Heliyon 10 (2024) e23754

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Development and validation of a nomogram for predicting the risk of poor prognosis in patients with cerebral infarction

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ARTICLE INFO

Keywords:
Cerebral infarction
Functional prognosis
Risk factors
Nomogram

ABSTRACT

Objective: To identify factors related to poor prognosis in patients with cerebral infarction (CI) and to construct and validate a personalized prediction model based on these factors.
Methods: A retrospective analysis was conducted on the clinical and follow-up data of 857 patients with CI who were diagnosed in the neurology department of a tertiary A hospital in Anhui Province, China from April 2020 to March 2022. Based on follow-up data and the Modified Rankin Scale (mRS) score one year after discharge, patients were divided into a good prognosis group (793 cases, mRS $\leq$2) and a poor prognosis group (64 cases, mRS >2). Multivariate logistic regression analysis was used to identify independent risk factors, which were then used to establish a nomogram model. The predictive performance of the model was evaluated using the area under the receiver operating characteristic curve (ROC, AUC), and the calibration curve was used to evaluate the calibration of the nomogram.
Results: There was a statistically significant difference in the distribution of eight variables between the groups, including post-discharge use of biguanide hypoglycemic drugs, insulin, systolic blood pressure, exercise status, alcohol consumption, smoking status, age, and gender ($P < 0.05$). Multivariate logistic regression analysis suggested that gender, smoking after discharge, alcohol consumption, lack of exercise, and oral administration of biguanide hypoglycemic drugs are independent risk factors for poor prognosis in patients with CI ($P < 0.05$). The personalized poor prognosis nomogram constructed based on these five predictive factors showed good discriminative ability and predictive stability, with AUCs of 0.768 (95 % CI: 0.712–0.825) and 0.775 (95 % CI: 0.725–0.836) before and after internal validation, respectively. The calibration curve confirmed the accuracy and consistency of the nomogram ($P = 0.956$).
Conclusion: Female gender, smoking, alcohol consumption, lack of exercise, and post-discharge use of biguanide hypoglycemic drugs are independent risk factors for poor prognosis in patients with CI. The constructed nomogram shows good predictive efficiency for post-discharge prognosis and can help in clinical decision-making.

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https://doi.org/10.1016/j.heliyon.2023.e23754
Received 13 July 2023; Received in revised form 17 November 2023; Accepted 12 December 2023
Available online 16 December 2023
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1. Introduction

In recent years, the incidence and disability rates of cerebral infarction (CI) have been rising, which has seriously affected the quality of life of patients, burdening their families and exerting considerable pressure on society [1,2]. CI is a cerebrovascular disease that causes necrosis or softening of brain tissue due to ischemia and hypoxia. Clinically, its progression can be controlled by improving cerebral circulation, protecting the brain, lowering intracranial pressure, and through intravenous thrombolysis. Despite these treatments, recurrence and poor prognosis may occur, posing a threat to patient safety [3,4]. Therefore, timely and effective prognostic risk assessment is crucial for determining appropriate treatment and nursing plans and formulating reasonable rehabilitation goals for patients with CI [5].

The nomogram model is a visual prediction model established based on multivariate logistic regression analysis. By assigning scores to independent influencing factors, it guides the development of personalized intervention measures [6,7]. However, at present, there are no large-scale studies on prognostic risk assessment in this field. For instance, the stroke recurrence risk prediction model constructed by Yuan et al. [8] focused on young people as the main study population, limiting its representativeness and generalizability. Similarly, the nomogram for the prognosis of patients with aortic occlusion-acute ischemic stroke constructed by Zeng et al. [9] included only 243 study samples, limiting its representativeness. To address these issues, our study retrospectively analyzed the clinical and post-discharge follow-up data of 857 patients with CI who were diagnosed in the neurology department of a tertiary A hospital in Anhui Province, China from April 2020 to March 2022. A personalized adverse prognosis risk assessment model was constructed and validated, aiming to assist in the development of clinical treatment, rehabilitation, and continuous care plans for these patients.

