Diabetes, Metabolic Syndrome and Obesity

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ORIGINAL RESEARCH

Development and Validation of a Community–Based Prediction Model for Depression in Elderly Patients with Diabetes: A Cross–Sectional Study

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Background: In elderly diabetic patients, depression is often overlooked because professional evaluation requires psychiatrists, but such specialists are lacking in the community. Therefore, we aimed to create a simple depression screening model that allows earlier detection of depressive disorders in elderly diabetic patients by community health workers.

Methods: The prediction model was developed in a primary cohort that consisted of 210 patients with diabetes, and data were gathered from December 2022 to February 2023. The independent validation cohort included 99 consecutive patients from February 2023 to March 2023. Multivariable logistic regression analysis was used to develop the predictive model. We incorporated common demographic characteristics, diabetes–specific factors, family structure characteristics, the self–perceived burden scale (SPBS) score, and the family APGAR (adaptation, partnership, growth, affection, resolution) score. The performance of the nomogram was assessed with respect to its calibration (calibration curve, the Hosmer–Lemeshow test), discrimination (the area under the curve (AUC)), and clinical usefulness (Decision curve analysis (DCA)).

Results: The prediction nomogram incorporated 5 crucial factors such as glucose monitoring status, exercise status, monthly income, sleep disorder status, and the SPBS score. The model demonstrated strong discrimination in the primary cohort, with an AUC of 0.839 (95% CI, 0.781–0.897). This discriminative ability was further validated in the validation cohort, with an AUC of 0.857 (95% CI, 0.779–0.935). Moreover, the nomogram exhibited satisfactory calibration. DCA suggested that the prediction of depression in elderly patients with diabetes mellitus was of great clinical value.

Conclusion: The prediction model provides precise and user–friendly guidance for community health workers in preliminary screenings for depression among elderly patients with diabetes.

Keywords: prediction model, depression, elderly, diabetes, community–based

Introduction

In 2020, the elderly population in China constituted 18.7% (260.4 million individuals) of the total population. Among the Chinese elderly population, approximately 30% have diabetes mellitus (DM), predominantly type 2 diabetes mellitus (T2DM), as reported by the Seventh National Population Census.[1] The prevalence of diabetes in elderly individual has surged in tandem with population ageing, making them the largest subgroup of individuals with diabetes. Research conducted both domestically and internationally has revealed that diabetes incidence is highest among individuals aged 65 to 79, declining after the age of 80, thus emphasizing the elevated diabetes risk during old age.[2–4] Recent studies have confirmed the significance of effective self–management, encompassing physical, psychological, and medical care, in enhancing glycaemic control among older adults with diabetes.[5,6] Several researchers have proposed a potential interplay

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between diabetes and psychological factors. Conditions such as depression and anxiety have been implicated in the aetiology of diabetes and can impact the disease trajectory.[7–12]

Studies have shown that the incidence of depression is greater in elderly diabetic patients than in other individuals, as 30% of patients have depressive symptoms, and 12% to 18% meet the diagnostic criteria for depression.[8,11,13,14]

Numerous unresolved inquiries persist in clinical research pertaining to depressive disorders among elderly people. The precise factors underlying the increased prevalence of depression among elderly individuals with diabetes remain incompletely elucidated. The screening rate for depression in diabetic patients remains low, resulting in a high prevalence of undiagnosed cases.[15]

The fundamental tenets of treating geriatric depression include accurate identification of atypical symptoms and adherence to individualized medication routines. To enhance care for individuals with geriatric depression, it is imperative to establish and enhance a multidisciplinary team collaborative care model involving specialists, primary health care personnel, social workers, and family members. This model should extend the focus of care beyond clinical symptom alleviation to encompass comprehensive functional recovery.[12]

Currently, several reliable depression screening scales are available both domestically and internationally. These include the Geriatric Depression Scale (GDS–30),[16] Self–Rating Depression Scale (SDS),[17] Center of Epidemiological Survey–Depression Scale (CES–D),[18] and Hamilton Depression Scale (HAMD).[19] The SDS is primarily used to assess the severity of depressive symptoms, while the CES–D serves primarily as an epidemiological tool, although its symptom determination remains a subject of debate. The HAMD is more suitable for use with individuals with diagnosed depression than are large–scale population surveys. However, all these scales necessitate guidance from a professional psychiatrist.[20,21] Community health workers, who lack specialized training face challenges in effectively utilizing these diagnostic methods for mental illness.[20,22,23]

In this study, we developed a clinical prediction model that incorporates pertinent risk factors associated with diabetes in elderly individuals. The model provides a convenient tool to guide community health workers in conducting preliminary screenings for depression in elderly patients with diabetes, aiming to facilitate early detection and treatment.

