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Original Article

Machine learning enables construction of a nomogram based on risk factors for adverse emotions in patients with diabetic foot infection

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Abstract: Objective: To identify risk factors and construct a nomogram model using logistic regression to predict mood disturbance in patients with diabetic foot infection. Methods: We retrospectively analyzed 313 patients with diabetic foot infection who received treatment at our hospital between October 2020 and January 2023. Patients were grouped based on their post-treatment Self-Rating Anxiety Scale (SAS ≥50) and Self-Rating Depression Scale (SDS ≥53) scores into two groups: 134 patients with adverse mood and 179 with stable mood. The patients were divided into a test group (n=220) and a validation group (n=93) at a 7:3 ratio. Clinical data and laboratory indicators were collected to screen characteristic factors using four machine learning models. Common risk factors were screened using logistic regression, visualized, and incorporated into a nomogram. The clinical value, accuracy, and predictive value of the model were evaluated using receiver operating characteristic curves (ROCs), calibration curves, and decision curve analyses (DCAs). Results: Analysis identified Wagner classification, comorbidities, glycated hemoglobin (HbA1c), gender, and history of diabetes as common features across four machine learning models. Multifactorial logistic regression confirmed that Wagner classification, comorbidities, HbA1c, gender, and history of diabetes were independent risk factors for adverse mood in patients with diabetic foot infection. We constructed a nomogram based on the five characteristic factors. ROC curve analysis yielded an area under the curve (AUC) of 0.829, indicating high predictive accuracy for mood disturbances in the test group. Calibration curve and DCA analysis demonstrated the model's stability and clinical relevance, further supported by external validation. Conclusion: This study enhanced the predictive accuracy for mood disorders in patients with diabetic foot infections by leveraging machine learning to identify and visualize significant risk factors through a nomogram. This may be a valuable tool for clinical assessments and intervention.

Keywords: Regression modeling, diabetic foot infection, adverse emotions, risk factors, predictive modeling

Introduction

Diabetes mellitus is a metabolic disease characterized by persistent hyperglycemia caused primarily by insulin resistance and insufficient insulin secretion [1]. Among various types of diabetes, type 2 diabetes mellitus (T2DM) is the most prevalent, marked by a failure of the pancreas to secrete sufficient insulin or the failure of the body to use insulin effectively [2]. A study [3] has shown that people with T2DM often have mood disorders such as anxiety and depression. A national study [4] has shown that 21.8% of 496 patients with T2DM suffered from anxiety or depression. Similarly, international surveys have shown that diabetic patients are twice as likely to suffer from depression compared to non-diabetic patients, with the prevalence of anxiety disorders reaching 28% [5, 6]. This high prevalence may be related to socioeconomic and personal factors such as ongoing glucose testing, lifestyle changes asso-

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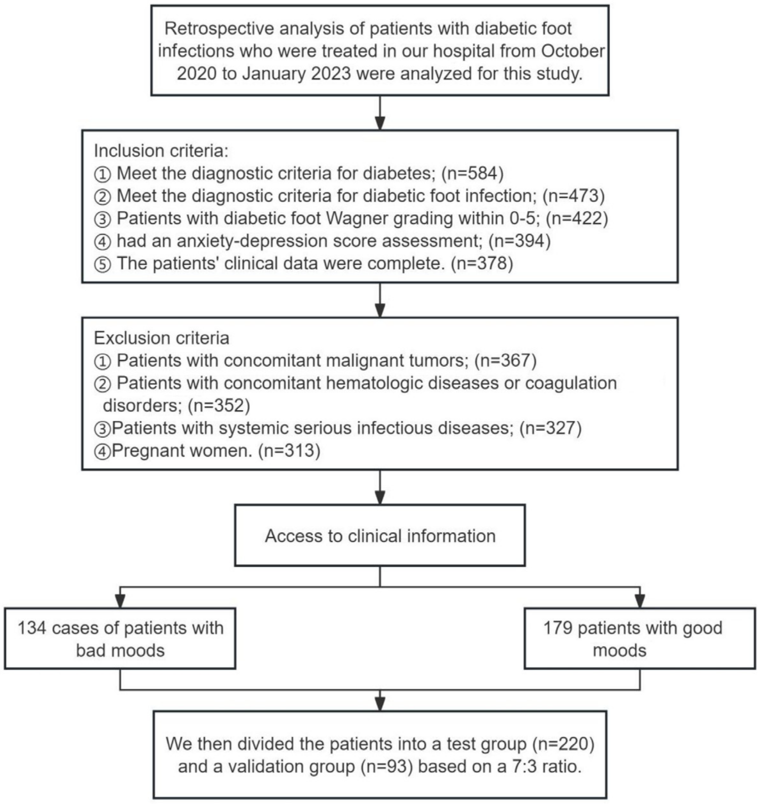

Figure 1. Case inclusion flowchart.

ciated with insulin injection, increased healthcare cost, excessive concern about complications, and the stress of long-term treatment [7].

Symptoms of anxiety include excessive worry, fidgeting, and easy fatigue, while depression is characterized by low mood and loss of interest in activities [8]. These mood disorders not only increase the frequency of medical visits for diabetic patients but also exacerbate the management of serious complications such as diabetic foot-a chronic condition that significantly worsens the physical and mental health of patients [9, 10]. Research indicates that patients with diabetic foot often suffer from underlying psychosomatic disorders, experiencing isolation, helplessness, anxiety, and depression due to disrupted sleep, reduced mobility, and other challenges; the cumulative effect of these factors can escalate psychological stress [11-14]. Among patients with type 2 diabetes, those with depression are twice as likely to face amputation and mortality within five years of developing their first diabetic foot ulcer, compared to those without depression [15]. Despite extensive knowledge in managing diabetes and its complications, the critical importance of mental health is frequently underestimated by physicians.