2. Materials and methods

2.1. Research subjects

In this retrospective cohort study, we analyzed the clinical and follow-up data of 857 patients with CI who were diagnosed in the department of neurology of a tertiary first-class hospital in Anhui Province from April 2020 to March 2022. The inclusion criteria were as follows: (1) diagnosis and treatment in accordance with the stroke prevention guidelines issued by the American Heart Association/American Stroke Association in 2021 [10], confirmed by skull CT or MRI, and treated in the hospital; (2) availability of complete medical records; (3) survival for at least 12 months after diagnosis; (4) normal cognitive function, effective communication ability, and compliance with treatment. Exclusion criteria were: (1) missing or incomplete clinical data; (2) presence of malignant tumors; (3) hematological disorders; (4) liver, kidney, or heart dysfunction; and (5) severe brain injury.

This study was approved by the Ethics Committee of the First Affiliated Hospital of the University of Science and Technology of China (No. 2023-RE-141). The requirement of obtaining informed consent from the participants was waived owing to the retrospective nature of the study.

2.2. Collection of baseline clinical and follow-up data

We collected baseline clinical data of the participants, including gender, age, blood pressure, blood sugar, etc. One year after discharge, the nurses in the Continuing Care Center of our hospital followed up with the patients through the stroke patient follow-up network platform independently developed by our hospital, and collected follow-up data of the patients, including post-discharge habits such as smoking, drinking, and exercise; frequency and values of blood pressure and blood glucose measurements; and the use of various medications such as antithrombotic or anticoagulant drugs (aspirin, clopidogrel, warfarin, rivaroxaban, etc.), antihypertensive drugs (ACEI, ARB, diuretics β Receptor blockers, calcium antagonists, etc.), hypoglycemic drugs (insulin, sulfonylureas, α Glycosidase inhibitors, biguanides, etc.), and statin-based lipid-lowering drugs. In addition, the modified Rankin scale (mRS) scores were evaluated and recorded. We used the mRS scores one year after discharge as a prognostic indicator: an mRS score of $\leq$2 points for mRS indicated a good prognosis, and a score of $>$2 points indicated a poor prognosis [11].

2.3. Statistical analysis

Statistical analysis was conducted using R version 3.6.1 (https://www.r project. org) and IBM SPSS 26.0 software. Quantitative data conforming to a normal distribution are expressed as mean $\pm$ standard deviation, and two independent samples *t*-test was used for comparison between two groups. Data not following a normal distribution are represented by the median and interquartile range [M (P25, P75)], with the Wilcoxon rank sum test used for intergroup comparisons. Categorical data are described as number (percentage) and compared using the Chi-square test. Multivariate logistic regression analysis was used to screen for independent risk factors for poor prognosis, leading to the development of a personalized nomogram model. The predictive performance of the nomogram was evaluated using the AUC, and the calibration curve was used to evaluate the calibration of the nomogram.

Table 1
Comparison of relevant data between the modeling and validation groups.