Materials and Methods

Participants

The study was conducted from December 2022 to February 2023, and involved Participants from 13 cities in Jiangsu Province, China. The primary cohort consisted of 210 participants who met the screening criteria and were diagnosed with diabetes by physicians. An additional 99 participants were recruited from February 2023 to March 2023 using the same criteria.

Inclusion Criteria

Aged 50 years or older, diagnosed with diabetes, able to clearly express themselves, and able to cooperate in completing the questionnaire survey.[24,25]

Exclusion Criteria

Our study applied certain exclusion criteria to ensure the homogeneity and validity of the sample. Individuals who had a family history of mental illness; who had communication disorders, dementia, or confusion; who had recently experienced major life events such as car accidents or the loss of relatives; or who had other diseases characterized by a poor prognosis were excluded from the study. These exclusions were made to maintain the focus on our target population and minimize confounding factors that could affect the study outcomes.

Demographics

Demographic data, including age, sex, lifestyle factors (smoking status, exercise status, sleep disorder status), duration of diabetes, education level, monthly income, understanding of treatment options, glucose monitoring status, blood sugar level, health care payer identity, one–child family status, and family support status, were collected via questionnaires.

These data were analysed to compare the depression–positive and depression–negative groups as well as the primary and validation cohorts.

Depressive Symptoms

Depression diagnoses in the study were conducted using two Methods: clinician diagnosis based on the criteria of the International Classification of Diseases (ICD) or Diagnostic and Statistical Manual (DSM), and the GDS–30 scale assessed by a psychiatrist. A total of 121 diabetic subjects with depression and 188 diabetic subjects without depression (including participants from both the primary and validation cohorts) were selected for the case and control groups, respectively. The GDS–30 consists of 30 items and is widely used for assessing depression in older adults due to its accuracy, with a Cronbach's alpha of 0.85. A score of 10 or higher indicates elevated depressive symptoms.

Self – Perceived Burden Scale (SPBS)

The psychological burden experienced by individuals when receiving care from others is commonly referred to as "self–perceived burden" (SPB). SPB encompasses feelings of guilt, distress, responsibility, and a diminished sense of self arising from the impact of one's illness and care needs on others. The Self–Perceived Burden Scale (SPBS) comprises 10 items that assess these feelings towards caregivers, with response options ranging from 1 (none of the time) to 5 (all of the time). The sum of each item constitutes the total score of the SPBS. The total SPBS score, is divided into four levels: no apparent perceived burden (<20 points), mild perceived burden (20–29 points), moderate perceived burden (30–40 points), and severe perceived burden (>40 points). The SPBS has demonstrated strong internal consistency, with a Cronbach's alpha coefficient of 0.92.[26,27]

The Family APGAR (Adaptation, Partnership, Growth, Affection, Resolve)

Family functioning plays a crucial role in patient care and can significantly impact a patient's mental well–being. The Family APGAR questionnaire is widely used as a reliable tool for assessing family function. The Family APGAR consists of five functional domains: adaptation, partnership, growth, affection, and resolve. Each domain is evaluated through a set of five questions, with response options ranging from 0 (hardly ever) to 2 (almost Always). The total score on the Family APGAR ranges from 0 to 10, with higher scores indicating better family functioning. The questionnaire demonstrated good internal consistency, as evidenced by a Cronbach's alpha coefficient of 0.84.[28–30]

Statistical Analyses

Statistical analyses were performed using SPSS 25 (IBM Corp)., Stata 15 (Stata Corp)., and R 3.6.2 (https://www.r-project.org/). The results are presented as odds ratios (ORs) with corresponding 95% confidence intervals (CIs). A significance level of $P < 0.05$ was considered to indicate statistical significance.

