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ORIGINAL RESEARCH

Nomogram Predicting 90-Day Readmission in Patients with Diabetes: A Prospective Study

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Purpose: Readmission within a period time of discharge is common and costly. Diabetic patients are at risk of readmission because of comorbidities and complications. It is crucial to monitor patients with diabetes with risk factors for readmission and provide them with target suggestions. We aim to develop a nomogram to predict the risk of readmission within 90 days of discharge in diabetic patients.
Patients and Methods: This is a prospective observational survey. A total of 784 adult patients with diabetes recruited in two tertiary hospitals in central China were randomly assigned to a training set or a validation set at a ratio of 7:3. Depression, anxiety, self-care, physical activity, and sedentary behavior were assessed during hospitalization. A 90-day follow-up was conducted after discharge. Multivariate logistic regression was employed to develop a nomogram, which was validated with the use of a validation set. The AUC, calibration plot, and clinical decision curve were used to assess the discrimination, calibration, and clinical usefulness of the nomogram, respectively.
Results: In this study, the 90-day readmission rate in our study population was 18.6%. Predictors in the final nomogram were previous admissions within 1 year of the index admission, self-care scores, anxiety scores, physical activity, and complicating with lower extremity vasculopathy. The AUC values of the predictive model and the validation set were 0.905 (95% CI=0.874–0.936) and 0.882 (95% CI=0.816–0.947). Hosmer–Lemeshow test values were $p = 0.604$ and $p = 0.308$ (both > 0.05). Calibration curves showed significant agreement between the nomogram model and actual observations. Decision curve analysis indicated that the nomogram improved the clinical net benefit within a probability threshold of 0.02–0.96.
Conclusion: The nomogram constructed in this study was a convenient tool to evaluate the risk of 90-day readmission in patients with diabetes and contributed to clinicians screening the high-risk populations.
Keywords: readmission, rehospitalization, diabetes, nomogram, prediction model, diabetes mellitus

Introduction

The prevalence of diabetes mellitus continues to increase. Specifically, it is estimated that 147 million will have a diagnosis of diabetes by 2045 in China, which still remains the largest number of adult diabetic patients during the same period of time.[1] Diabetes is a metabolic disease characterized by chronic hyperglycemia, which might result in damage to the organs and in turn leads to the gradual decline of function. Due to the high incidence of complications and comorbidities, patients with diabetes are at greater risk of admission and readmission than patients without diabetes.[2]

Readmission is an undesirable medical outcome and is defined as patients who return to a hospital or healthcare facility for inpatient care within a period of time after discharge.[3] Readmission to hospital is an important indicator that is commonly used internationally for the evaluation of medical outcomes and quality of care delivery. As early as 2011, China's healthcare sector introduced a 31-day readmission rate for healthcare institutions as a healthcare quality management indicator.[4] The occurrence of readmissions also leads to increased healthcare costs. The costs associated with hospital admissions for people with diabetes in the United States were $124 billion in 2012, of which the costs associated with readmissions would be approximately $25 billion when an estimated 30-day readmission rate of 20%.[5] Controlling readmission is considered a high-priority and imperative care quality measure and a target for cost reduction. It has been estimated that the 30-day hospital readmission rates among patients with diabetes can reach 16.0% to 20.4%,

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with even higher readmission rates at 90 days or longer.[2,6] Studies have also shown that the majority of Chinese patients with diabetes are readmitted after 61–90 days of hospitalization.[7] In addition, previous studies have found that readmission rates for diabetics are 5.5 times higher than for non-diabetics, leading to increased healthcare costs.[8]

Currently, some predictive models for early identifying the risk of unplanned readmission have been developed based on a series of clinical characteristics and laboratory parameters, including the Diabetes Early Readmission Risk Index (DERRI), which could be used to predict the risk of all-cause 30-day readmission among hospitalized patients with diabetes. DERRI was developed and validated by Rubin et al based on a retrospective cohort study of nearly 18 thousand adult patients with diabetes using electronic medical records, which indicated that more than 10 variables including insurance, complications, race, and several laboratory indicators such as serum creatinine were predictors of risk of readmission among patients with diabetes.[9,10] Soh et al also developed a predictive model for 30-day unplanned readmissions in patients with diabetes based on administrative data, which ultimately included four main variables: length of stay, ischemic heart disease, peripheral vascular disease, and number of drugs. And this model performed well with good internal and external validity for identifying patients with diabetes at risk of unplanned 30-day readmission.[11] A recent study developed a 30-day readmission prediction model utilizing American medical claims data to assist insurers and policymakers with risk stratification.[12] The study identified sociodemographic variables (eg, age, gender) and healthcare utilization factors (eg, discharge status, length of stay, and index admission diagnosis) as predictors of 30-day readmission among diabetic patients.

Nevertheless, although the present models were based on large sample sizes, the variables analyzed are derived from electronic medical records, making it difficult to comprehensively cover the factors that are strongly associated with the development of diabetes, especially those subjective patient data that are lacking in medical databases. For example, previous studies showed that depression, anxiety, and adverse psychological conditions serve as negative predictors of readmission, and effective self-management plans can reduce the incidence of readmission.[13–15] While there is inconsistency in the findings across studies. Besides, the positive associations between sedentary time and bouts and physical activity with cardiometabolic disease risk factors such as diabetes, obesity, and hypertension have been widely determined.[16] Given this fact, it is crucial to validate that physical activity and sedentary behavior are therefore associated with the readmission of patients with diabetes.