Variables	Category	Total (n = 857)	Good prognosis group (n = 793)	Poor prognosis group (n = 64)	Statistic	P
Statin-based lipid-lowering drugs, n (%)	no	255 (29.75)	239 (30.14)	16 (25.00)	0.748[a]	0.387
	yes	602 (70.25)	554 (69.86)	48 (75.00)		
Glycosidase inhibitors, n (%)	no	783 (91.37)	724 (91.30)	59 (92.19)	0.059[a]	0.808
	yes	74 (8.63)	69 (8.70)	5 (7.81)		
Biguanide hypoglycemic drugs, n (%)	no	753 (87.86)	707 (89.16)	46 (71.88)	16.584[a]	<0.001
	yes	104 (12.14)	86 (10.84)	18 (28.13)		
Sulfonylureas, n (%)	no	814 (94.98)	753 (94.96)	61 (95.31)	0.016[a]	0.900
	yes	43 (5.02)	40 (5.04)	3 (4.69)		
Insulin, n (%)	no	798 (93.12)	743 (93.69)	55 (85.94)	5.559[a]	0.018
	yes	59 (6.88)	50 (6.31)	9 (14.06)		
Hypoglycemic drugs, n (%)	no	635 (74.10)	592 (74.65)	43 (67.19)	1.720a	0.190
	yes	222 (25.90)	201 (25.35)	21 (32.81)		
Calcium antagonists, n (%)	no	388 (45.27)	354 (44.64)	34 (53.13)	1.721[a]	0.190
	yes	469 (54.73)	439 (55.36)	30 (46.88)		
Receptor blockers, n (%)	no	821 (95.80)	761 (95.96)	60 (93.75)	0.722[a]	0.396
	yes	36 (4.20)	32 (4.04)	4 (6.25)		
Diuretics, n (%)	no	837 (97.67)	774 (97.60)	63 (98.44)	0.180[a]	0.671
	yes	20 (2.33)	19 (2.40)	1 (1.56)		
ARB, n (%)	no	733 (85.53)	675 (85.12)	58 (90.63)	1.450[a]	0.228
	yes	124 (14.47)	118 (14.88)	6 (9.38)		
ACEI, n (%)	no	833 (97.20)	771 (97.23)	62 (96.88)	0.027[a]	0.87
	yes	24 (2.80)	22 (2.77)	2 (3.13)		
Rivaroxaban, n (%)	no	847 (98.83)	784 (98.87)	63 (98.44)	0.094[a]	0.759
	yes	10 (1.17)	9 (1.13)	1 (1.56)		
Warfarin, n (%)	no	841 (98.13)	780 (98.36)	61 (95.31)	3.003[a]	0.083
	yes	16 (1.87)	13 (1.64)	3 (4.69)		
Clopidogrel, n (%)	no	803 (93.70)	742 (93.57)	61 (95.31)	0.305[a]	0.581
	yes	54 (6.30)	51 (6.43)	3 (4.69)		
Aspirin, n (%)	no	229 (26.72)	206 (25.98)	23 (35.94)	3.000[a]	0.083
	yes	628 (73.28)	587 (74.02)	41 (64.06)		
Postprandial 2-h blood glucose, n (%)	<11.1 mmol/L	808 (94.28)	748 (94.33)	60 (93.75)	0.036[a]	0.849
	≥11.1 mmol/L	49 (5.72)	45 (5.67)	4 (6.25)		
Fasting blood glucose, n (%)	<7.0 mmol/L	786 (91.72)	728 (91.80)	58 (90.63)	0.108[a]	0.742
	≥7.1 mmol/L	71 (8.28)	65 (8.20)	6 (9.38)		
Frequency of blood glucose measurement, n (%)	Regular measurement	199 (23.22)	179 (22.57)	20 (31.25)	2.501[a]	0.114
	Not measured	658 (76.78)	614 (77.43)	44 (68.75)		
Diastolic blood pressure, n (%)	100–109 mmHg	7 (0.82)	5 (0.63)	2 (3.13)	5.733[a]	0.125
	80–89 mmHg	441 (51.46)	413 (52.08)	28 (43.75)		
	90–99 mmHg	72 (8.40)	66 (8.32)	6 (9.38)		
	<80 mmHg	337 (39.32)	309 (38.97)	28 (43.75)		
Systolic blood pressure, n (%)	120–139 mmHg	523 (61.03)	491 (61.92)	32 (50.00)	10.337[a]	0.016
	140–159 mmHg	119 (13.89)	108 (13.62)	11 (17.19)		
	160–179 mmHg	5 (0.58)	3 (0.38)	2 (3.13)		
	<120 mmHg	210 (24.50)	191 (24.09)	19 (29.69)		
Frequency of blood pressure measurement, n (%)	Regular measurement	700 (81.68)	650 (81.97)	50 (78.13)	0.584[a]	0.445
	Not measured	157 (18.32)	143 (18.03)	14 (21.88)		
Exercise situation, n (%)	Regular exercise	659 (76.90)	625 (78.81)	34 (53.13)	21.999[a]	<0.001
	Lack of exercise	198 (23.10)	168 (21.19)	30 (46.88)		
Alcohol consumption, n (%)	Never drink or abstain from alcohol	772 (90.08)	722 (91.05)	50 (78.13)	11.067[a]	<0.001
	drink now	85 (9.92)	71 (8.95)	14 (21.88)		
Smoking situation, n (%)	Never smoke or have already quit smoking	743 (86.70)	698 (88.02)	45 (70.31)	16.101[a]	<0.001
	Smoking now	114 (13.30)	95 (11.98)	19 (29.69)		
Gender, n (%)	Female	267 (31.16)	238 (30.01)	29 (45.31)	6.463[a]	0.011
	Male	590 (68.84)	555 (69.99)	35 (54.69)		
Age, medium [IQR]	/	63.00 [55.00,71.00]	63.00 [54.00,71.00]	67.00 [57.00,75.00]	−2.306[b]	0.021

Note: a. Pearson's chi-square test, b. Mann–Whitney rank sum test.

