mechanically ventilated, as they represent a high-risk group for developing pressure injuries. A total of 29,448 patients were selected, of whom 2,052 developed pressure injuries. The data was randomly split into a training set (70%, $n = 20{,}614$) and an internal validation set (30%, $n = 8{,}834$).

Inclusion criteria and exclusion

The selection criteria included adult patients (age ≥ 18 years) who had complete data for the variables of interest and patients with mechanical ventilation duration more than 48 h. Patients with more than 50% missing data or multiple ICU admissions (only the first admission was considered) or patients with hematologic tumors were excluded.

Data collection

Data were collected on various factors potentially related to the development of pressure injuries, based on existing literature and clinical relevance. These factors included demographic information (age, gender), comorbidities (sepsis, renal disease, myocardial infarction, chronic pulmonary disease), ICU-specific metrics (length of ICU stay, admission type), vital signs, and laboratory values within the first 24 h of ICU admission (e.g., PaO2/FiO2 ratio, hemoglobin, platelets, albumin). The primary outcome was the development of pressure injuries during the ICU stay.

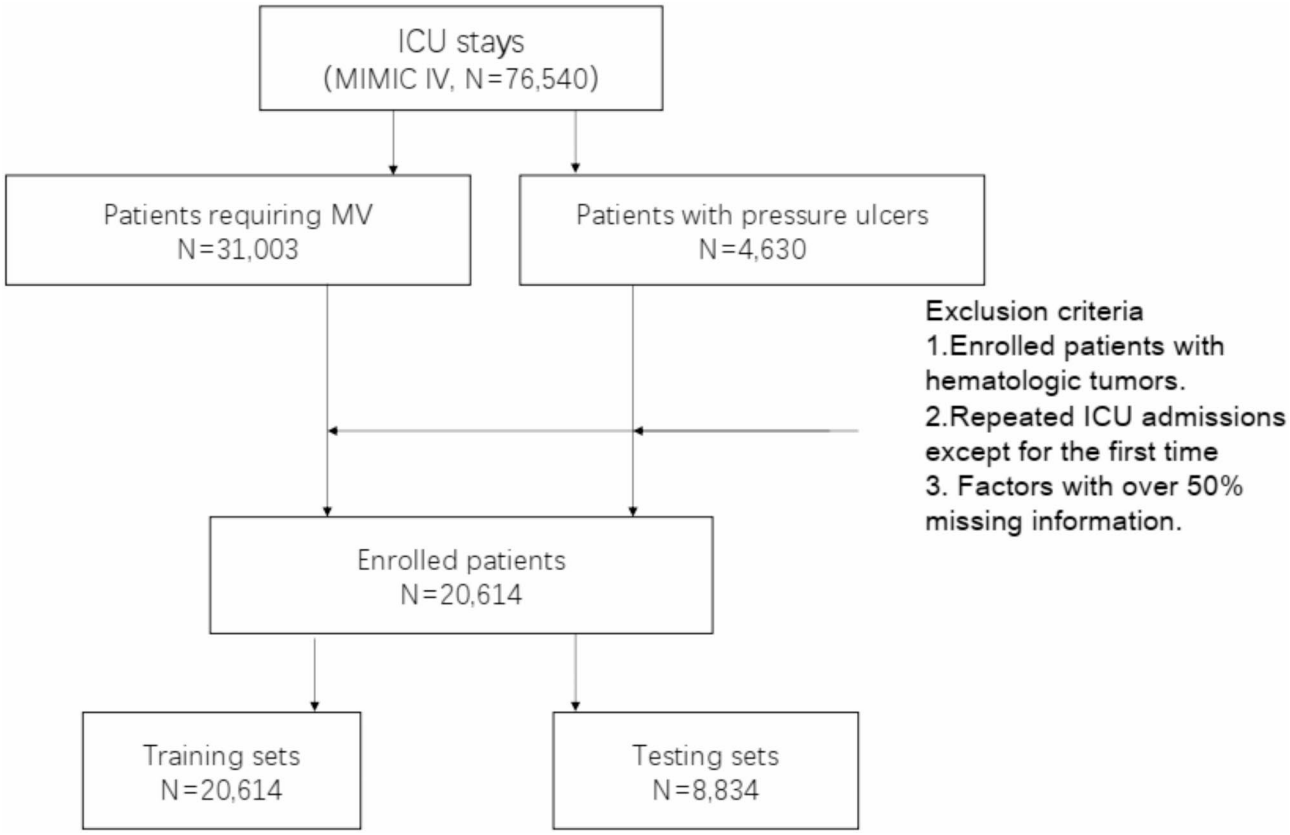

Fig. 1. Flow diagram of the patient selection in MIMIC IV 2.2. (MIMIC-IV, Medical Information Mart for Intensive Care).

Model development and validation
The predictive model was developed using the XGBoost algorithm, a powerful machine learning technique known for its robustness in handling structured data. The model was trained on the training set, with hyperparameters optimized using the caret package in R. The key parameters included a learning rate (eta) of 0.1, a maximum depth of 2, and 100 boosting rounds. The model's performance was evaluated on the internal validation set using the area under the receiver operating characteristic (ROC) curve (AUC) to assess its discriminatory ability.