The nomogram model has emerged as a convenient and intuitive tool that can predict clinical events in simple graphs. Nomograms can visualize abstract and complex regression models, such as the logistic regression model and Cox proportional hazards model, and quantify the probability of clinical outcomes based on easily accessed variables.[17] To date, nomograms have become one of the most commonly used statistical techniques because of their simplicity, intuition, and ease of use, and it has been widely used in predicting medical prognosis and outcomes, especially in cancers, surgery, and chronic diseases.[18] In addition, nomogram prediction models for predicting 30-day readmission after hip surgery[19] and 180-day readmission for chronic heart failure[20] have also been developed and validated. However, this measurement has not been used in predicting readmission in patients with diabetes. Constructing a risk prediction tool in an intuitive form for readmission based on subjective and modifiable factors may be a good complement to readmission screening and may provide a roadmap for intervention. The aim of the current study was to develop and validate a nomogram to assess the risk and probability of 90-day readmission in patients with diabetes based on a prospective survey to help guide healthcare professionals to provide personalized health interventions.

Material and Methods

Study Design and Participants

This prospective observational study was conducted from June 2023 to June 2024. China. We selected patients hospitalized for diabetes between June 2023 and February 2024 at two tertiary hospitals in Wuhan, Hubei province, where both two were the most famous hospitals in the central China region. The patients would be enrolled in the study if they met the following criteria: patients diagnosed with type 1 and type 2 diabetes, age ≥18 years old, were successfully discharged (patients were discharged on medical advice after improvement or recovery from treatment), voluntarily participated in this survey, and were willing to sign a written informed consent. Moreover, the exclusion criteria were as follows: patients with severe physical or mental illnesses that prevented them from completing the questionnaire, and patients who were transferred after hospitalization. Patients with poorer treatment compliance were excluded. Besides, patients who abandoned treatment or died during the study period were also excluded because they were not at risk of unplanned readmission.

This study was approved by the ethics committee of Huazhong University of Science and Technology Tongji Medical College (Approval number: S1099). Participants involved in this study signed an informed consent form.

Data Collection

Patients with diabetes were recruited consecutively by trained personnel following the inclusion and exclusion criteria. Data were collected from all participants through health records and questionnaires. The survey included general socio-demographic information, behavioral factors (such as physical activity, sedentary behavior, and self-care), and other potentially related psychological factors. The follow-up was conducted by a trained researcher. After patients with diabetes were discharged for 90 days, the researcher contacted patients through WeChat and phone calls to document readmissions in the study hospital or other hospital units.

Readmission

The primary outcome was all-cause readmission, defined as inpatients who return to the hospital at any time point during a period of 90 days following discharge from the hospitalization. Only the first readmission was recorded for patients with multiple readmissions within 90 days of discharge.

Predictors

The candidate predictors were factors potentially correlated with readmission selected in consideration of feasibility in a clinical environment and primary care and based on previous studies. Candidate socio-demographic factors included age, sex, marital status, residence, smoking, drinking, and household income. Disease-related factors include the type of diabetes, HbA1c, complications, comorbidities, and previous hospital admissions within 1 year before index admission. In addition, we collected some data on other potential predictors including behavioral factors and psychological factors.

Behavioral factors include physical activity, sedentary behavior, and self-care. The International Physical Activity Questionnaire – Long Form (IPAQ-LF) was used to assess physical activity. The IPAQ consists of a total of 27 items, investigating 4 aspects of daily routine such as leisure and recreation, household activities, transportation modes, and work physical activity.[21] Individuals were categorized into light, moderate, and vigorous physical activity level groups according to the IPAQ classification criteria. The Chinese version of the IPAQ had moderate to good retest reliability, and the intragroup correlation coefficient for total physical activity was 0.67.[22] While sedentary time was self-reported. Patients' self-care was assessed using the Summary Diabetes Self Care Activities (SDSCA), which was initially revised by Toobert.[23] The questionnaire consists of 11 items covering 6 dimensions, including general diet, special diet, exercise, glucose monitoring, foot care, and medication, to measure general self-care behaviors of patients with diabetes in the past 1 week. Scoring was cumulative over days, ten entries were positively scored, one entry was negatively scored, and each entry was scored on an eight-point scale from 1 to 7. Higher scores indicate better self-care skills. The Chinese version of SDSCA showed good reliability.[24]

Psychological factors including depression and anxiety were assessed using the Patient Health Questionnaire-9 items (PHQ-9) and the 7 Item-Generalized Anxiety Disorder Scale (GAD-7), respectively. PHQ-9 is a widely used depression screening tool in primary care and outpatient settings with good reliability and validity.[25] Respondents rate the frequency of the following nine symptoms over the previous two-week period on a four-point Likert scale (never = 0, several days = 1, more than half the days = 2, nearly every day = 3), including depressed mood, anhedonia, sleep problems, feelings of tiredness, changes in appetite or weight, feelings of worthlessness, difficulty concentrating, feelings of sluggishness or worry and suicidal ideation. GAD-7 is a validated self-assessment of anxiety tool used to understand the patient's anxiety in the past two weeks. The reliability of the Chinese version of the GAD-7 has been tested with a Cronbach's α coefficient of 0.93.[26] The scale consists of 7 items on a 4-point scale of 0–3, with a total score of 0–21, with higher scores indicating more severe anxiety symptoms.