Therefore, screening patients with diabetic foot infections at high risk for severe emotional distress is of great importance. Such proactive screening can help implement targeted intervention to manage both the physical and emotional aspects of diabetic complications, ultimately improving patients' prognosis and quality of life. To this end, we screened for adverse emotional factors based on a machine learning model and employed nomogram visualization to provide clinicians with a predictive tool for assessing disease risk.

Patients and methods

Sample sources

This study involved a retrospective analysis of data from patients with diabetic foot infection who were treated in our hospital between October 2020 and January 2023. This study was approved by the medical Ethics Committee of Baoji Central Hospital (**Figure 1**).

Inclusion and exclusion criteria

Inclusion criteria: ① Patients diagnosed with diabetes according to the 2020 edition of the Diabetes Medical Diagnosis and Treatment Criteria [16]; ② Patients with diabetic foot infections meeting the 2019 Guidelines for the Diagnosis and Treatment of Diabetic Foot Infections [17]; ③ Patients with diabetic foot graded of Wagner 0-5 [18]; ④ Anxiety and depression scores of patients assessed using the Self-Rating Anxiety Scale (SAS) and Self-Rating Depression Scale (SDS) [19]; ⑤ Patients with complete clinical data; ⑥ Patients aged 18 years and older.

Exclusion criteria: ① Patients with concomitant malignant tumors; ② Patients with combined hematologic diseases or coagulation disorders; ③ Patients with systemic serious infectious diseases; ④ Pregnant women.

Access to clinical information

Patient clinical information was retrieved from an electronic medical record system. Key data included age, sex, education, marital status, monthly household income, smoking history, incident foot infections, duration of diabetes history, comorbidities, Wagner classification, glycosylated hemoglobin, risk of amputation, and SAS versus SDS scores.

Adverse mood assessment criteria

The SAS, comprising 20 items scored on a 4-point scale (1-4), evaluates the severity of anxiety symptoms. The total score (80) is adjusted to 100 after multiplication by 1.25. The SDS was used to rate the severity of depression, with each item rated on a 4-point scale (1-4), totaling 80 points. Similarly, the total score was adjusted to 100 after multiplication by 1.25. Patients were classified as having an adverse mood if their SAS scores exceeded 50 and their SDS scores surpassed 53.

Sample grouping

According to the inclusion criteria, we identified a total of 313 eligible cases for this study. This cohort included 134 patients identified with adverse mood and 179 with stable mood. We then divided the patients into a test group (n=220) and a validation group (n=93) based on a 7:3 ratio.

Machine learning model feature screening

We employed four machine learning models-eXtreme Gradient Boosting (XGBoost), Support Vector Machine (SVM), Least Absolute Shrinkage and Selection Operator (Lasso), and Random Forest (RF)-to identify key features affecting the emotional state of patients with diabetic foot infections.

XGBoost: XGBoost is an advanced implementation of gradient boosting decision trees, known for its speed and performance. It uses a sequential process where each new tree corrects errors made by the previous tree, optimizing the overall model performance. XGBoost handles missing data and prevents overfitting effectively through regularization and can process large datasets quickly, making it ideal for our analysis. SVM: SVM is a powerful classification technique that identifies the optimal hyperplane for separating data into different classes. By maximizing the margin between the classes, SVM ensures the model's generalizability to new data. This model is particularly effective for high-dimensional data and maintains robustness even with small sample sizes.

Lasso: Lasso regression is beneficial for improving prediction accuracy and model interpretability by performing both variable selection and regularization. Through L1 regularization, Lasso shrinks the coefficients of less important features to zero, effectively selecting a simpler model that avoids overfitting. This automatic feature selection is crucial for identifying the most relevant predictors in our dataset. RF: RF is an ensemble learning method that constructs multiple decision trees during training and aggregates their predictions to improve accuracy and robustness. It improves model accuracy and controls overfitting by averaging the results of multiple trees. RF is highly effective for handling large datasets with many features and provides insights into feature importance.

Outcome measurement

Primary outcomes: 1. The risk factors for adverse mood in patients with diabetic foot infections were identified using four machine learning models. 2. A predictive model for diabetic foot infections leading to adverse mood was developed using a nomogram. 3. The stability of the model was externally validated using the data from the validation group. 4. The clinical value of the model was assessed using data from the validation group.

Secondary outcomes: 1. The clinical data differences between the test group and the validation group were compared. 2. The baseline data differences in patients within the test group were analyzed.

Statistical analysis

The data were pre-processed using SPSS 26.0 software. The counted data were expressed as rates (%) and analyzed for differences between groups using the chi-square test. In-depth statistical analysis was performed using R (4.3.2). Specific methods and tools used included: "gbtree" was utilized as the enhancer and binary logistic regression as the objective function, and the performance of the model was evaluated. The "glmnet" package was used for modeling Lasso regression. The "xgboost" package was used to model the xgboost regression. SMV regression was conducted using the "caret" package. The "randomForest" package was used for RF regression modeling. The "rms" package was used for nomogram modeling. rmda "package for DCA (Decision Curve Analysis) and calibration curve plotting". The "rocr" package was used to create ROC curves. Statistical significance was set at a *p*-value of less than 0.05.

Results

Comparison of baseline data between patients in the test and validation groups

Patients were divided into a test group and a validation group based on a 7:3 ratio. Comparison of baseline data between the two groups showed no significant differences in age, gender, education, marital status, monthly household income, smoking history, incidence of foot infections, duration of diabetes, comorbidities, Wagner classification, glycosylated hemoglobin levels, amputation risk, or emotional state (all P>0.05, **Table 1**).

Comparison of baseline data of patients with different moods in test group

Patients with SAS score ≥50 and SDS score ≥53 scores were classified into an adverse mood group, resulting in 94 patients classified into the adverse mood category and 126 in the stable mood category within the test group. Baseline data comparison revealed no statistical differences in age, education, marital status, and monthly household income between the two sub-groups (all P>0.05). However, the adverse mood group had significantly higher proportions of females, individuals with foot infections lasting ≥6 months, a diabetes history of ≥10 years, ≥3 comorbidities, a Wagner classification of ≥2, glycosylated hemoglobin levels of ≥7, and a higher risk of amputation compared to the stable mood group (all P<0.05, **Table 2**).