SHAP analysis
To interpret the model and identify the most influential predictors of pressure injury development, SHAP (SHapley Additive exPlanations) values were calculated using the shapviz R package. SHAP values provide insights into how each feature contributes to the model's predictions. The top ten factors influencing pressure injury risk were identified, and SHAP summary plots were generated to visualize their impact.

Statistical analysis
All statistical analyses were conducted using R version 4.3.0. Missing data were addressed using multiple imputation techniques, and strict measures were taken to prevent data leakage by maintaining separation between training and validation datasets. Continuous variables were summarized as mean ± standard deviation or median with interquartile range (IQR), while categorical variables were expressed as frequencies and percentages. Group comparisons were performed using the Chi-square test for categorical variables and independent samples t-tests or nonparametric tests for continuous variables, with bias managed through stratified sampling and adjustment for confounders. Data transformations included normalization and standardization. To mitigate overfitting, we employed techniques such as early stopping during model training and regularization methods. Hyperparameter tuning was conducted using a grid search method. Model performance was assessed through AUC, mean squared error (MSE), precision, F1 score, sensitivity, specificity, and Brier score, all accompanied by 95% confidence intervals. ROC and calibration curve analyses further evaluated predictive capabilities.

Results
Patient characteristics
The study cohort consisted of 29,448 mechanically ventilated ICU patients from the MIMIC-IV database. The training set included 20,614 patients, while the validation set included 8,834 patients. We utilized the NPUAP/EPUAP classification system for pressure ulcers, with a total of 2,052 patients diagnosed with pressure injuries. The distribution of stages was as follows: Stage 1 (1,636, 79.7%), Stage 2 (82, 4.0%), Stage 3 (23, 1.1%), Stage 4 (19, 0.9%), and unknown stage (292, 14.2%). There were no statistically significant differences between the two groups of patients. The baseline characteristics of patients in the training and validation sets were similar, ensuring a balanced distribution of demographic and clinical factors (Table 1).

Model performance
The XGBoost model demonstrated good performance in predicting the development of pressure injuries, with an AUC of 0.797 (95% CI: 0.786–0.808) in the training set (Fig. 2A) and 0.739 (95% CI: 0.721–0.758) in the validation set (Fig. 2B). The sensitivity of the model was 0.82 (95% CI: 0.80–0.84) in the training set and 0.75 (95% CI: 0.72–0.78) in the validation set, highlighting its effectiveness in identifying pressure ulcer development, while specificity was 0.85 (95% CI: 0.84–0.86) and 0.80 (95% CI: 0.78–0.82) respectively, indicating a strong capacity to correctly identify non-developing patients. The MSE was consistently low at 0.12 for both sets, and precision was recorded at 0.76 in the training set and 0.70 in the validation set (95% CI: 0.68–0.73), suggesting high accuracy in positive predictions. The F1 score was 0.79 in the training set and 0.72 in the validation set (95% CI: 0.70–0.75), reflecting a good balance between sensitivity and precision. The calibration curves indicated that the model's predictions were well-calibrated, with predicted probabilities closely matching observed outcomes both in training set (Fig. 2C) and testing set (Fig. 2D) with a brier score of 0.15.

Clinical utility
Decision curve analysis (DCA) showed that the XGBoost model provided a net clinical benefit across a wide range of threshold probabilities, supporting its potential utility in clinical practice (Fig. 2E). The model's performance suggests it could be effectively used to identify high-risk patients and guide early interventions to prevent pressure injuries in mechanically ventilated ICU patients.

SHAP analysis
SHAP analysis identified the ten most influential factors for predicting pressure injury development: 'sepsis', 'age', 'the count of platelet', 'length of ICU stay', 'PaO2/FiO2 ratio', 'hemoglobin concentration', 'admission type', 'renal disease', 'albumin concentration', and 'ethnicity'. These factors were ranked based on their average absolute SHAP values, highlighting their relative importance in the model (Fig. 3A). To demonstrate how the XGBoost model evaluates the contributions of individual patient features, we utilize SHAP force plots to interpret individual predictions for two patients (Fig. 3B and C). The color indicates the contribution of each feature, with red indicating that the feature has a negative effect on the prediction (arrow pointing left, SHAP value decreases) and yellow indicating that the feature has a positive effect on the prediction (arrow pointing right, SHAP value increases). The length of the color bar indicates the strength of the contribution, and E[f(x)] indicates the SHAP reference value, which is the mean predicted by the model. For a "true positive" group of patients, the XGBoost model predicted in-hospital mortality with a SHAP. Figure 4 illustrates the interaction summary plot for the top 10 most significant interacting features. The features have been sorted in descending order of their interaction importance: 'sepsis', 'age', 'the count of platelet', 'length of ICU stay', 'PaO2/FiO2 ratio', 'hemoglobin concentration',