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Data Analysis

Data were processed and analyzed using the R (version 4.3.3). The variables are expressed as median and interquartile range and frequency. The rank-sum test and chi-square test were used for comparison between groups, and the Fisher exact probability test was used when it did not meet the chi-square test. Multiple imputation was used to handle missing values for demographic information and candidate predictors using the "missRanger" package for R. The data were randomly divided into a 70% training set and a 30% validation set using the R "sample" function.

Univariate logistic regression analysis was used to screen the potential predictors (p<0.05) of readmission. Considering the multicollinearity between the variables, the significant variables in the univariate logistic regression analysis (p<0.05) were included in the LASSO regression analysis, using "glmnnt" package in R software version 4.3.3. We applied tenfold cross-validation to confirm the optimal parameters for LASSO regression and determined coefficients based on the lambda value (min) corresponding to the minimum deviation from distance, and variables with non-zero coefficients were filtered in. The selected variables were included in multivariate logistic regression analysis to determine the predictors of readmission. Model selection was based on the backward stepwise method. The nomogram was generated using the "rms" software package in "R" software version 4.3.3 according to the results of the logistic regression analysis.

The nomogram was validated with 1000 bootstrap resamples. Calibration curves were plotted to assess model calibration, namely, the degree of agreement between predicted probabilities and observed outcomes, and this process is also done using the "rms" package in R software. Hosmer–Lemeshow (HL) test was performed to assess the model goodness-of-fit, and the discriminative ability was further assessed by the area under the receiver operating characteristics (ROC) curve (AUC). An AUC larger than 0.70 indicated a good discrimination performance. ROC curves were plotted using the "pROC" and "ggplot2" packages in R software. In addition, decision curve analysis (DCA) was employed to quantify the model's net benefit at various threshold probabilities to evaluate the clinical usefulness of the nomogram, using the "ggDCA" package in R software. All tests were 2-tailed and p <0.05 was regarded as statistically significant.

Results

After a one-year prospective questionnaire investigation, all 842 patients who completed the questionnaire were followed up. Fifty-eight patients were excluded because of incomplete data or because they withdrew early from the study, bringing the final total to 784 available samples in the dataset who were randomly assigned to either the training set or validation set at a ratio of 7:3. The 90-day readmission rate in our study population was 18.6%. As shown in Table 1, there was no statistical difference in the basic characteristics of the 548 participants in the training set and the 246

Table 1 Characteristics of the Training and Validation Sets

Variable	Training set	Validation set	p
Age	58.00 (50.00, 65.00)	58.00 (51.00, 65.00)	0.411
BMI	24.34 (22.12, 26.37)	24.38 (22.05, 26.48)	0.626
Gender			0.575
Female	186 (33.9)	85 (36)	
Marriage			0.089
Married	517 (94.3)	217 (91.9)	
Unmarried	9 (1.6)	11 (4.7)	
Divorced	9 (1.6)	2 (0.8)	
Widower	13 (2.4)	6 (2.5)	
Residence			0.825
Countryside	105 (19.2)	42 (17.8)	
Town	133 (24.3)	55 (23.3)	
Urban areas	310 (56.6)	139 (58.9)	

(*Continued*)

Table 1 (Continued).

Variable	Training set	Validation set	p
Household income			0.271
<1500	12 (2.2)	4 (1.7)	
1500–4999	131 (23.9)	71 (30.1)	
5000–9999	265 (48.4)	110 (46.6)	
≥10,000	140 (25.5)	51 (21.6)	
Smoking			0.305
Never	257 (46.9)	106 (44.9)	
Quit smoking (>1 year)	91 (16.6)	50 (21.2)	
Current smoking	200 (36.5)	80 (33.9)	
Drinking			0.329
Never	255 (46.5)	111 (47)	
Quit drinking (>1 year)	94 (17.2)	31 (13.1)	
Current drinking	199 (36.3)	94 (39.8)	
Type of diabetes			0.630
I	20 (3.6)	7 (3)	
II	528 (96.4)	229 (97)	
HbA1c	8.50 (7.10, 10.10)	8.50 (7.00, 10.10)	0.430
Complications			0.280
Without complications	251 (45.8)	118 (50)	
With complications	297 (54.2)	118 (50)	
Comorbidities	1.00 (0.00, 2.00)	1.00 (0.00, 2.00)	0.226
Previous hospital admissions (1 year before index admission)	0.00 (0.00, 1.00)	0.00 (0.00, 1.00)	0.790
Anxiety	1.00 (0.00, 4.00)	0.00 (0.00, 3.00)	0.047
Depression	2.00 (0.00, 4.00)	2.00 (0.00, 4.00)	0.626
Self-care	37.00 (26.00, 48.00)	37.00 (25.00, 49.00)	0.979
Physical activity			0.511
Light	157 (28.6)	66 (28)	
Moderate	252 (46)	118 (50)	
Vigorous	139 (25.4)	52 (22)	
Sedentary time /hours	8.00 (5.50, 9.50)	7.50 (5.38, 9.50)	0.670
Complications			
Diabetic foot ulcer	39 (7.1)	11 (4.7)	0.197
Diabetic retinopathy	150 (27.4)	55 (23.3)	0.235
Diabetic neuropathy	168 (30.7)	61 (25.8)	0.174
Diabetic lower extremity vasculopathy	63 (11.5)	30 (12.7)	0.629
Diabetic nephropathy	56 (10.2)	33 (14)	0.128
Diabetic ketoacidosis	8 (1.5)	5 (2.1)	0.546
Comorbidity			
Hypertension	250 (45.6)	101 (42.8)	0.466
Coronary heart disease	88 (16.1)	39 (16.5)	0.871
Hyperlipidemia	96 (17.5)	53 (22.5)	0.106
Cerebral hemorrhage	33 (6)	11 (4.7)	0.448
Chronic kidney disease	17 (3.1)	13 (5.5)	0.107

participants in the validation set. The measurement results of physical activity, sedentary time, and self-care level in the two sets were not statistically significant. Two-thirds of all participants were male and the rest were female, and the majority of participants were middle-aged. Table 1 shows this in more detail.