Establishment of a Predictive Model

The relationship between diabetes and mental status was assessed in both the primary and validation cohorts. Categorical variables were analysed using the nonparametric Mann–Whitney *U*-test. Variables with a significance level of $P<0.2$ were selected for inclusion in the multivariate regression models. A multivariable stepwise logistic regression model was developed using the primary cohort, incorporating demographic characteristics, diabetes characteristics, family characteristics, sleep disorders, the SPBS score, and the Family APGAR score to screen for depression. Based on the results of the multivariate logistic regression, a nomogram was constructed to facilitate quick depression screening by community health workers in elderly individuals with diabetes.[31]

Validation of the Diabetes Depression Nomogram

Receiver operating characteristic (ROC) curve analysis was performed for the primary cohort data to calculate AUC as a measure of predictive accuracy. The logistic regression formula, developed using the primary cohort, was applied to all patients in the validation cohort, with total points calculated for each patient. This model was used to derive the AUC and

calibration curve for the validation cohort. To further assess calibration, the Hosmer–Lemeshow test was performed, and calibration curves were plotted to evaluate the nomogram's fit.[32]

Clinical Use

DCA was conducted to evaluate the clinical utility of the diabetes depression nomogram.[33,34]

Results

Participant Characteristics

A total of 210 individuals with T2DM were evaluated in the primary cohort recruited between December 2022 and February 2023, including 120 males and 90 females. From February 2023 to March 2023, 99 individuals with T2DM were recruited as the validation cohort. Table 1 presents the statistical data of the primary cohort, covering general information (age, sex, smoking status, education level, exercise status, sleep disorder status, monthly income), diabetes–

Table 1 Characteristics of Subjects in the Primary and Validation Cohorts

Characteristic	Primary Cohort			Validation Cohort		
	Depression (+)	Depression (-)	p	Depression (+)	Depression (-)	p
Age, years			0.972			0.392
50–60	34 (43.0)	54 (41.2)		17 (40.5)	24 (42.1)	
60–70	29 (36.7)	53 (40.5)		10 (23.8)	22 (38.6)	
70–80	10 (12.7)	19 (14.5)		11 (26.2)	6 (10.5)	
>80	6 (7.6)	5 (3.8)		4 (9.5)	5 (8.8)	
Sex			0.594			0.508
Male	47 (59.5)	73 (55.7)		20 (47.6)	31 (54.4)	
Female	32 (40.5)	58 (44.3)		22 (52.4)	26 (45.6)	
Smoking status			0.057			0.760
Yes	37 (46.8)	44 (33.6)		16 (38.1)	20 (35.1)	
No	42 (53.2)	87 (66.4)		26 (61.9)	37 (64.9)	
Education levels			0.752			0.470
Junior high	44 (55.7)	71 (54.2)		27 (64.3)	34 (59.6)	
High school	9 (11.4)	20 (15.3)		2 (4.8)	5 (8.8)	
Specialist	16 (20.3)	15 (11.5)		5 (11.9)	9 (15.8)	
Bachelor's Degree or above	10 (12.7)	25 (19.1)		8 (19.0)	9 (15.8)	
Duration of Diabetes, years			0.799			0.787
<5	37 (46.8)	57 (43.5)		17 (40.5)	24 (42.1)	
5–10	25 (31.6)	57 (43.5)		18 (42.9)	25 (43.9)	
>10	17 (21.5)	17 (13.0)		7 (16.7)	8 (14.0)	
Understanding of treatment options			0.226			0.107
Yes	44 (55.7)	84 (64.1)		22 (52.4)	39 (68.4)	
No	35 (44.3)	47 (35.9)		20 (47.6)	18 (31.6)	
Glucose monitoring status			0.004*			<0.001*
Yes	43 (54.4)	97 (74.0)		17 (40.5)	46 (80.7)	
No	36 (45.6)	34 (26.0)		25 (59.5)	11 (19.3)	
Blood sugar level, mmol/L			0.081			0.011*
<8	33 (41.8)	67 (51.1)		13 (31.0)	32 (56.1)	
8–10	36 (45.6)	58 (44.3)		24 (57.1)	22 (38.6)	
>10	10 (12.7)	6 (4.6)		5 (11.9)	3 (5.3)	

(*Continued*)

Table 1 (Continued).