Four machine learning models to screen for adverse emotional characteristic factors

We used four machine learning models-Lasso, Xgboost, SVM, and RF-to identify significant factors affecting the mood of the patients. Lasso regression (1se) identified seven factors: sex, time to foot infection, history of diabetes, comorbidities, Wagner classification, glycated hemoglobin, and risk of amputation (**Figure 2A**, **2B**). Xgboost regression (Gain ≥0.05) revealed ten factors: Wagner classification, comorbidities, history of diabetes, glycated hemoglobin (repeated three times indicating its significant influence), risk of amputation, monthly household income, time to foot infection, age, and sex (**Figure 2C**). SVM regression identified five factors: Wagner classification, comorbidities, glycated hemoglobin, sex, and history of diabetes (**Figure 2D**). RF regression highlighted seven factors: sex, time to foot infection, history of diabetes, comorbidities, Wagner classification, glycated hemoglobin, and risk of amputation (**Figure 2E**). An analysis using a Venn diagram demonstrated that Wagner classification, comorbidities, glycated hemoglobin, sex, and history of diabetes were consistent across all models (**Figure 2F**).

Logistic regression analysis of risk factors for mood disorders

We further evaluated the five mood-influencing factors identified by machine learning using univariate and multivariate logistic regression analyses. Multifactorial logistic regression results indicated that Wagner classification (P<0.001, OR: 7.131), comorbidities (P<0.001, OR: 4.189), glycated hemoglobin (P<0.001, OR: 3.110), sex (P=0.012, OR: 0.424), and history of diabetes (P=0.002, OR: 3.022) were independent risk factors for adverse mood among patients with diabetic foot infections (**Figure 3**).

Nomogram modeling of adverse emotions in patients with diabetic foot infections

Based on the 5 characterization factors, we constructed a nomogram model (**Figure 4A**). The calculated formula: -0.096843349 + Sex* 0.857194336 + History_of_diabetes1* - 1.106071679 + Comorbidities1* - 1.432546278 + Wagner_classification0*1.964396391 + Glycated_hemoglobin1* - 1.13467096. To evaluate the predictive efficacy, stability, and clinical value of the model, we analyzed it using ROC curves, calibration curves, and Decision Curve Analysis (DCA) curves, respectively, as shown in **Figure 4B**. ROC curve analysis revealed that the AUC of the nomogram for predicting poor mood in patients with diabetic foot infection in the

Table 1. Comparison of baseline data between patients in the test and validation groups

	Test group (n=220)	Validation group (n=93)	χ^2-value	*P*-value
Age				
≥60 years	118	53	0.296	0.586
<60 years	102	40		
Sex				
Male	128	54	<0.001	0.985
Female	92	39		
Educational attainment				
High School or above	119	42	2.087	0.149
Below high school	101	51		
Marital status				
Married	177	75	0.002	0.969
Other	43	18		
Monthly household income				
≥4000 yuan	97	41	<0.001	0.999
<4000 yuan	123	52		
Smoking history				
Yes	130	55	<0.001	0.994
No	90	38		
Duration of foot infection				
≥6 months	77	34	0.069	0.792
<6 months	143	59		
Duration of diabetes				
≥10 years	73	27	0.518	0.472
<10 years	147	66		
Complications				
≥3	72	31	0.011	0.917
<3	148	62		
Wagner Grading				
≥2	78	39	1.173	0.279
<2	142	54		
Glycosylated hemoglobin level				
≥7	89	37	0.012	0.912
<7	131	56		
Risk of amputation				
Yes	104	42	0.117	0.732
No	116	51		
Emotional situation				
Bad mood	94	40	0.002	0.963
Good mood	126	53		

test group was 0.829, indicating strong predictive power. The calibration curve demonstrated high model stability, as the actual prediction values (depicted in blue) closely aligned with the ideal prediction values (shown in red) (**Figure 4C**). Lastly, the DCA curve demonstrated that the model offers substantial clinical benefits across a decision threshold interval of 0%-93%, peaking at a clinical benefit of 57.27% (**Figure 4D**).

External validation of the nomogram model

We further assessed the clinical value of our model by using data from the validation group for external validation. The ROC curve analysis

Table 2. Analysis of baseline data of patients with different moods in the test group of patients

	Adverse mood group (n=94)	Good mood group (n=126)	χ^2-value	*P*-value
Age				
≥60 years	55	63	1.568	0.210
<60 years	39	63		
Sex				
Male	43	85	10.434	0.001
Female	51	41		
Educational attainment				
High school or above	46	73	1.756	0.185
Blow high school	48	53		
Marital status				
Married	73	104	0.815	0.367
Other	21	22		
Monthly household income				
≥4000 yuan	36	61	2.234	0.135
<4000 yuan	58	65		
Smoking history				
Yes	54	80	0.826	0.363
No	40	46		
Duration of foot infection				
≥6 months	42	35	6.761	0.009
<6 months	52	91		
Duration of diabetes				
≥10 years	43	30	11.683	<0.001
<10 years	51	96		
Complication				
≥3	46	26	19.586	<0.001
<3	48	100		
Wagner Grading				
≥2	54	24	34.688	<0.001
<2	40	102		
Glycosylated hemoglobin				
≥7	51	38	12.977	<0.001
<7	43	88		
Risk of amputation				
Yes	57	47	11.763	<0.001
No	37	79		

for this group showed that the AUC was 0.745 in the validation set, demonstrating good predictive performance (**Figure 5A**). Delong's test analysis resulted in a D value of -1.423 between the validation group and the test group model, indicating no significant difference (P=0.157). This suggests that the model performed similarly in both groups. The calibration curve analysis confirmed the model's stability, as the actual predicted values (depicted in blue) closely aligned with the ideal prediction values (shown in red) (**Figure 5B**). Additionally, DCA curve demonstrated that the model provided clinical benefits within a decision threshold interval of 0%-89%, peaking at a benefit rate of 56.98% (**Figure 5C**). This further underscores the model's utility in predicting mood disturbance in patients with diabetic foot infections across different patient populations.