Several factors, including BMI, residence, household income, smoking, HbA1c, and physical activity differed significantly ($p<0.05$) between the readmitted group and the non-readmitted group. As shown in Table 2, the univariate analyses showed that residence, smoking, HbA1c, the existence of complications and different complications, the number

Table 2 Univariable and Stepwise Multivariable Logistic Analysis of Risk Factors for Readmission

Variable	Univariable analysis			Multivariable analysis		
	β	OR (95% CI)	p	β	OR (95% CI)	p
Age	0.003	1.003 (0.984,1.022)	0.772			
BMI	−0.038	0.963 (0.902,1.026)	0.245			
Gender (Female)	0.165	1.180 (0.760,1.813)	0.456			
Marriage						
Married		reference				
Unmarried	−0.712	0.490 (0.026,2.715)	0.504			
Divorced	0.114	1.121 (0.165, 4.719)	0.888			
Widower	0.163	1.177 (0.261, 3.928)	0.807			
Residence						
Countryside		reference				
Town	−0.321	0.725 (0.405, 1.298)	0.279			
Urban areas	−0.803	0.448 (0.268, 0.757)	0.002			
Household income						
<1500		reference				
1500–4999	1.140	3.127 (0.572, 58.345)	0.284			
5000–9999	1.212	3.360 (0.635, 62.016)	0.250			
≥10,000	0.547	1.727 (0.308, 32.462)	0.610			
Smoking						
Never		reference				
Quit smoking	−0.073	0.930 (0.477, 1.731)	0.824			
Current smoking	0.478	1.613 (1.026, 2.541)	0.038			
Drinking						
Never		reference				
Quit drinking	0.349	1.418 (0.779, 2.525)	0.242			
Current drinking	0.422	1.524 (0.960, 2.428)	0.074			
Type of diabetes(II)	0.376	1.457 (0.479, 6.322)	0.554			
HbA1c	0.092	1.097 (1.000, 1.202)	0.049			
Complications (With complications)	1.494	4.454 (2.739, 7.523)	<0.001			
Number of comorbidities	0.388	1.474 (1.220, 1.786)	<0.001			
Previous hospital admissions (1 year before index admission)	1.170	3.221 (2.505, 4.221)	<0.001	1.037	2.822 (2.038,3.978)	<0.001
Anxiety	0.291	1.337 (1.258, 1.427)	<0.001	0.133	1.142 (1.060,1.232)	0.001
Depression	0.314	1.369 (1.272, 1.482)	<0.001			
Self-care	−0.090	0.914 (0.894, 0.932)	<0.001	−0.072	0.931 (0.906,0.954)	<0.001
Physical activity						
Light		reference			reference	
Moderate	−1.965	0.140 (0.084, 0.229)	<0.001	−0.692	0.501 (0.256,0.979)	0.043
Vigorous	−2.556	0.078 (0.035, 0.156)		−1.283	0.277 (0.110,0.645)	0.004
Sedentary time /hours	0.314	1.369 (1.251, 1.506)				
Diabetic foot ulcer	0.989	2.689 (1.334, 5.272)	0.004			
Diabetic retinopathy	0.617	1.854 (1.188, 2.874)	0.006			
Diabetic neuropathy	1.374	3.951 (2.566, 6.121)	<0.001			
Diabetic lower extremity vasculopathy	1.827	6.212 (3.584, 10.852)	<0.001	1.040	2.829 (1.249,6.410)	0.012
Diabetic nephropathy	0.079	1.083 (0.529, 2.066)	0.818			
Diabetic ketoacidosis	1.398	4.047 (0.943, 17.364)	0.051			
Hypertension	0.891	2.438 (1.593, 3.771)	<0.001			
Coronary heart disease	0.818	2.266 (1.356, 3.731)	0.001			
Hyperlipidemia	0.335	1.398 (0.821, 2.321)	0.204			
Cerebral hemorrhage	0.876	2.401 (1.112, 4.975)	0.021			
Chronic kidney disease	0.794	2.213 (0.748, 5.956)	0.126			

of comorbidities, previous hospital admissions within 1 year, anxiety, depression, sedentary time, self-care, and physical activity were associated with the risk of readmission. In the current study, the non-zero coefficients as potential predictors of 90-day readmission were chosen in the LASSO regression model. Then, we incorporate these potential factors associated with readmission into the multiple logistic regression model. In the ultimate model, previous hospital

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admission ($p<0.001$), anxiety ($p=0.001$), self-care ($p<0.001$), moderate physical activity ($p=0.043$), vigorous physical activity ($p=0.004$) and complicated with diabetic lower extremity vasculopathy ($p=0.012$) were determined as predictors of readmission in patients with diabetes. A nomogram was constructed by incorporating the aforementioned factors with significant differences (Figure 1). Each predictor score was plotted, and the likelihood of readmission can be predicted by summing the individual factor scores. According to the nomogram, more frequent previous admission within 1 year was identified as the strongest risk factor of readmission, followed by anxiety scores, and diabetic lower extremity vasculopathy. Meanwhile, the nomogram also highlighted the protective factors including self-care scores and moderate to vigorous intensity physical activity. The generated nomogram can be used to quantitatively and intuitively predict the risk of readmission in patients with diabetes.