Factors	Training sets *N* = 20,614	Testing sets *N* = 8,834	*P*
Age (mean, y)	65.5 ± 0.1	65.7 ± 0.2	0.090
Female (N, %)	8,360(40.6)	3,588(40.5)	0.922
COPD (N, %)	5,006(24.3)	2,208(25.0)	0.194
Diabetes (N, %)	4,657(22.6)	1,969(22.3)	0.569
Myocardial infarct (N, %)	3,383(16.4)	1,452(16.4)	0.003
Congestive heart failure (N, %)	5,179(25.1)	2,212(25.0)	0.879
Peripheral vascular disease (N, %)	2,257(10.9)	985(11.2)	0.613
Cerebrovascular disease (N, %)	2,839(13.8)	1,211(13.7)	0.884
Dementia (N, %)	614 (3.0)	275 (3.1)	0.537
Renal disease (N, %)	3,735(18.1)	1,575(17.8)	0.553
Mild liver disease (N,%)	2,202(10.7)	905(10.2)	0.263
Paraplegia (N, %)	835(4.1)	370(4.2)	0.585
The presence of metastasis (N, %)	1,045(5.1)	476(5.4)	0.257
AIDS (N, %)	94(0.5)	48(0.5)	0.321
Cancer (N, %)	2,306	1,014	0.468
Respiration(PaO2/FIO2)	195.2 ± 0.7	195.1 ± 1.1	0.516
Glasgow score (mean)	14.4 ± 0.01	14.4 ± 0.02	0.668
Hemoglobin (mean, g/L)	9.9 ± 0.02	10.0 ± 0.02	0.434
Platelets count(10^6/L)	183.1 ± 0.7	182.5 ± 1.1	0.674
WBC (10^9/L)	15.2 ± 0.1	15.5 ± 0.1	0.998
Albumin (mean, g/L)	3.2 ± 0.0	3.2 ± 0.0	0.809
Sepsis (N, %)	13,920(67.5)	5,948(67.3)	0.742
Shock (N, %)	2,274(11.0)	997 (11.3)	0.524
Lactate (mean, mmol/L)	2.9 ± 0.0	3.0 ± 0.0	0.115
Los of ICU (mean, day)	4.4 ± 0.0	4.4 ± 0.1	0.426
BMI (mean, kg/m^2)	23.5 ± 0.0	23.0 ± 0.1	0.806
Emergency admission (N, %)	13,515(65.6)	5,779(65.4)	0.608
Ethnicity (N, %)			0.836
Asian	541(2.6)	231(2.6)	
White	13,859(67.2)	5,867(66.4)	
Black	1,644(8.0)	682(77.2)	
Others	2,066(10.0)	897(10.2)	
Unknown	2,774(13.5)	1,157(13.1)	

Table 1. Characteristics of study participants from training set and validation set. COPD, Chronic Obstructive Pulmonary Disease; AIDS, Acquired Immunodeficiency Syndrome; WBC, white blood cell; Los, length of stay; BMI, Body Mass Index.

'admission type', 'renal disease', 'albumin concentration', and 'ethnicity'. The interaction summary plot reveals that certain feature pairs have a significant combined impact on the model's predictions. For instance, the interaction between sepsis and age, as well as sepsis and los of ICU, displays notable SHAP interaction values, suggesting that these pairs of features interact strongly to influence the model's output.

Discussion

In this study, we developed and validated a predictive model for pressure injury development in mechanically ventilated ICU patients using the XGBoost machine learning algorithm. The model demonstrated strong predictive performance with an AUC of 0.797 in the training set and 0.739 in the internal validation set. Our findings underscore the utility of machine learning approaches in identifying high-risk patients and enhancing clinical decision-making processes. One way to consider our model's performance is to place our results alongside the Braden Scale[6]. The Braden Scale is the most commonly used tool in North America for predicting risk for pressure injury and measures cumulative risk for pressure injuries via seven categories: sensory perception, activity, mobility, moisture, nutrition, and friction/shear. Total scores range from 9 (very high risk) to 23 (very low risk)[6]. Our model's performance (area under the ROC curve = 0.79 vs. 0.68 for the Braden Scale[7]) suggests the model would be a useful way to differentiate among critical care patients in order to apply preventive measures that are not feasible for every patient because of cost, such as specialty beds. Jenny[8]conducted a systematic review to identify risk factors independently predictive of pressure injury development among critical-care patients. They founded that age, mobility/activity, perfusion, and vasopressor infusion frequently emerged as important factors in pressure injury development.