Discussion

Due to prolonged high glucose and hypoxia status in diabetic foot patients, they often suffer

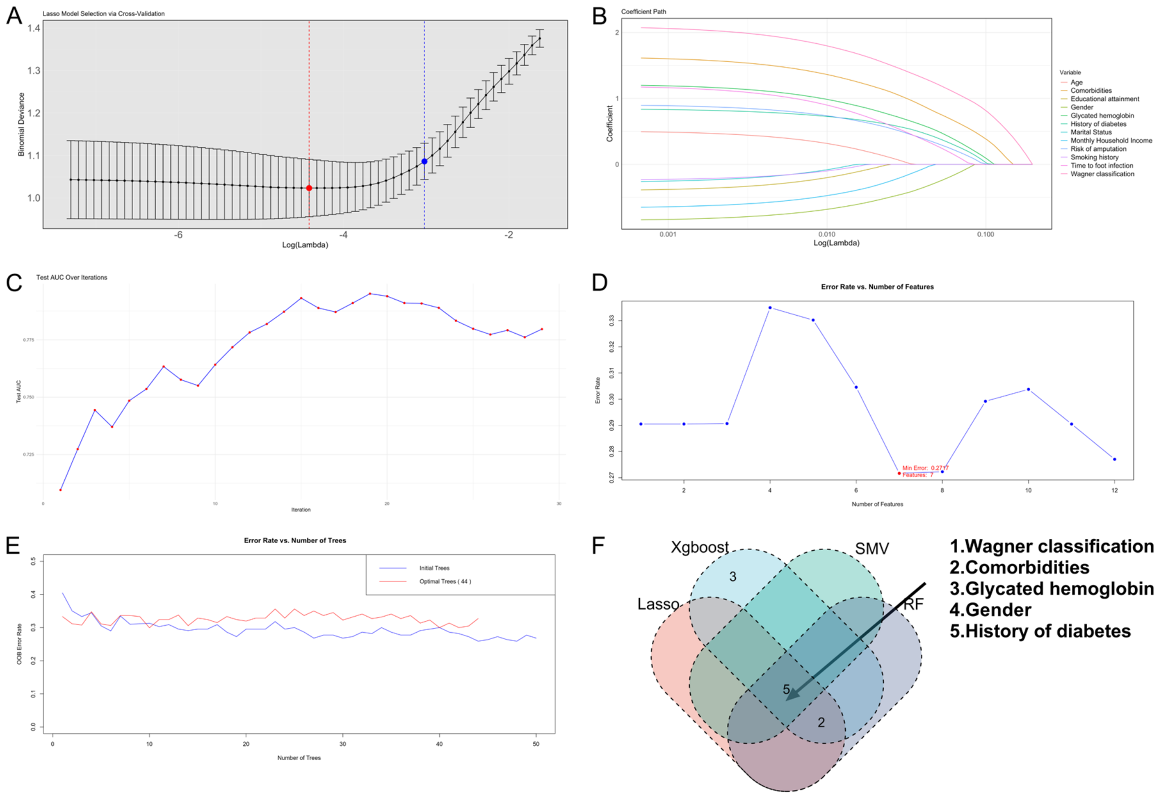

Figure 2. Identifying risk factors for mood distrubace by using four machine learning models. A, B. Lasso regression model. C. Xgboost Regression model. D. SVM model. E. RF model. F. Common factors across 4 machine learning models identified by Wayne Diagram. Note: XGBoost, eXtreme Gradient Boosting; SVM, Support Vector Machine; Lasso, Least Absolute Shrinkage and Selection Operator; RF, Random Forest.

from severe complications such as foot abscesses, gangrene, and infection. This progression significantly extends hospital stays, increases the risk of amputation, and exacerbates the economic burden on patients [20, 21]. Rohde et al. analyzed 8,175 patients with T2DM and found that a considerable number of deaths among these patients were due to preexisting depression, which was exacerbated by unhealthy lifestyles and comorbidities associated with depression [22]. Additionally, findings from an open randomized controlled trial indicated that patients with diabetic foot frequently experience anxiety and depression, severely worsening their quality of life [23]. Therefore, diabetic foot infections not only intensify the physical burden on patients but may also amplify psychological stress, leading to worse mental health. This dual burden makes patients more vulnerable to depression and anxiety, adversely affecting both treatment outcome and quality of life. Thus, it is crucial to conduct thorough screenings and assessments for risk factors of anxiety and depression in patients with diabetic foot, considering their high risk for multiple complications, particularly mental health challenges.

In our study, we used four machine learning models to identify characteristic factors influencing negative mood outcomes in patients with diabetic foot. XGBoost is renowned for its efficiency with large-scale datasets and optimizing multiple decision trees to improve prediction accuracy [24]; SVM is effective in high-dimensional data classification and maintains robust generalization capabilities even with small sample sizes [25]. Lasso minimizes overfitting through L1 regularization, making it well-suited for variable selection [26]. RF manages nonlinear relationships well and mitigates overfitting risks by averaging multiple decision tree outputs [27]. While each model has distinct advantages, the integration of these methods allowed us to refine our analysis. Using a Venn diagram, we identified common factors such as