Characteristic	Primary Cohort			Validation Cohort		
	Depression (+)	Depression (-)	p	Depression (+)	Depression (-)	p
Exercise status			<0.001*			0.015*
Mild	39 (49.4)	22 (16.8)		17 (40.5)	12 (21.1)	
Moderate	38 (48.1)	103 (78.6)		25 (59.5)	41 (71.9)	
Vigorous	2 (2.5)	6 (4.6)		0 (0.0)	4 (7.0)	
Monthly income, RMB			0.091			0.925
<1000	41 (51.9)	48 (36.6)		23 (54.8)	32 (56.1)	
1000–3000	19 (24.1)	52 (39.7)		10 (23.8)	15 (26.3)	
3000–5000	13 (16.5)	12 (8.2)		8 (19.0)	4 (7.0)	
>5000	6 (2.9)	19 (14.5)		1 (2.4)	6 (10.5)	
Payer in Healthcare			0.606			0.068
Oneself	24 (30.4)	29 (22.1)		17 (40.5)	7 (12.3)	
Family member	15 (19.0)	36 (27.5)		2 (4.8)	13 (22.8)	
Medical insurance	40 (50.6)	66 (50.4)		23 (54.8)	37 (64.9)	
One-Child family			0.316			0.022
Yes	23 (29.1)	30 (22.9)		12 (28.6)	6 (10.5)	
No	56 (70.9)	101 (77.1)		30 (71.4)	51 (89.5)	
Sleep disorder			<0.001*			<0.001*
Yes	47 (59.5)	21 (16.0)		27 (64.3)	6 (10.5)	
No	32 (40.5)	110 (84.0)		15 (35.7)	51 (89.5)	
Caregiver			0.743			0.733
Oneself	25 (31.6)	21 (16.0)		13 (31.0)	10 (17.5)	
Spouse	26 (32.9)	77 (58.5)		13 (31.0)	34 (59.6)	
Child	18 (22.8)	25 (19.1)		11 (26.2)	11 (19.3)	
Care workers	6 (7.6)	0 (0.0)		1 (2.4)	1 (1.8)	
Others	4 (5.1)	8 (6.1)		4 (9.5)	1 (1.8)	
Support from family			0.091			0.057
None	16 (20.3)	8 (6.1)		10 (23.8)	6 (10.5)	
Little	6 (7.6)	2 (1.5)		6 (14.3)	2 (3.5)	
General	23 (29.1)	62 (47.3)		10 (23.8)	21 (36.8)	
Full	34 (43.0)	59 (45.0)		16 (38.1)	28 (49.1)	
SPBS score			<0.001*			0.003*
Not obvious	14 (17.7)	48 (36.6)		2 (4.8)	14 (24.6)	
Mild	31 (39.2)	54 (41.2)		21 (50.0)	29 (50.9)	
Moderate	23 (29.1)	24 (18.3)		14 (33.3)	13 (22.8)	
Severe	11 (13.9)	5 (3.8)		5 (11.9)	1 (1.8)	
APGAR score			0.037*			0.027*
Good function	36 (45.6)	76 (58.0)		18 (42.9)	35 (61.4)	
Mild-Moderate functional impairment	33 (41.8)	49 (37.4)		18 (42.9)	21 (36.8)	
Severe functional impairment	10 (12.7)	6 (4.6)		6 (14.3)	1 (1.8)	

Note: *p<0.05.
Abbreviations: RMB, Renminbi; SPBS, self-perceived burden scale; APGAR, The Family APGAR (Adaptation, Partnership, Growth, Affection, Resolve).

related details (duration of diabetes, glucose monitoring status, understanding of treatment options, blood sugar level), family–related factors (caregiver identity, health care payer identity, one–child family status, family support status), and SPBS and APGAR assessments, for a total of 17 indicators. In the primary cohort, after comparing the depression (+) and depression (-) groups, 9 indicators with p<0.2 were selected for further logistic regression analysis to develop the

predictive model. Table 1 also includes the basic data of the patients in the validation cohort. When comparing the depression (+) and depression (-) groups in the validation cohort, significant differences were found in indicators such as glucose monitoring status, blood sugar level, exercise status, sleep disorder status, SPBS, and APGAR assessments ($p<0.05$). Other than monthly income ($p=0.043$), no significant differences were observed between the primary and validation cohorts across other factors.

In the primary cohort, the proportion of males with depression (+) was 59.5%, while it was 40.5% for females, with a p value of 0.594. Similarly, in the validation cohort, the proportion of males with depression (+) was 47.6%, while it was 52.4% for females, with a p value of 0.508. There was no significant difference between the sexes in this study. There was no significant difference in age group distribution between the primary cohort ($p=0.972$) and the validation cohort ($p=0.392$). In the primary cohort, the incidence of depressive disorders was 37.6%; in the validation cohort, the incidence of depressive disorders was 42.4%.