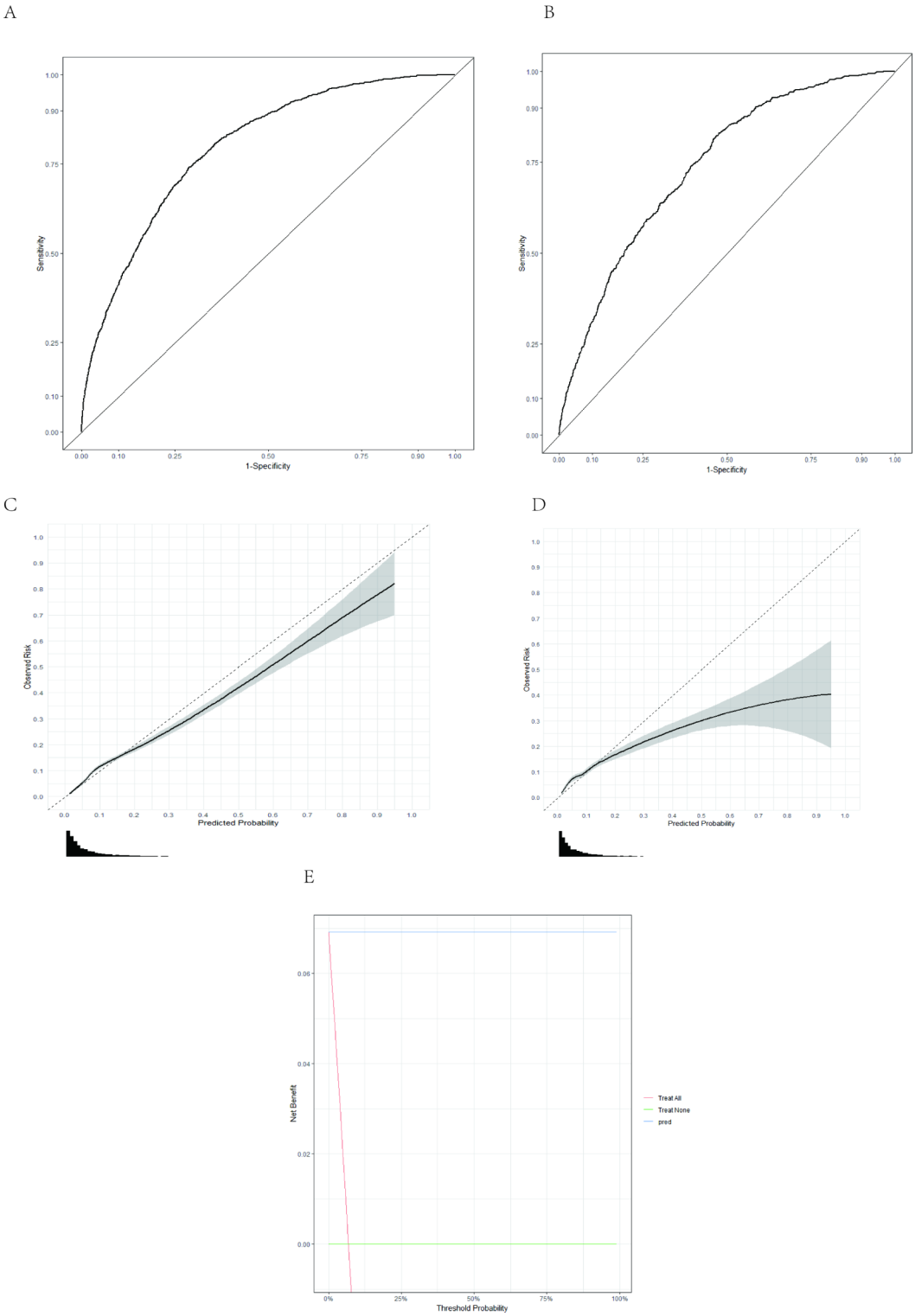

Fig. 2. The performance of the predicted model in the training set (A) and validation set (B). Calibration curves of the predicted model for predicting pressure injury both in the training set (C) and validation set (D). Decision-curve analysis of the predicted model in validation set (E).

While ethnicity as a risk factor can point to genetic predispositions for skin conditions or varying susceptibilities, it often reflects broader socio-economic disparities and differences in health care access or delivery[9]. Interventions should account for such disparities, ensuring equitable care and prevention measures across different ethnic groups. The study was carried out in Indonesia where the incidence of pressure injuries has been reported to be as high as 33.3%[10]. The incidence of pressure injuries is higher in Indonesia than in other