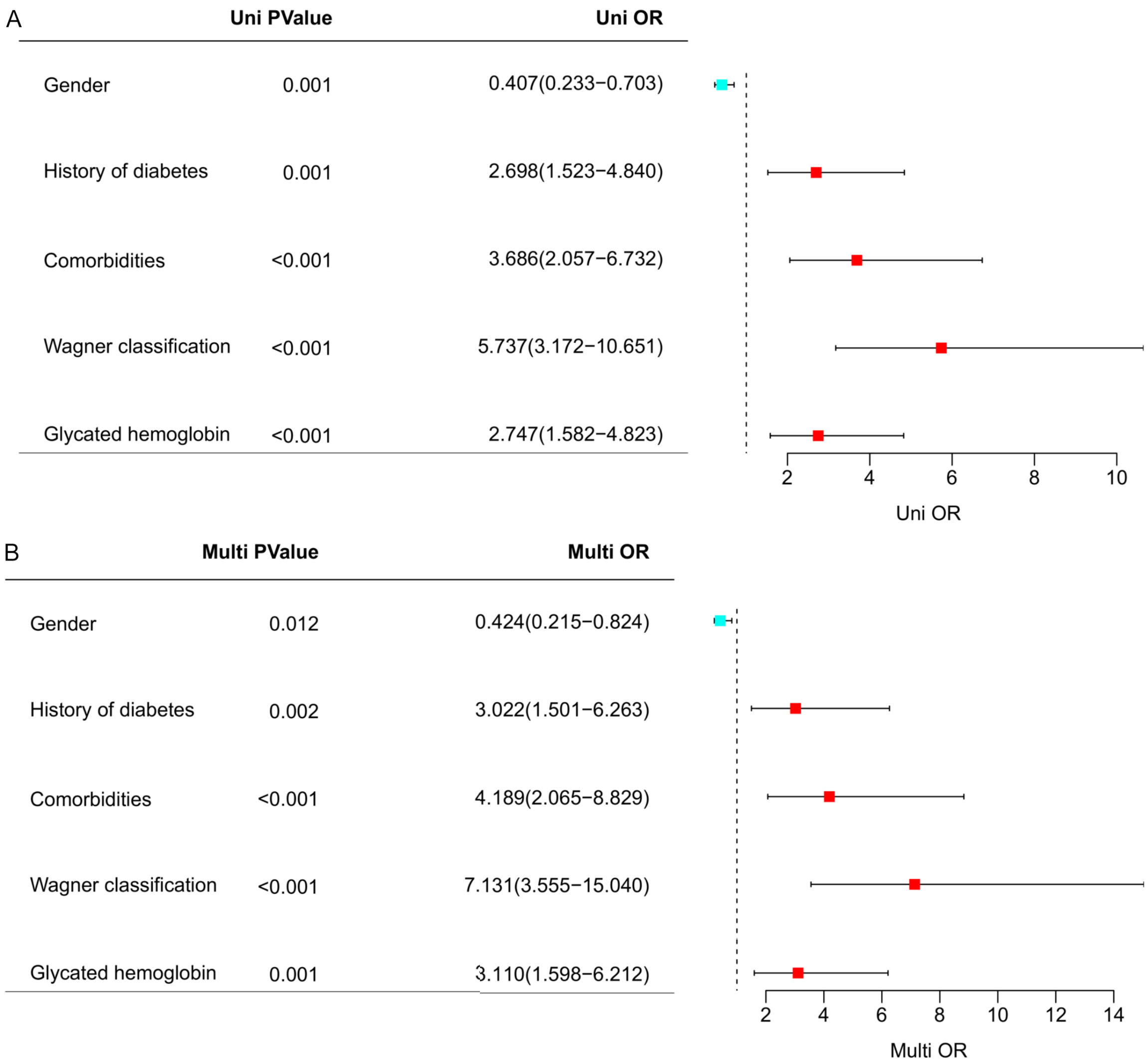

Figure 3. Risk factors for mood disturbance in patients with diabetic foot infection. A. Univariate logistic regression analysis of risk factors for mood disturbance in patients with diabetic foot infection; B. Multivariate logistic regression analysis of independent risk factors for mood disturbance in patients with diabetic foot infection.

Wagner classification, number of comorbidities, glycosylated hemoglobin level, sex, and history of diabetes as central elements of our study. The synthesis of these characteristics not only leveraged the strengths of each model but also enhanced our understanding of the risk factors associated with negative emotions in patients with diabetic foot infection. Ultimately, we further analyzed these factors through logistic regression to pinpoint Wagner classification, number of comorbidities, glycosylated hemoglobin level, sex, and history of diabetes as independent risk factors for dysphoria in this patient population. This approach significantly improved the precision of our assessment, providing crucial insight into managing and mitigating adverse emotional outcomes in patients suffering from diabetic foot infection.

We categorized the identified risk factors into physiological (Wagner classification, number of complications, and glycated hemoglobin level) and psychosocial (gender, history of diabetes) profiles. Each factor contributes distinctly to the overall risk of adverse mood outcome in diabetic foot patients. Wagner classification evaluates the severity of diabetic foot lesions. Higher Wagner classification indicates more severe lesions, often requiring frequent medical intervention and increasing the risk of amputation. The ongoing pain, functional limitations, and the constant threat of amputation can significantly heighten psychological stress,