Development of an Individualized Prediction Model

Logistic regression analysis revealed that glucose monitoring status (OR=0.470; 95% CI, 0.222~0.998), exercise status (OR=0.286; 95% CI, 0.140~0.584), monthly income (OR=0.689; 95% CI, 0.477~0.996), sleep disorder status (OR=6.555; 95% CI, 3.151~13.636), and the SPBS score (OR=1.744; 95% CI, 1.166~2.610) were independent predictors (Table 2). Smoking status might be useful in the diabetes–depression prediction model ($p=0.142$). We further presented the model as a nomogram (Figure 1).

Apparent Performance in the Primary Cohort and Validation Cohort

The calibration curve of the nomogram for the probability of diabetes–depression showed that the observed and predicted values fit well in both the primary cohort and the validation cohort (Figure 2), supported by the Hosmer– Lemeshow test Results (both $p>0.05$). The AUC was 0.839 (95% CI, 0.781~0.897) in the primary cohort and 0.857 (95% CI, 0.779~0.935) in the validation cohort. The Youden index, calculated as sensitivity + specificity - 1, was used. By selecting the maximum Youden index, the sensitivity of the predictive model was determined to be 70.9% and the specificity was determined to be 85.5%. In the validation cohort, the sensitivity of the predictive model was 88.1% and the specificity was 82.5%.

We removed the SPBS score from the primary cohort and obtained an AUC=0.812 (95% CI, 0.748~0.976) for the predictive model constructed with other influencing factors (glucose monitoring status, exercise status, monthly income, sleep disorder status, smoking status); this was a significant difference from the AUC of the model that included SPBS score ($p=0.03$). (Figure 3)

Clinical Use

The DCA curve was plotted with the net benefit rate as the ordinate and the threshold probability as the abscission, where the threshold probability was set as (0, 1). At a threshold probability of 0.15 to 0.9, the net benefit rate was > 0,

Table 2 Risk Factors for Depression in Older Diabetes

Intercept	β	Odds Ratio (95% CI)	p
Glucose monitoring status	−0.754	0.470 (0.222 to 0.998)	0.049
Exercise status	−1.251	0.286 (0.140 to 0.584)	0.001
Monthly income	−0.372	0.689 (0.477 to 0.996)	0.048
Sleep disorder status	1.880	6.555 (3.151 to 13.636)	<0.001
Smoking status	0.541	1.718 (0.834 to 3.538)	0.142
SPBS score	0.556	1.744 (1.166 to 2.610)	0.007
Constant	−0.901		

Abbreviations: CI, confidence interval; SPBS, self-perceived burden scale.

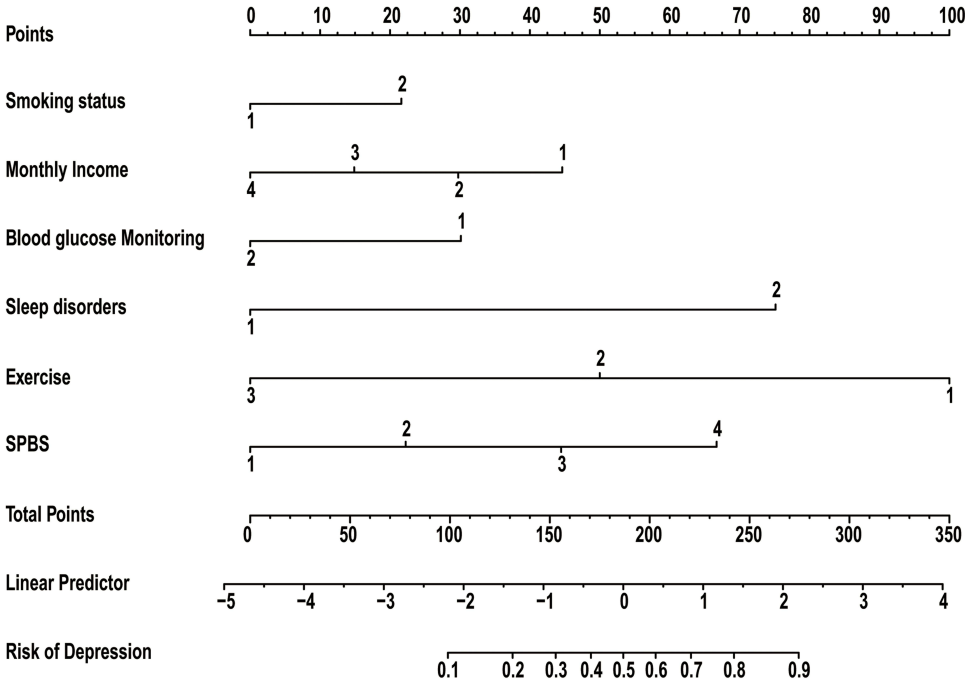

Figure 1 Development of a depression nomogram in the primary cohort.