After building up the prediction model using the training set, we consequently used the validation set to verify the predictive power. AUC values were calculated to assess the discrimination of the predictive model. As shown in Figure 2 the ROC analysis showed the AUC value was 0.905 (95% CI=0.874–0.936) in the training set and was 0.882 (95% CI=0.816–0.947) in the validation set, respectively, indicating a good discrimination. In the training set, the sensitivity and the specificity were 0.820 and 0.831, respectively. And in the validation set the sensitivity and specificity were 0.861 and 0.830, respectively.

A calibration plot and the HL goodness of fit test were used to evaluate the nomogram, indicating that the model had a good fit for both the training set ($\chi^2=6.385$, $p=0.604$) and validation set ($\chi^2=9.415$, $p=0.308$). Figure 3 shows the calibration plots for the training set (Figure 3A) and validation set (Figure 3B), indicating high uniformity between the predicted and actual probabilities of readmission in the training set and validation set.

We performed a decision curve analysis to assess the clinical utility of the nomogram model. The decision curve in training and validation sets is shown in Figure 4. The results showed that the nomogram model could yield net benefits for patients with diabetes who are facing with risk of readmission when the threshold probability is between 0.02 and 0.96 in the training set or between 0.03 and 0.79 in the validation set.

Discussion

As lifestyle-related disease, the global incidence of diabetes is increasing. Diabetic patients often have complication and comorbidity burdens that complicate disease control, resulting in readmission rates rising as well. Determining major

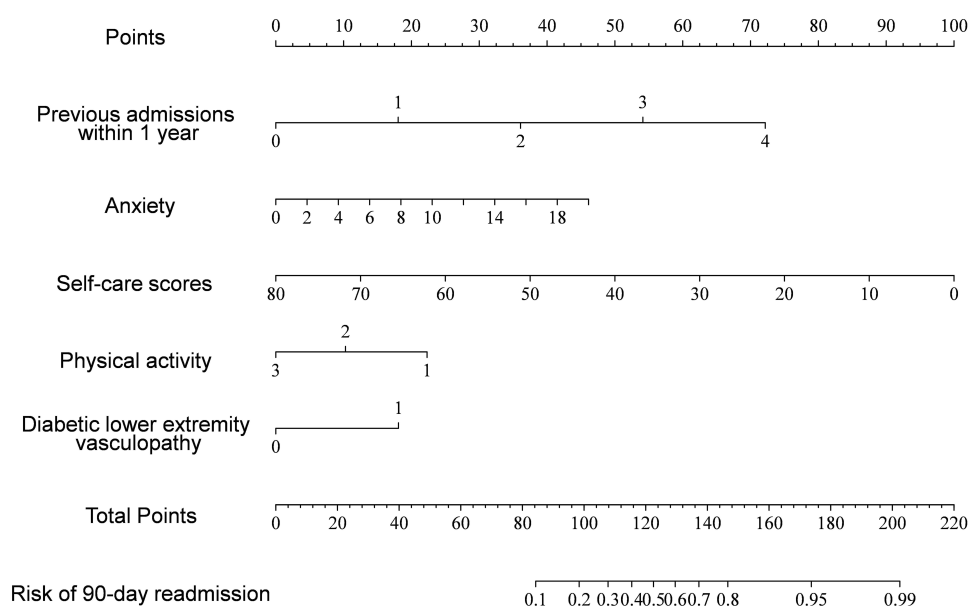

Figure 1 Nomogram to estimate the risk of readmission among diabetic patients. The nomogram combined previous admissions within 1 year, self-care score, anxiety score, physical activity level, and diabetic lower extremity vasculopathy. Find the points corresponding to each factor in the nomogram, sum all the points, and find the corresponding admission probability below through the total point line.