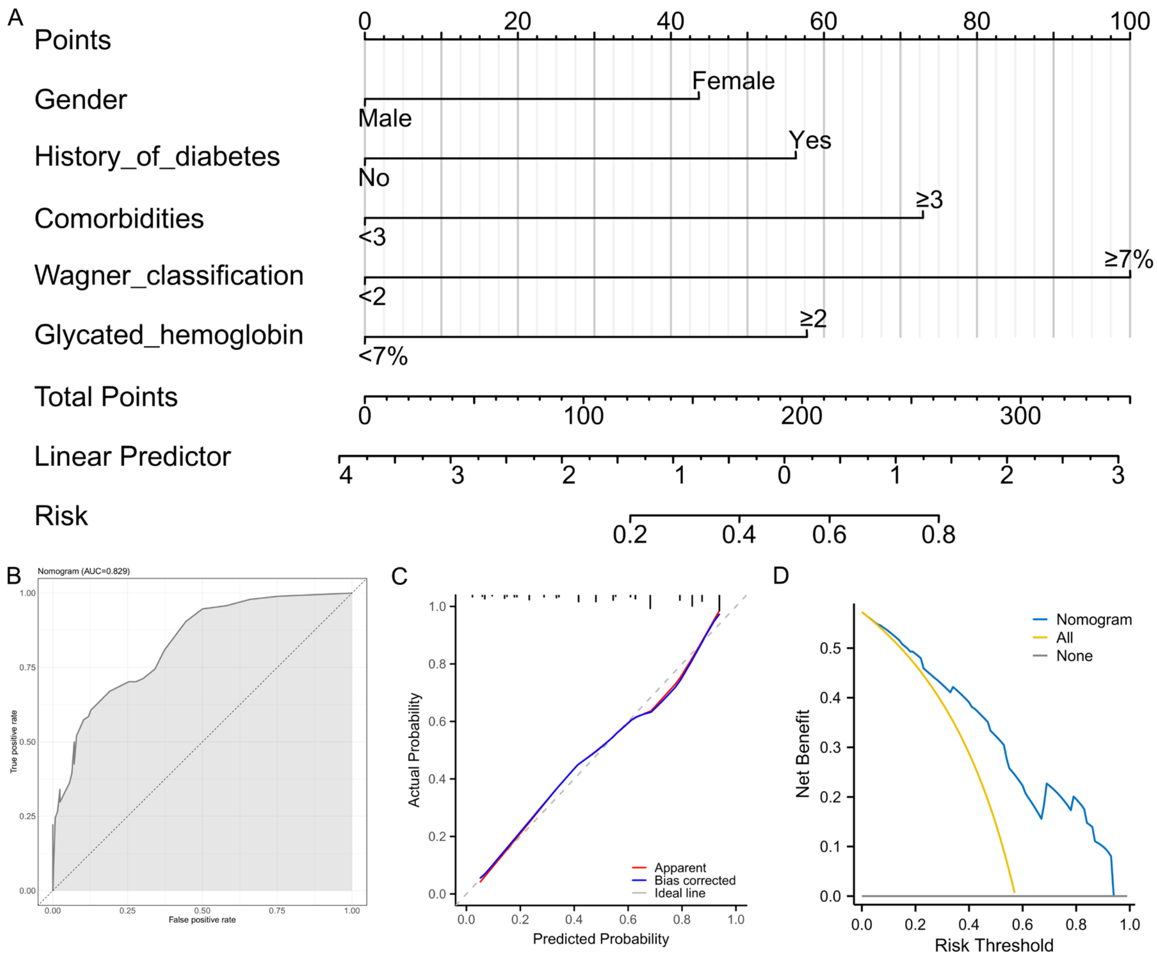

Figure 4. Construction of a nomogram model and its internal validation. A. Nomogram model constructed with 5 characteristic factors; B. ROC curve for validating the model's predictive performance in the test group; C. Calibration curve for validating the model's stability in the test group; D. DCA curve for validating the model's clinical benefit in test group. Note: ROCs, Receiver operating characteristic curves; DCAs, Decision curve analyses.

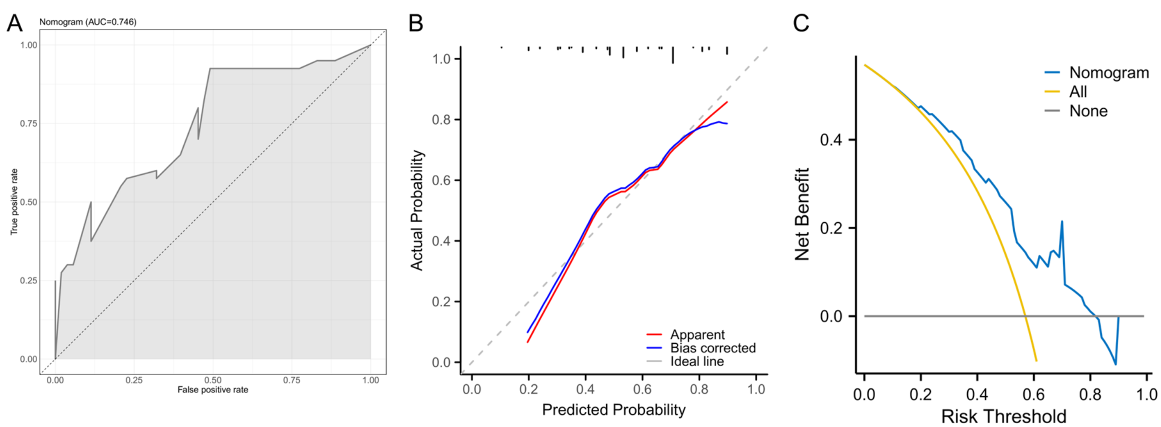

Figure 5. Extermal validation of the nmodel in validation set. A. ROC curve for validating the model's predictive performance in the validation set; B. Calibration curve for validating the model's stability in the validation set; C. DCA curve for validating the model's clinical benefit in validation set. Note: ROCs, Receiver operating characteristic curves; DCAs, Decision curve analyses.

leading to anxiety and depression [28]. The coexistence of multiple comorbidities complicates the management of diabetes and heightens treatment complexity [29]. Conditions like cardiovascular disease and renal failure not only worsen the medical prognosis but also amplify patients' fears and anxiety, affecting their long-term survival and quality of life. Elevated glycated hemoglobin levels suggest poor glycemic control, correlating with a higher risk of complications and a poor health prognosis [30]. Challenges in managing glycemic levels can escalate psychological stress due to continuous medical needs and perceived declines in quality of life. Besides, research has shown that females with diabetes are more prone to experiencing depression and anxiety compared to males [31]. This disparity is often attributed to gender differences in emotional expression, social support-seeking behaviors, and the additional pressures women may face in balancing family and professional responsibilities. Individuals with a prolonged history of diabetes may experience emotional fatigue from continuous disease management and the persistent threat of complications, which can lead to feelings of helplessness and frustration [32]. Ahmad et al. have highlighted how the duration of diabetes and the presence of multiple comorbidities are linked with higher anxiety levels in patients with diabetic foot [33]. These studies corroborate our findings and underscore the importance of identifying both physiological and psychosocial factors to more effectively predict and manage mood disorders in patients with diabetic foot. By recognizing these factors, we can better tailor interventions to improve treatment outcome and improve the quality of life for these patients. This comprehensive approach not only addresses the physical aspects of the disease but also the crucial psychological components, ultimately improving overall patient care and quality of life.