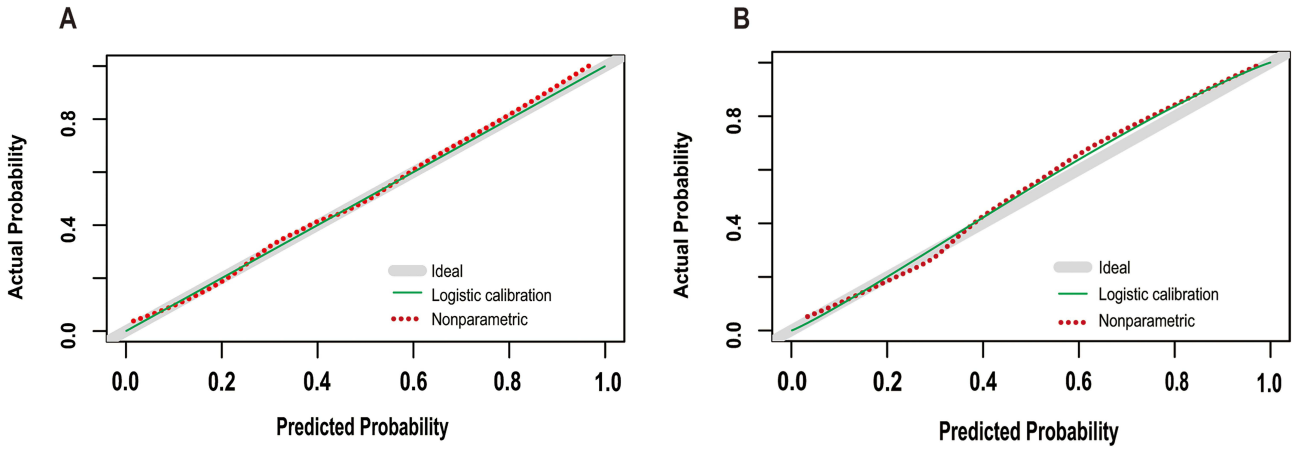

Figure 2 Calibration curves of the prediction model in each cohort. (**A**) Calibration curve of the model in the primary cohort. (**B**) Calibration curve of the model in the validation cohort.

suggesting that the prediction of depression in elderly patients with diabetes mellitus was of great clinical value (Figure 4).

Discussion

The prevalence of depression in diabetic patients is consistently reported to be approximately 10% to 15%, which is approximately twice the rate observed in nondiabetic individuals.[8,35,36] Despite the high incidence of depression in elderly diabetic patients, the atypical clinical presentation of depression often results in a lack of diagnosis. The diagnosis and treatment of depression fall within the domain of psychiatrists; however, the availability of professional community mental health services in China is generally limited. Additionally, cultural stigmas surrounding mental illness contribute to patients concealing their conditions, resulting in low rates of diagnosis. It has been reported that up to 90% of