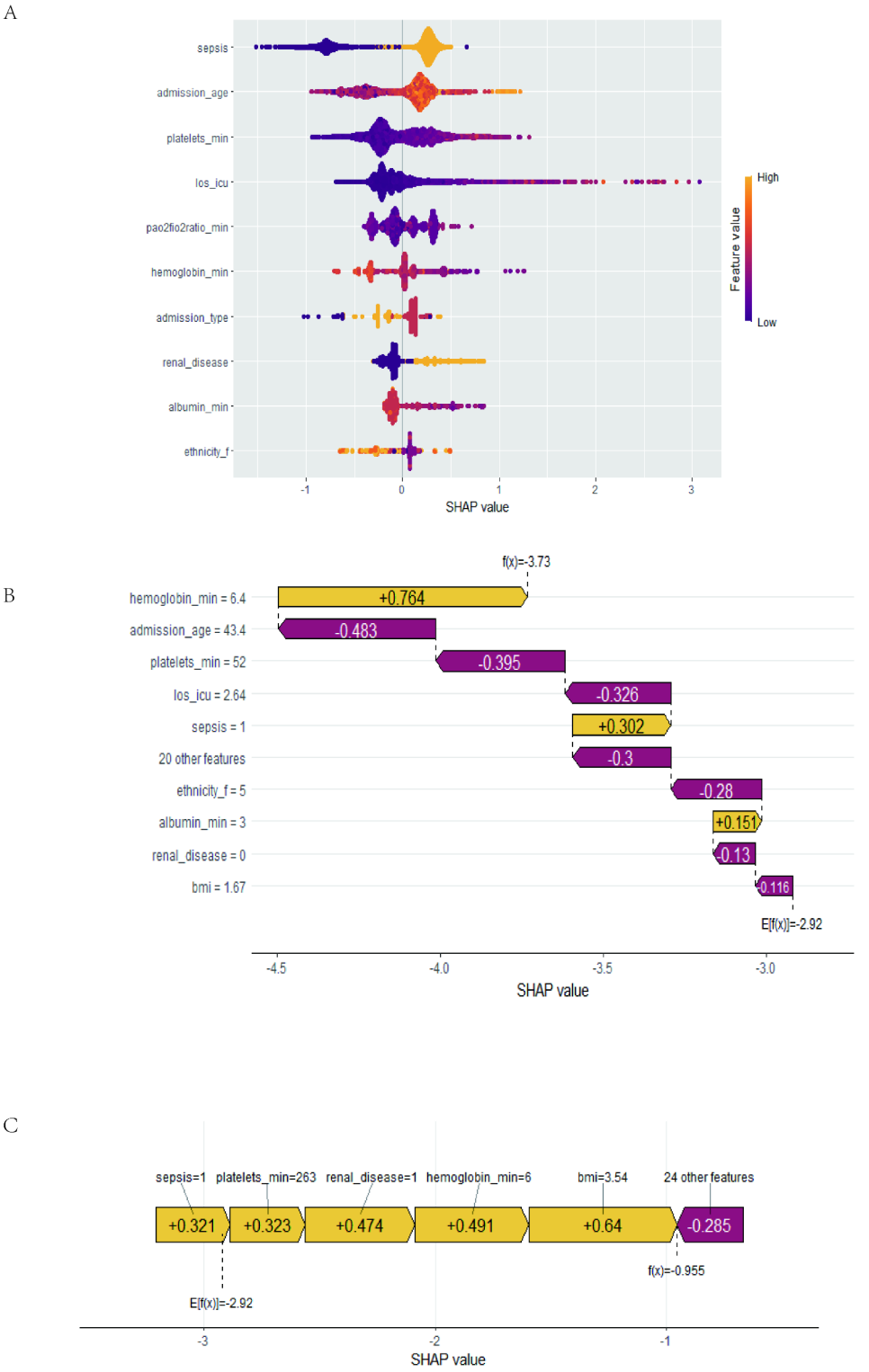

Fig. 3. A. Importance chart of SHAP variables, with the included features sorted by the average absolute value of SHAP from highest to lowest. B, C. SHAP force plot for two cases: Color indicates the contribution of each feature, purple indicates that the feature has a negative effect on the prediction (arrow to the left, SHAP value decreases), and yellow indicates that the feature has a positive effect on the prediction (arrow to the right, SHAP value increases). The length of the color bar indicates the strength of the contribution, and E[f(x)] indicates the SHAP reference value, which is the mean predicted by the model. f (x) represents the SHAP value of the individual.