Visualization of risk factors enhances the comprehension and communication of medical data, making it more accessible and actionable for clinical decision-making, research, and medical education. In our study, we used a nomogram to visually represent five critical risk factors, providing a clear and intuitive method for understanding complex medical information. The predictive accuracy of our nomogram model was confirmed by its AUC (Area Under the Curve) value of 0.829, indicating strong diagnostic capability. The model underwent both internal and external validations, affirming its generalizability and reliability across different patient populations. For comparison, Yu et al. [34] developed a prediction model for T2DM using Lasso and logistic regression, which included nine factors such as age, gender, poverty-income ratio (PIR), body mass index (BMI), education, smoking status, LDL cholesterol, sleep duration, and sleep disorders. Their model achieved a C-index of 0.780, signifying good predictive power, though slightly lower than our model. Similarly, Maimaitituerxun et al. [4] constructed a predictive model for anxiety, incorporating factors like age, diabetes-specific complications, education level, regular exercise, and high socialization, achieving an AUC of 0.80. This suggests that our nomogram model may be superior in accuracy to others.

These comparisons highlight that our model accurately distinguishes between diabetic foot patients at high-risk and low-risk for developing mood disturbance. This capability is particularly valuable for clinicians and healthcare providers, enabling them to implement early preventive measures and customize treatment strategy effectively. However, there are still several key limitations of this study. First, the sample selection was predominantly from specific hospitals or regions, which may restrict the generalizability of our findings as these samples may not fully represent the diversity of all diabetic foot patients. Second, although the nomogram model showed good predictive properties in this study, its ability to generalize has not been validated across different populations or geographic locations, so more study is needed to support the applicability and accuracy of the model. This may be done by broadening the sample range and validating the model's generalizability in future studies.

In summary, our study identified five key risk factors affecting the mood of patients with diabetic foot, including Wagner classification, number of complications, glycated hemoglobin level, sex, and history of diabetes, by utilizing machine learning models. The constructed nomogram demonstrated high accuracy in predicting mood disorders in diabetic foot patients.

Disclosure of conflict of interest

None.

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References

[1] Gregg EW, Cheng YJ, Srinivasan M, Lin J, Geiss LS, Albright AL and Imperatore G. Trends in cause-specific mortality among adults with and without diagnosed diabetes in the USA: an epidemiological analysis of linked national survey and vital statistics data. Lancet 2018; 391: 2430-2440.

[2] Han E, Han KD, Lee YH, Kim KS, Hong S, Park JH and Park CY. Fatty liver & diabetes statistics in Korea: nationwide data 2009 to 2017. Diabetes Metab J 2023; 47: 347-355.

[3] Horsbøl TA, Hoffmann SH, Thorsted AB, Rosenkilde S, Lehn SF, Kofoed-Enevoldsen A, Santos M, Iversen PB and Thygesen LC. Diabetic complications and risk of depression and anxiety among adults with type 2 diabetes. Diabet Med 2024; 41: e15272.

[4] Maimaitituerxun R, Chen W, Xiang J, Xie Y, Kaminga AC, Wu XY, Chen L, Yang J, Liu A and Dai W. Prevalence of anxiety and associated factors among inpatients with type 2 diabetes mellitus in China: a cross-sectional study. Psychiatr Q 2023; 94: 371-383.

[5] Sartorius N. Depression and diabetes. Dialogues Clin Neurosci 2018; 20: 47-52.

[6] Mersha AG, Tollosa DN, Bagade T and Eftekhari P. A bidirectional relationship between diabetes mellitus and anxiety: a systematic review and meta-analysis. J Psychosom Res 2022; 162: 110991.

[7] Kunik ME, Evans TL, Christie IC, True G, Bradford A, Vasudevan MM and Hundt NE. The impact of veteran support and resources for diabetes (iNSPiRED) on diabetes distress: results from a randomized, parallel-group trial. Gen Hosp Psychiatry 2023; 85: 55-62.

[8] McInerney AM, Lindekilde N, Nouwen A, Schmitz N and Deschênes SS. Diabetes distress, depressive symptoms, and anxiety symptoms in people with type 2 diabetes: a network analysis approach to understanding comorbidity. Diabetes Care 2022; 45: 1715-1723.

[9] Armstrong DG, Tan TW, Boulton AJM and Bus SA. Diabetic foot ulcers: a review. JAMA 2023; 330: 62-75.

[10] Voelker R. What are diabetic foot ulcers? JAMA 2023; 330: 2314.

[11] Crocker RM, Palmer KNB, Marrero DG and Tan TW. Patient perspectives on the physical, psycho-social, and financial impacts of diabetic foot ulceration and amputation. J Diabetes Complications 2021; 35: 107960.

[12] Williams JK, Collings R, Kent B and Paton J. Prevalence and incidence of mental health issues amongst adults with diabetes at risk of foot complications in the European Union: a systematic review protocol. JBI Evid Synth 2022; 20: 2094-2101.

[13] Hoban C, Sareen J, Henriksen CA, Kuzyk L, Embil JM and Trepman E. Mental health issues associated with foot complications of diabetes mellitus. Foot Ankle Surg 2015; 21: 49-55.

[14] Stancu B, Ilyés T, Farcas M, Coman HF, Chiş BA and Andercou OA. Diabetic foot complications: a retrospective cohort study. Int J Environ Res Public Health 2022; 20: 187.