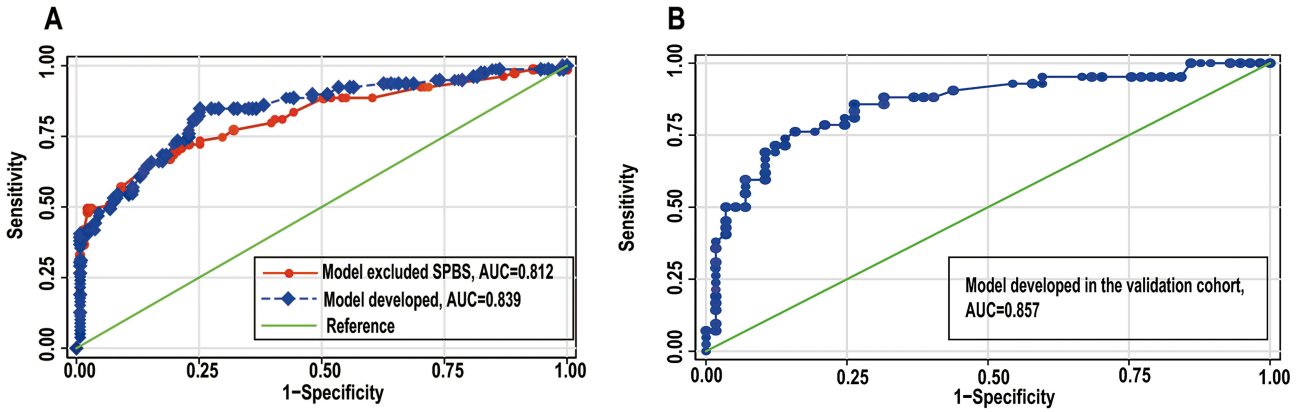

Figure 3 The AUC of the prediction model. (**A**) The AUC was 0.839 (95% CI, 0.781~0.897) in the primary cohort, and the AUC was 0.812 (95% CI, 0.748~0.976) after removing the SPBS score (p<0.05). (**B**) The AUC was 0.857 (95% CI, 0.779~0.935) in the validation cohort.

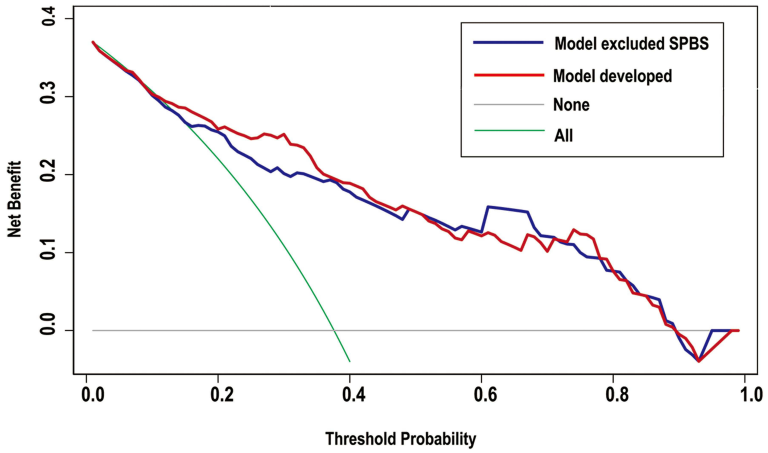

Figure 4 Decision curve analysis for the model with and without the SPBS score.

individuals with severe mental illnesses remain untreated.[6,37] Given these challenges, there is a pressing need to prioritize early prevention and screening efforts and develop an effective screening method.

We developed and validated a user–friendly screening model for depression in elderly diabetic individuals, and it was specifically designed to be used by community health workers without professional qualifications. The nomogram is based on five variables: glucose monitoring status, exercise status, monthly income, sleep disorder status, and the SPBS score. Although smoking status showed a potential association with depression in elderly individuals with diabetes, further investigation with a larger sample size is required to confirm this relationship.

Previous research has established that age, sex (specifically female sex), low family income, lower education level, high glycosylated haemoglobin values, and a high BMI are risk factors associated with depression in patients with T2DM. Our study partially aligns with these findings, as we also identified common demographic characteristics, diabetes characteristics, family characteristics, and sleep disorders as risk factors. In addition, we included the SPBS score and family functioning (Family APGAR score) as additional risk factors in our investigation.

SPB has been linked to depression, influencing communication in caregiver relationships and how individuals adapt to functional and psychosocial changes associated with ageing and diseases.[26] In China, home–based care for older individuals remains prevalent. As age and the incidence of chronic diseases increase, the perception of being a burden on the family becomes more prominent. The Family APGAR score, encompassing adaptability, partnership, growth, affection, and resolve, is a tool used to assess critical aspects of family functioning. Significant deficits or distortions in any of these aspects can lead to

psychological dysfunction. Our findings indicate that the SPBS score serves as an independent predictor of depression in elderly individuals with diabetes mellitus, while the Family APGAR score did not exhibit the same predictive capacity, despite the significant differences between the positive and negative depression groups in the primary cohort. In addition to glucose monitoring status, exercise status, monthly income, and sleep disorder status, other factors were incorporated into a predictive model for diabetes–depression in older individuals, and the model demonstrated excellent discriminatory ability (AUC=0.812). The inclusion of the SPBS score in the prediction model further improved its accuracy, resulting in an increase in the AUC of 0.839 (p=0.03). These findings highlight the potential of integrating multiple factors into clinical predictive models, particularly those that align with the demographic characteristics of specific countries or regions, to achieve optimal results.