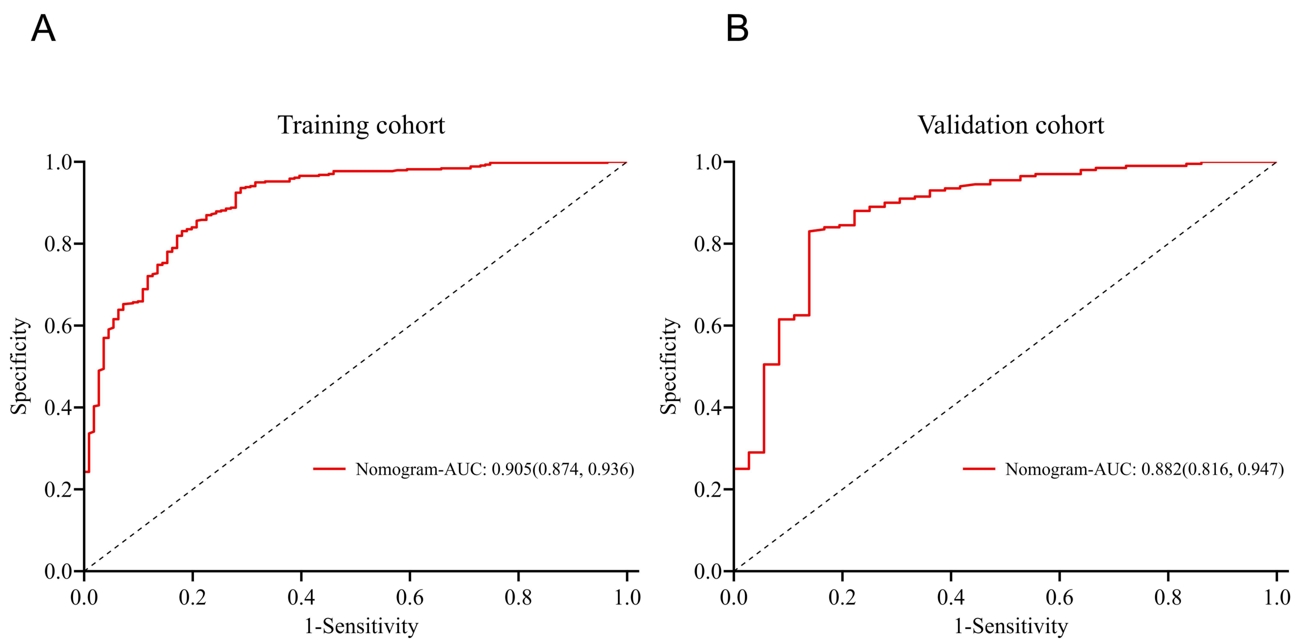

Figure 2 Nomogram ROC curves generated from the training dataset (**A**). Nomogram ROC curves generated using the validation dataset (**B**).

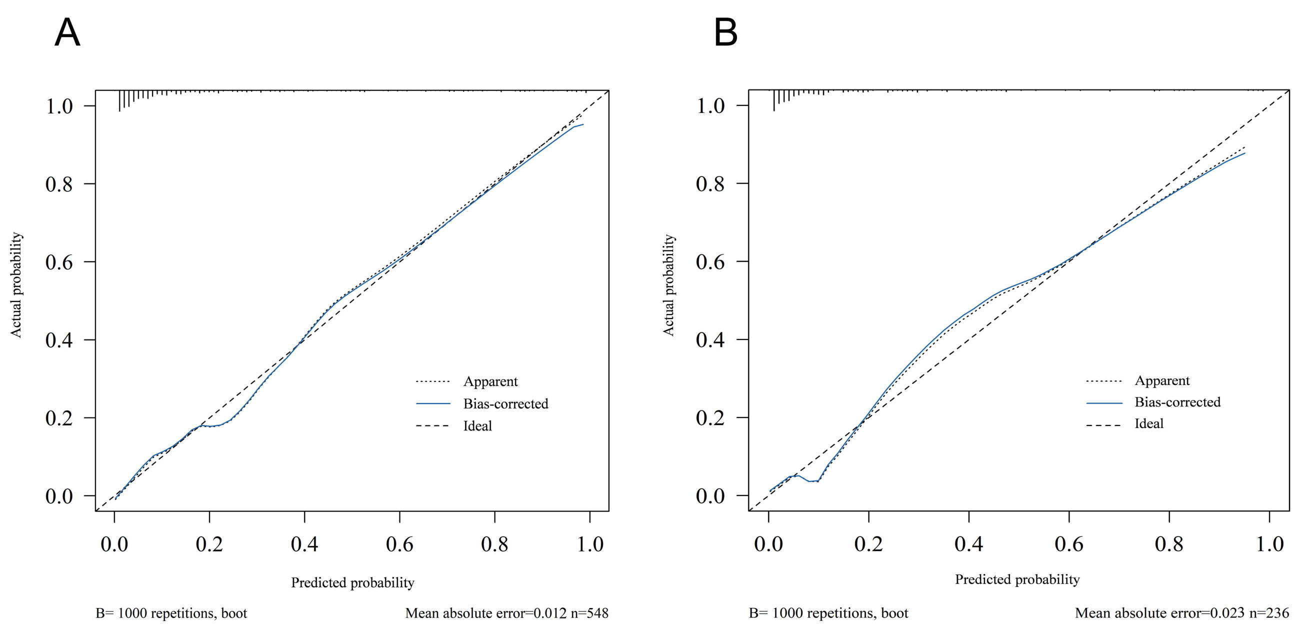

Figure 3 Calibration plots of the (**A**) training and (**B**) validation sets based on the prediction model.

predictors for readmission and developing patient-centered disease management can help minimize unplanned hospitalizations and associated costs.