[15] Boulton AJ, Kirsner RS and Vileikyte L. Clinical practice. neuropathic diabetic foot ulcers. N Engl J Med 2004; 351: 48-55.

[16] Wang A, Lv G, Cheng X, Ma X, Wang W, Gui J, Hu J, Lu M, Chu G, Chen J, Zhang H, Jiang Y, Chen Y, Yang W, Jiang L, Geng H, Zheng R, Li Y, Feng W, Johnson B, Wang W, Zhu D and Hu Y. Guidelines on multidisciplinary approaches for the prevention and management of diabetic foot disease (2020 edition). Burns Trauma 2020; 8: tkaa017.

[17] Lipsky BA, Senneville É, Abbas ZG, Aragón-Sánchez J, Diggle M, Embil JM, Kono S, Lavery LA, Malone M, van Asten SA, Urbančič-Rovan V and Peters EJG; International Working Group on the Diabetic Foot (IWGDF). Guidelines on the diagnosis and treatment of foot infection in persons with diabetes (IWGDF 2019 update). Diabetes Metab Res Rev 2020; 36 Suppl 1: e3280.

[18] Oley MH, Oley MC, Kepel BJ, Faruk M, Wagiu AMJ, Sukarno I, Tulong MT and Sukarno V. Hyperbaric oxygen therapy for diabetic foot ulcers based on wagner grading: a systematic review and meta-analysis. Plast Reconstr Surg Glob Open 2024; 12: e5692.

[19] Tung VS, Thong NV, Mai NP, Linh LT, Son DC, Ha TT, Hoa NT, Long NT and Tuan NV. Diagnostic value in screening severe depression of the hamilton depression rating scale, hamilton anxiety rating scale, beck depression inventory scale, and Zung's self-rating anxiety scale among patients with recurrent depression disorder. Acta Inform Med 2023; 31: 249-253.

[20] Aragón-Sánchez J, Víquez-Molina G, López-Valverde ME, Rojas-Bonilla JM and Murillo-Vargas C. Conservative surgery for diabetic foot osteomyelitis is not associated with longer survival time without recurrence of foot ulcer when compared with amputation. Int J Low Extrem Wounds 2023; 22: 328-331.

[21] Primadhi RA, Septrina R, Hapsari P and Kusumawati M. Amputation in diabetic foot ulcer:

a treatment dilemma. World J Orthop 2023; 14: 312-318.

[22] Rohde C, Nielsen JS, Schöllhammer Knudsen J, Thomsen RW and Østergaard SD. Risk factors associated with mortality among individuals with type 2 diabetes and depression across two cohorts. Eur J Endocrinol 2022; 187: 567-577.

[23] Qin Q, Oe M, Nakagami G, Kashiwabara K, Sugama J, Sanada H and Jais S. The effectiveness of a thermography-driven preventive foot care protocol on the recurrence of diabetic foot ulcers in low-medical resource settings: an open-labeled randomized controlled trial. Int J Nurs Stud 2023; 146: 104571.

[24] Tyagi P, Sharma A, Semwal R, Tiwary US and Varadwaj PK. XGBoost odor prediction model: finding the structure-odor relationship of odorant molecules using the extreme gradient boosting algorithm. J Biomol Struct Dyn 2024; 42: 10727-10738.

[25] Wei Y, Rao X, Fu Y, Song L, Chen H and Li J. Machine learning prediction model based on enhanced bat algorithm and support vector machine for slow employment prediction. PLoS One 2023; 18: e0294114.

[26] Hu X, Shen F, Zhao Z, Qu X and Ye J. An individualized gait pattern prediction model based on the least absolute shrinkage and selection operator regression. J Biomech 2020; 112: 110052.

[27] Ahn S, Lee SE and Kim MH. Random-forest model for drug-target interaction prediction via Kullbeck-Leibler divergence. J Cheminform 2022; 14: 67.

[28] Polikandrioti M, Vasilopoulos G, Koutelekos I, Panoutsopoulos G, Gerogianni G, Babatsikou F, Zartaloudi A and Toulia G. Quality of life in diabetic foot ulcer: associated factors and the impact of anxiety/depression and adherence to self-care. Int J Low Extrem Wounds 2020; 19: 165-179.

[29] Rees G, Xie J, Fenwick EK, Sturrock BA, Finger R, Rogers SL, Lim L and Lamoureux EL. Association between diabetes-related eye complications and symptoms of anxiety and depression. JAMA Ophthalmol 2016; 134: 1007-1014.

[30] Vesco AT, Howard KR, Anderson LM, Papadakis JL, Hood KK and Weissberg-Benchell J. Examining indirect effects of anxiety on glycated hemoglobin via automatic negative thinking and diabetes-specific distress in adolescents with type 1 diabetes. Can J Diabetes 2021; 45: 473-480.

[31] Hargittay C, Gonda X, Márkus B, Sipkovits Z, Vörös K, Kalabay L, Rihmer Z and Torzsa P. The relationship between anxiety and diabetes. Orv Hetil 2021; 162: 1226-1232.

[32] Nguyen LA, Pouwer F, Winterdijk P, Hartman E, Nuboer R, Sas T, de Kruijff I, Bakker-Van Waarde W, Aanstoot HJ and Nefs G. Prevalence and course of mood and anxiety disorders, and correlates of symptom severity in adolescents with type 1 diabetes: results from diabetes LEAP. Pediatr Diabetes 2021; 22: 638-648.

[33] Ahmad A, Abujbara M, Jaddou H, Younes NA and Ajlouni K. Anxiety and depression among adult patients with diabetic foot: prevalence and associated factors. J Clin Med Res 2018; 10: 411-418.

[34] Yu X, Tian S, Wu L, Zheng H, Liu M and Wu W. Construction of a depression risk prediction model for type 2 diabetes mellitus patients based on NHANES 2007-2014. J Affect Disord 2024; 349: 217-225.