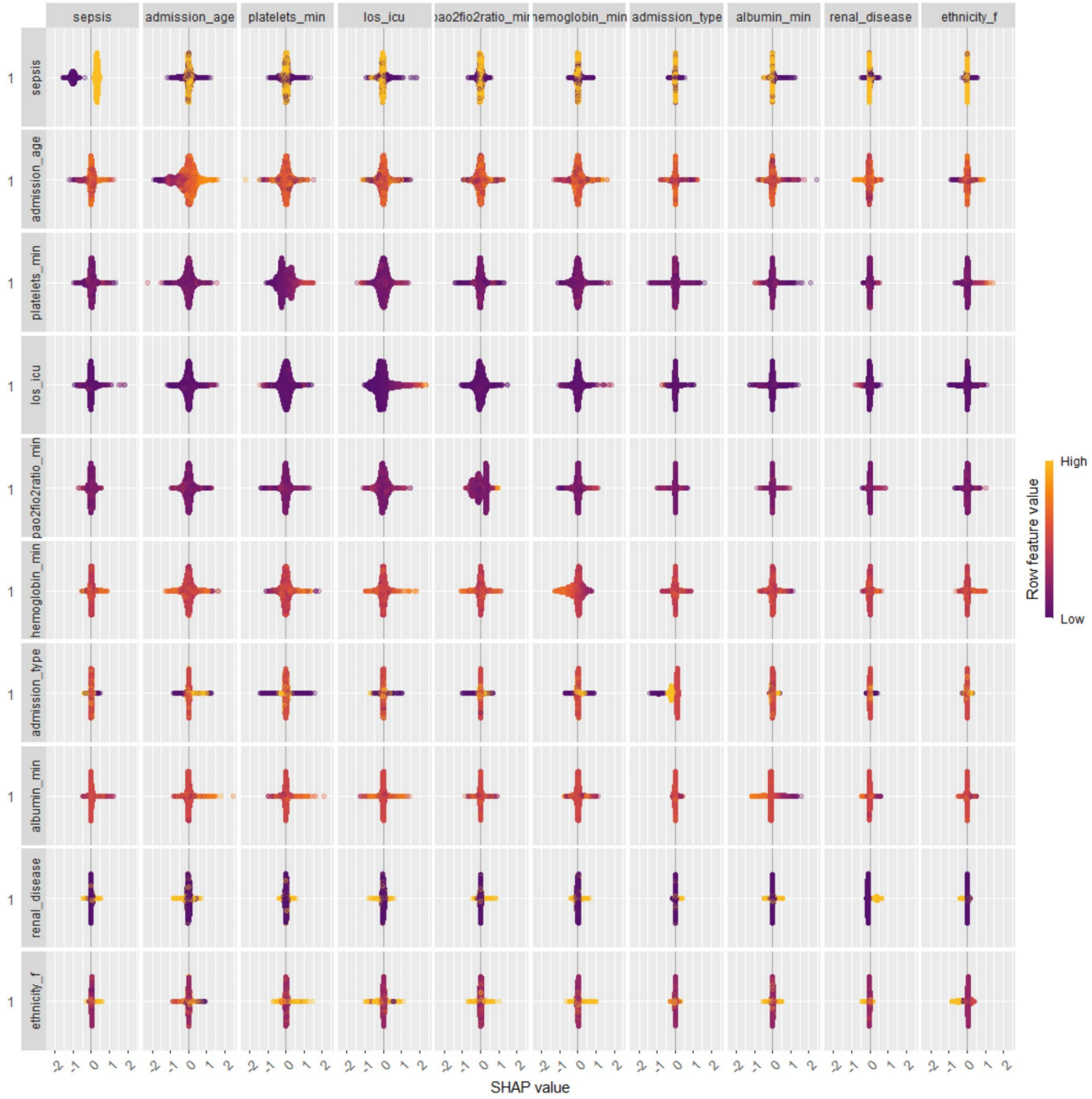

Fig. 4. Interaction summary plot generated using SHAP values. This plot displays the top 10 most interacting features of the model. On the x-axis and y-axis, the features are listed according to their interaction importance, with the feature names ordered as follows: 'sepsis', 'age', 'the count of platelet', 'length of ICU stay', 'PaO2/FiO2 ratio', 'hemoglobin concentration', 'admission type', 'renal disease', 'albumin concentration', and 'ethnicity'. Each point on the plot represents the SHAP interaction value for a specific feature interaction, highlighting how pairs of features together impact the model's predictions.

Asian countries, where the incidence ranges from 2.1–31.3%[11,12]. Other international studies have reported incidence rates of 7–29% in an intensive care unit (ICU) or acute care setting[13,14].

Sepsis emerged as the most significant predictor, consistent with its systemic impacts on the body. Studies have consistently shown that sepsis leads to widespread inflammation and coagulation abnormalities, which impair microcirculation and tissue perfusion, crucial factors in the pathogenesis of pressure injuries[15]. The hyperinflammatory state associated with sepsis increases the risk of skin breakdown and inhibits wound healing processes, highlighting the need for vigilant monitoring and early intervention in septic patients, especially for the patients with chronic renal disease and respiratory insufficiency. Chronic kidney disease and acute renal failure contribute to pressure injury risk through mechanisms like fluid overload, metabolic disturbances, and impaired nutritional status, which is in agreement with previous studies[16]. The accumulation of uremic

toxins and altered protein metabolism can weaken skin and tissue health, making prevention and management particularly challenging in renal-compromised patients. The PaO2/FiO2 ratio, a measure of respiratory function and oxygenation, reflects the patient's ability to deliver oxygen to tissues. Lower ratios indicate inadequate oxygenation, leading to cellular hypoxia, which compromises tissue integrity and healing[17–19].

Age is also a well-documented risk factor for pressure injury development. Older patients often have thinner, less elastic skin, and a decreased ability to redistribute pressure, increasing their vulnerability[20]. Findings for age is consistent with the results from a systematic review conducted by Coleman and colleagues in an acute, rehabilitative, long-term-care population[21]. Additionally, polypharmacy, comorbidities, and impaired mobility often present in older adults further exacerbate this risk. This emphasizes the importance of geriatric-specific preventive care strategies in the ICU. Previous literature indicates that factors such as low protein levels[22] and low hemoglobin[23]are significant risk factors for the development of pressure injuries. Therefore, it is crucial to monitor the nutritional status of elderly patients undergoing mechanical ventilation and to implement proactive measures to mitigate these high-risk factors.