In the current study, by integrating clinical characteristics and easily accessible patient-level variables and using several statistical techniques to determine the predictors, we developed and validated a nomogram for predicting 90-day readmission in diabetic patients. In this study, patients with diabetes experience a high risk of readmission within 90 days after discharge. Among various subjective factors, anxiety, self-care, and physical activity were identified as key factors influencing readmission in our nomogram. And of these, self-care and moderate- and vigorous-intensity physical activity

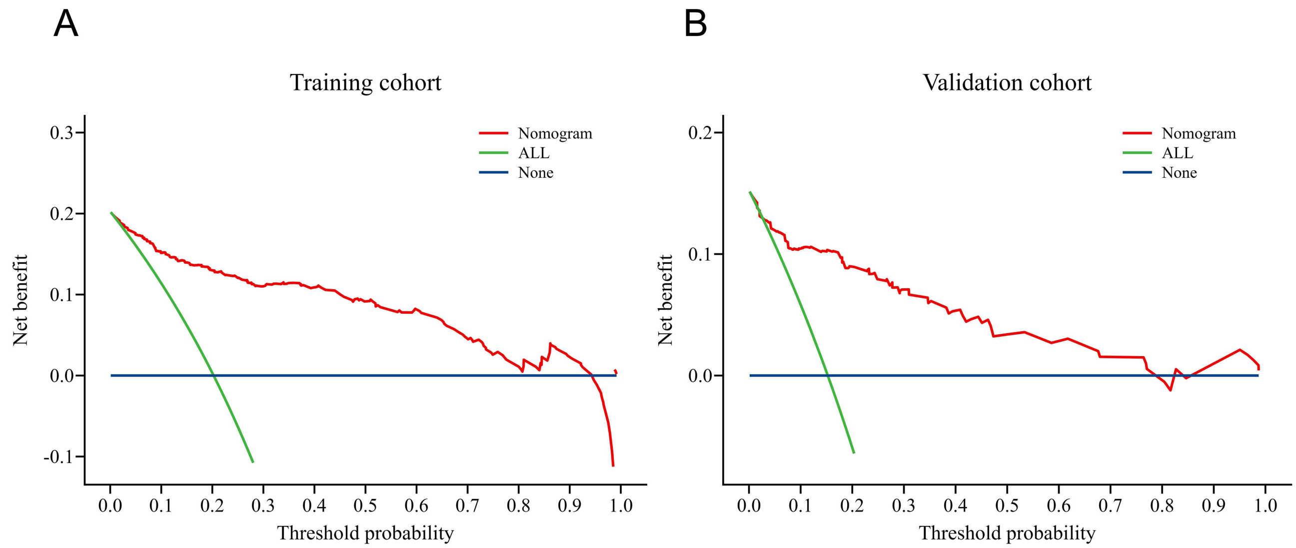

Figure 4 Decision curve in the training set (**A**) and validation set (**B**) based on the prediction model. The green line represents the net benefit of assuming that all patients would be readmitted to the hospital, the blue line represents the net benefit of not assuming that any patients would be readmitted to the hospital, and the red line represents the expected net benefit per patient based on the predictive nomogram.

are protective factors of readmission in patients with diabetes. Besides, previous hospital admissions within 1 year prior to the index admission and complicated with lower extremity vasculopathy were identified as key factors contributing to the risk of 90-day readmission in patients with diabetes. Validation confirmed the good performance of the nomogram with respect to discrimination and calibration. In addition, the nomogram's clinical significance was subsequently validated through decision curve analysis.

Previous research has endeavored to employ administrative and claims data with enormous sample size for predicting diabetic readmission, applying statistical modeling methods including logistic regression model and machine learning.[12,27] The most renowned predictive model for the readmission of diabetic patients is the DERRI and its derivatives,[10,28] which have undergone extensive internal and external validations. These models encompass a range of variables, including general socio-demographic factors (eg, employment status, health insurance), treatment-related aspects (eg, length of hospitalization, discharge status), and laboratory parameters included in the data source. The performance-enhanced DERRI achieved a C-statistic of 0.82,[28] indicating high predictive accuracy. In contrast, the performance of readmission risk prediction models developed using machine learning techniques was notably high, with C-statistics predominantly exceeding 0.9.[29,30] However, it is important to note that none of these models have undergone external or independent validation. Methodologically, while our work employed a logistic regression model, we also integrated LASSO for simultaneous variable selection, thereby enhancing the accuracy of the predictive model. The development of a nomogram facilitates the visualization of the final results, enabling clinicians to efficiently score and estimate the probability of patient readmission, supporting the formulation of individualized clinical decisions. In selecting predictors, we concentrated on patient-level modifiable factors, opting for variables that are challenging to gather from healthcare administrative databases and identifying several influences that may be correlated. This approach broadens the perspective of previous studies and underscores the significance of directing interventions toward the patients themselves.

Because the time framework for readmission is not consistent across studies, such as 30 and 90 days or even longer, there is little adequate data to compare. The occurrence of 90-day readmission in patients with diabetes in the current study was 18.6%, which is higher than the result of 9.7% reported by Liu et al[7] and 11.3% reported by Kozioł et al[13], but lower than that in older patients with diabetes in America reported by Kim in 2010 (26.3%).[31] Frequent hospitalization is directly related to the waste of healthcare resources and increased healthcare costs. Hence, the identification of patients with diabetes at high risk is imperative to prevent readmission and associated adverse outcomes.

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Frequent hospitalizations reflect complex disease conditions. In the ultimate prediction model, previous hospital admissions within 1 year after the index admission were determined as an important risk factor for 90-day readmission in patients with diabetes, which is consistent with a previous study[9] that concluded that hospital discharge within 90 days before the index admission was associated with nearly 2-fold greater odds of readmission in patients with diabetes. And it has previously been evaluated in patients with chronic obstructive pulmonary disease in a real-world study, concluding that readmission risk increased in patients with previous frequent hospitalizations.[32] This association may be due to the fact that frequent admissions typically involve patients with more complex disease conditions and poorer health. Besides, it may also be related to a more cautious attitude to health. Patients with diabetes or other chronic disease who are more health-conscious may be more active in seeking medical help when they feel their blood glucose is out of control, leading to a higher rate of readmission.