Individuals with T2DM, especially those who are obese, are at increased risk of experiencing sleep disturbances.[38] By addressing specific symptoms of sleep disorders, such as nocturia (waking up to go to the bathroom) or daytime sleepiness, we can potentially enhance quality of life (QOL) for people living with T2DM.[39]

It is now recommended that capillary blood glucose monitoring be used for all patients with T2DM.[40] Research indicates that employing well–standardized measures for collaborative and structured self–monitoring of blood glucose (SMBG) can significantly reduce depressive symptoms and diabetes–related distress over time in many T2DM patients who are moderately depressed or distressed and have poor glycaemic control.[41]

Aerobic exercise has been shown to alleviate depressive–like behaviour and increase the levels of antidepressant biomarkers in zebrafish after ten consecutive days of activity.[42] Additionally, physical exercise may enhance sleep quality in older adults with T2DM, reducing depression and delaying the onset of cognitive impairment.[43]

Age and sex did not emerge as predictors in our study, potentially due to the distinct population characteristics of older individuals compared to the general diabetic population.

The developed nomogram serves as a practical and efficient tool for community health workers to assess the risk of depression in elderly diabetic patients. As a graphical representation, it facilitates risk calculations without the need for a calculator, enhancing its usability.[14] The nomogram exhibited satisfactory discrimination in the primary cohort (AUC=0.839), which was notably improved in the validation cohort (AUC=0.857). Since the prevalence of depression was similar in both cohorts, the enhanced discrimination suggested that the factors utilized in the prediction model from the primary cohort can be directly applied to the validation cohort.

The clinical utility of the depression nomogram in guiding treatment decisions for elderly diabetic patients was assessed to establish its rationality. DCA was employed to evaluate the impact on patient prognosis. DCA utilizes threshold probability to determine net benefits and provides insights into clinical consequences. The findings from DCA in the primary cohort indicated that interventions guided by the nomogram yielded greater benefits than did the "treat–all" and "treat–none" approaches, except for a narrow range of threshold probabilities. Therefore, we concluded that employing this model for screening and intervention can improve clinical outcomes in older diabetic patients with depression.

Conclusion and Limitations

In summary, the predictors of depression in elderly individuals with diabetes include glucose monitoring status, exercise status, monthly income, sleep disorder status, and the SPBS score. Our predictive model demonstrated high discrimination with an AUC value of 0.839, indicating its strong ability to distinguish between those with and without depression. The model also exhibited excellent calibration, ensuring that the predicted probabilities closely matched the actual outcomes. Additionally, DCA showed a high net benefit across a range of threshold probabilities, further highlighting its clinical applicability and utility in making informed decisions about patient care. This indicates that the model has high stability and broad applicability, suggesting significant potential for widespread use.

However, this study had certain limitations. First, it was conducted at a single centre with a small sample size. Second, the model was designed to be simple and easy to use in grassroots communities and families, which led to the exclusion of clinically significant factors such as chronic disease history, disease severity, and medication status. Future studies should explore these factors in greater detail for a more comprehensive analysis.

Abbreviations

SPBS, Self – Perceived Burden Scale; APGAR, Adaptation, Partnership, Growth, Affection, Resolve; T2DM, type 2 diabetes mellitus; GDS–30, Geriatric Depression Scale; SDS, Self–Rating Depression Scale; CES–D, Center of Epidemiological Survey – Depression Scale; HAMD, Hamilton Depression Scale; ICD, International Classification of Diseases criteria; DSM, Diagnostic and Statistical Manual criteria; ORs, Odds ratios; CIs, confidence intervals; ROC, Receiver Operating Curve; AUC, area under the curve; DCA, Decision Curve Analysis; QOL, quality of life; SMBG, self–monitoring of blood glucose.

Ethics Approval and Consent to Participate

The study obtained ethical approval from the Ethics Committee of Tongji Hospital, which is affiliated with Tongji Medical College of Huazhong University of Science and Technology (Approval No. TJ-IRB20221222). The research adhered to the ethical principles outlined in the Helsinki Declaration for medical research involving human participants. Informed consent was obtained from all participants.

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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 report no conflicts of interest in this work.

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