The type of ICU admission often reflects the patient's baseline health status and urgency of care, which can inherently affect the risk for pressure injuries. Emergency admissions are typically associated with acute illnesses and limited preparation time for preventive care, unlike elective admissions which allow for planned preoperative optimization. A pressure injury can develop in several hours, depending upon risk factors and use of pressure injury prevention activities[24]. This highlights the need for heightened vigilance and early intervention for patients admitted emergently. Additionally, Longer ICU stays are inherently associated with increased pressure injury risk due to prolonged immobilization and exposure to a high-intervention environment. Extended bed rest and the critical nature of these patients often result in continuous pressure on bony prominences without sufficient relief or repositioning, underlining the necessity for proactive pressure injury prevention protocols in long-term ICU patients. In previous literature, long hospital stays, especially in ICU, is a risk factor for pressure injury[24–27].

Prevention and management of pressure injuries

Effective management of pressure ulcers involves a multifaceted approach that prioritizes prevention, early detection, and appropriate treatment strategies[28]. Key elements include regular skin assessments to identify at-risk individuals, the implementation of pressure-relieving devices such as special mattresses and cushions, and maintaining a moist wound environment to promote healing. Additionally, adequate nutritional support and hydration are essential for optimal recovery. The use of advanced therapies, including vacuum-assisted closure (VAC) and hydrocolloid dressings, can further enhance healing rates by improving blood flow and reducing infection risks. Continuous education for healthcare providers and caregivers is crucial to ensure adherence to evidence-based practices and improve patient outcomes in pressure ulcer management.

Limitations

Despite the strengths of this study, including the large sample size and robust machine learning methodology, several limitations should be noted. Firstly, the study was based on retrospective data from the MIMIC-IV database, which may limit the generalizability of the findings to other populations and healthcare settings. Although our model performed well in internal validation, it was not externally validated using data from a different hospital or patient population. External validation is crucial to confirm the model's applicability in diverse clinical environments. Secondly, we also acknowledge that several variables, such as patient mobility and specific preventive interventions, were not incorporated into the model. These factors could significantly influence patient outcomes and the development of pressure ulcers. Future investigations should aim to include such variables to enhance the model's predictive power and comprehensiveness, thus providing a more holistic approach to pressure ulcer prevention. Furthermore, the integration of our predictive model into existing ICU workflows or electronic health records is critical for optimizing its usability. By embedding the model within the clinical decision-making process, healthcare teams can access real-time risk assessments, allowing for proactive interventions tailored to high-risk patients. This integration may facilitate a more systematic approach to pressure ulcer prevention, ultimately improving patient outcomes and reducing incidence rates in vulnerable populations.

Conclusion

This study demonstrates that machine learning, specifically the XGBoost algorithm combined with SHAP analysis, can effectively predict the risk of pressure injury development in mechanically ventilated ICU patients. The model's performance in both the training and validation sets highlights its potential utility in clinical practice. By identifying key risk factors and providing interpretable insights, this model could serve as a useful tool for guiding early interventions, ultimately improving patient outcomes and reducing the incidence of pressure injuries in this vulnerable population. Future work should aim to validate the model in diverse settings and explore the integration of additional variables to enhance predictive accuracy.

Data availability

The datasets used and/or analysed during the current study are available from corresponding author upon reasonable request.

Received: 24 October 2024; Accepted: 3 March 2025
Published online: 22 March 2025