The greater burden of comorbidities had been determined as a major risk factor for 90-day readmission in patients with diabetes. This risk factor has been reported in previous studies. Consistent with the findings of a previous population-based retrospective epidemiological survey conducted in Poland[13] that indicated that readmission within 90 days of discharge was most strongly associated with acute diabetic complications prior to the index admission, followed by peripheral artery disease, heart failure, and other comorbidities, the results of the present study showed that the existence of diabetic lower extremity vasculopathy was identified as a significant predictor of the 90-day readmission among several comorbidities and complications. Peripheral arterial disease, as a common complication of diabetes mellitus, most commonly in the arteries of the lower limbs, is not only a risk factor for the development of diabetic foot ulcers but also a risk factor for amputation.[33] Foot ulcers due to diabetic lower extremity vasculopathy have a high rate of recurrence and a one-fold increase in amputation compared to foot ulcers due to diabetic neuropathy.[34] Management of diabetes might be complicated by the patients' more severe complications and comorbidities resulting in more frequent hospitalizations.

Notably, this is the first time that physical activity has been found to be predictive of the risk of readmission within 90 days of discharge. The protective role of moderate and vigorous-intensity physical activity on readmission was identified compared to light-intensity physical activity, which may be related to the direct effects of physical activity on health. Qian et al conducted a cross-sectional analysis of a large cohort of adults with type 2 diabetes, demonstrating that timing of bout-related moderate and vigorous physical activity is associated with cardiorespiratory fitness.[35] The associations between physical activity and health improvement in patients with diabetes were further validated in readmission in the present study. In previous studies, light-intensity physical activity was also considered to contribute to all-cause readmissions in patients with heart failure.[36] The significant association between physical activity and reduced risk of late readmission highlights the potential long-term benefits of sustained physical activity. Regular physical activity may contribute to better overall metabolic control, improved cardiovascular health, and better glycemic control, thereby reducing the likelihood of complications that could lead to late readmission.[37]

In addition, our nomogram predictive model showed that high anxiety scores and low self-care scores were also associated with an increased risk of 90-day readmission. A study by Chopera et al also found that diabetic patients suffering from anxiety were more likely to be readmitted to the hospital,[15] which may be related to the fact that anxiety can further exacerbate the patient's condition by affecting the hypothalamic-pituitary-target gland axis, which reduces insulin sensitivity or increasing glucagon, leading to persistent elevation of blood glucose. As for self-care, a previous retrospective case–control study by Yue et al[38] proved the relationship between regular blood glucose monitoring and readmission within 1 year in patients with type 2 diabetes mellitus, and further confirmed that self-care is a protective factor. Self-care directly reflects an individual's health literacy and attention to disease. Patients with low self-care scores generally targeted interventions may lower rates of readmission in these at-risk patients with diabetes, as suggestions may be provided to them about handling situations including encouraging medication compliance and instructing healthy diet.

This is the first nomogram to predict the risk of readmission in patients with diabetes based on subjective measurement data, and it could compensate for some of the shortcomings of previous diabetes readmission predictive tools. Using planar coordinates connected by disjointed line segments, a nomogram can predict the probability of a clinical outcome event in an intuitive form by adding up the scores of each predictor to obtain a total score.[39] The nomogram has been used in research in many clinical fields. Through validation, our nomogram model performed good discrimination, calibration and clinical utility, indicating that the model is valuable for the effective screening of individuals with diabetes at high risk of readmission. As an efficient and intuitive assessment tool, our predictive model combined with several subjective data that are almost unavailable in electronic medical records, can assist hospital medical and primary health care practitioners in screening the risk of readmission using several questions. However, compared to previous predictive models, this risk prediction model is not intended to replace them but to complement them. This study also provides a theoretical basis and entry point for researchers in the development of early prevention and intervention measures.

Limitations

This study has several limitations. Firstly, the use of questionnaires may compromise the accuracy of the measurements for physical activity and sedentary time. Secondly, data collection was restricted to specific geographical areas, limiting the generalizability of the findings. Finally, the analysis of additional results was constrained by the absence of information regarding laboratory values or test results.

Conclusions

This study developed and validated a risk prediction nomogram for 90-day readmission in patients with diabetes, which combines previous admissions, self-care scores, physical activity, anxiety scores, and complications. The developed nomogram can significantly improve the clinical net benefit. Facilitate estimation of the risk of readmission by processing easily accessible patient-level data. It provides a visual tool for medical workers, primary health workers, and patients themselves to manage diabetes. The developed predictive nomogram model will be valuable in early screening patients with diabetes and developing target intervention programs, providing a reference to formulate individualized and precise health education and follow-up programs, ultimately aiming to control the incidence of readmissions and enhance the quality of care.

Data Sharing Statement

The datasets analyzed during the current study are available from the corresponding author on reasonable request.

Ethics Approval and Informed Consent

Ethics approval and consent to participate: I confirm that all methods were carried out in accordance with relevant guidelines and regulations. I confirm that all experimental protocols were approved by the ethics committee of the Tongji Medical College, Huazhong University of Science and Technology (Approval number: S1099). I confirm that informed consent was obtained from all subjects and/or their legal guardians. Our study complies with the Declaration of Helsinki.

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Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors declare no conflicts of interest in this work.

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