References

1. Spilsbury, K. et al. Pressure ulcers and their treatment and effects on quality of life: hospital inpatient perspectives. *J. Adv. Nurs.* **57** (5), 494–504 (2007).
2. Frankel, H., Sperry, J. & Kaplan, L. Risk factors for pressure ulcer development in a best practice surgical intensive care unit. *Am. Surg.* **73** (12), 1215–1217 (2007).
3. Slowikowski, G. C. & Funk, M. Factors associated with pressure ulcers in patients in a surgical intensive care unit. *J. Wound Ostomy Cont. Nurs.* **37** (6), 619–626 (2010).
4. Raju, D., Su, X., Patrician, P. A., Loan, L. A. & McCarthy, M. S. Exploring factors associated with pressure ulcers: a data mining approach. *Int. J. Nurs. Stud.* **52** (1), 102–111 (2015).
5. Ali, S. et al. The enlightening role of explainable artificial intelligence in medical & healthcare domains: A systematic literature review. *Comput. Biol. Med.* **166**, 107555 (2023).
6. Braden, B. & Bergstrom, N. A conceptual schema for the study of the etiology of pressure sores. *Rehabil Nurs.* **12** (1), 8–12 (1987).
7. Hyun, S. et al. Predictive validity of the Braden scale for patients in intensive care units. *Am. J. Crit. Care.* **22** (6), 514–520 (2013).
8. Alderden, J., Rondinelli, J., Pepper, G., Cummins, M. & Whitney, J. Risk factors for pressure injuries among critical care patients: A systematic review. *Int. J. Nurs. Stud.* **71**, 97–114 (2017).
9. Lyder, C. H., Shannon, R., Empleo-Frazier, O., McGeHee, D. & White, C. A comprehensive program to prevent pressure ulcers in long-term care: Exploring costs and outcomes. *Ostomy Wound Manage.* **48** (4), 52–62 (2002).
10. Suriadi, S. H. et al. A new instrument for predicting pressure ulcer risk in an intensive care unit. *J. Tissue Viability.* **16** (3), 21–26 (2006).
11. Jun Seongsook, R. N., Jeong Ihnsook, R. N. & Lee Younghee, R. N. Validity of pressure ulcer risk assessment scales; Cubbin and Jackson, Braden, and Douglas scale. *Int. J. Nurs. Stud.* **41** (2), 199–204 (2004).
12. Suriadi, S. H., Sugama, J., Thigpen, B. & Subuh, M. Development of a new risk assessment scale for predicting pressure ulcers in an intensive care unit. *Nurs. Crit. Care.* **13** (1), 34–43 (2008).
13. Theaker, C., Kuper, M. & Soni, N. Pressure ulcer prevention in intensive care - a randomised control trial of two pressure-relieving devices. *Anaesthesia* **60** (4), 395–399 (2005).
14. Whittington, K. T. & Briones, R. National prevalence and incidence study: 6-year sequential acute care data. *Adv. Skin. Wound Care.* **17** (9), 490–494 (2004).
15. Singer, M. et al. The third international consensus definitions for Sepsis and septic shock (Sepsis-3). *JAMA* **315** (8), 801–810 (2016).
16. Seo, Y., Oh, H., Na, Y., Kim, M. & Seo, W. A prospective study of pressure injury healing rate and time and influencing factors in an acute care setting. *Adv. Skin. Wound Care.* **35** (12), 1–9 (2022).
17. Castilla, D. M., Liu, Z. J. & Velazquez, O. C. Oxygen: implications for wound healing. *Adv. Wound Care (New Rochelle).* **1** (6), 225–230 (2012).
18. Beckert, S., Konigsrainer, A. & Coerper, S. [The physiology of wound healing]. *Ther. Umsch.* **64** (9), 467–472 (2007).
19. Yang, J., Jin, X., Liu, W. & Wang, W. A programmable oxygenation device facilitates oxygen generation and replenishment to promote wound healing. *Adv. Mater.* **35** (52), e2305819 (2023).
20. Baumgarten, M. et al. Extrinsic risk factors for pressure ulcers early in the hospital stay: a nested case-control study. *J. Gerontol. Biol. Sci. Med. Sci.* **63** (4), 408–413 (2008).
21. Coleman, S. et al. A new pressure ulcer conceptual framework. *J. Adv. Nurs.* **70** (10), 2222–2234 (2014).
22. Chung, M. L. et al. Risk factors for pressure injuries in adult patients: A narrative synthesis. *Int. J. Environ. Res. Public. Health* **19**(2). (2022).
23. Alderden, J. et al. Predicting pressure injury in critical care patients: A Machine-Learning model. *Am. J. Crit. Care.* **27** (6), 461–468 (2018).
24. Naccarato, M. K. & Kelechi, T. Pressure ulcer prevention in the emergency department. *Adv. Emerg. Nurs. J.* **33** (2), 155–162 (2011).
25. Han, D. et al. Prolonged stay in the emergency department is an independent risk factor for hospital-acquired pressure ulcer. *Int. Wound J.* **17** (2), 259–267 (2020).
26. Lima Serrano, M., Gonzalez Mendez, M. I., Carrasco Cebollero, F. M. & Lima Rodriguez, J. S. Risk factors for pressure ulcer development in intensive care units: A systematic review. *Med. Intensiva.* **41** (6), 339–346 (2017).
27. Ahtiala, M., Soppi, E. & Saari, T. I. Sequential organ failure assessment (SOFA) to predict pressure ulcer risk in intensive care patients: A retrospective cohort study. *Ostomy Wound Manage.* **64** (10), 32–38 (2018).
28. Dini, V., Bertone, M. & Romanelli, M. Prevention and management of pressure ulcers. *Dermatol. Ther.* **19** (6), 356–364 (2006).

Acknowledgements

None.

Author contributions

"Yujuan Xue , Li Zheng and Xuezhong Xing wrote the main manuscript text and Zhennan Yuan prepared figures and table . All authors reviewed the manuscript."

Funding

None.

Declarations

Ethics approval and consent to participate

The data in this study were from two public de-identified databases. After completing Collaborative Institutional Training Initiative (CITI program), we got permission to access the database (Record ID: 36067767). This study involves human participants but the Ethics Committee(s) or Institutional Board(s) exempted this study.

Competing interests

The authors declare no competing interests.

Consent for publication

Not applicable.

Additional information

Correspondence and requests for materials should be addressed to Z.-n.Y. or X.-z.X.