3. Results

3.1. Single-factor analysis results of poor prognosis in patients with cerebral infarction

The comparison of clinical data and post-discharge follow-up data between the two groups of patients with good prognosis and poor prognosis for CI showed that there were statistically significant differences in the distribution of eight variables: taking biguanide hypoglycemic drugs after discharge, insulin use after discharge, systolic blood pressure, exercise status, alcohol consumption, smoking status, age, and gender between the two groups of patients ($P < 0.05$), as shown in Table 1.

3.2. Multivariate logistic regression analysis results of poor prognosis in patients with cerebral infarction

The multivariate logistic regression analysis identified several independent risk factors for poor prognosis in patients with CI, namely gender, smoking and drinking alcohol after discharge, lack of exercise, and use of biguanide hypoglycemic drugs ($P < 0.05$), as shown in Table 2.

3.3. Construction of nomogram prediction model for predicting the risk of poor prognosis in patients with cerebral infarction

Based on the five predictive factors selected by multivariate logistic regression, a nomogram prediction model for assessing the risk of poor prognosis in patients with CI was constructed using the "rms" package in R software, as shown in Fig. 1.

3.4. Analysis of discrimination and calibration of the nomogram model

The ROC curve was used to evaluate the discrimination ability of the nomogram model. The AUC of the nomogram model was 0.768 (95 % CI: 0.712–0.825), indicating good discriminative power, as shown in Fig. 2 (A). To prevent overfitting, Bootstrap self-sampling was performed 1000 times for internal validation on the nomogram model. After internal validation, the AUC was 0.775 (95 % CI: 0.725–0.836), indicating good predictive stability. Further details are found in Fig. 2 (B). The Brier score and the Spiegelhalter z-test were used to evaluate the calibration of the nomogram model. According to the calibration curve (Fig. 3), the Brier score of the nomogram was 0.063, and the Spiegelhalter z test showed that there was no statistically significant deviation between the prediction probability of the nomogram model and the actual frequency of poor prognosis ($z = 0.056$, $P = 0.956$), indicating that the nomogram has good calibration.

4. Discussion

CI refers to a cerebrovascular disease that causes cerebral atherosclerosis or plaque rupture and secondary thrombosis, narrowing or blocking of the vascular lumen, leading to ischemia, hypoxia, and necrosis of brain tissue. Patients with CI often exhibit varying degrees of neurological impairment [12]. CI has characteristics of severe illness, high disability and mortality rates, poor prognosis, and the risk of secondary complications such as cerebral hemorrhage and hernia [13,14]. Timely and accurate evaluation of the patient's neurological function recovery and prognosis after discharge is of great value for the development of personalized treatment, continuous care, and rehabilitation plans. Early prediction is also beneficial for medical personnel to implement intervention measures as soon as possible to improve patient prognosis [15].

The prognosis of patients with CI is influenced by many factors. This study confirmed, through multivariate regression analysis, that gender, post-discharge smoking and alcohol consumption, lack of exercise, and the use of biguanide hypoglycemic drugs are independent risk factors for poor prognosis in these patients. A study on the gender differences in short-term and long-term outcomes of patients with acute ischemic stroke in China reported that women, especially those aged 65 and above, are less likely to achieve

Table 2
Multivariate logistic regression analysis of poor prognosis in patients with cerebral infarction.

Variables	Estimate	SE	Z	P	Odds ratio	Lower of OR	Upper of OR
Constant	−4.271	0.932	−4.585	0.000	0.014	0.002	0.081
Age	0.020	0.013	1.521	0.128	1.020	0.995	1.047
Male gender	−0.668	0.305	−2.190	0.029	0.513	0.281	0.933
Smoking after discharge	1.201	0.348	3.453	0.001	3.324	1.661	6.540
Drinking alcohol after discharge	0.857	0.376	2.278	0.023	2.356	1.097	4.833
Lack of exercise	1.099	0.292	3.762	0.000	3.001	1.688	5.327
Systolic blood pressure 120–139 mmHg (Reference range <120 mmHg)	−0.224	0.329	−0.681	0.496	0.799	0.424	1.550
Systolic blood pressure 140–159 mmHg (Reference range <120 mmHg)	−0.056	0.424	−0.133	0.894	0.945	0.400	2.143
Systolic blood pressure 160–179 mmHg (Reference range <120 mmHg)	1.739	1.028	1.691	0.091	5.694	0.621	42.055
Administer insulin after discharge	0.732	0.423	1.731	0.083	2.079	0.859	4.576
Oral administration of biguanide hypoglycemic drugs after discharge	1.218	0.327	3.722	0.000	3.379	1.749	6.346

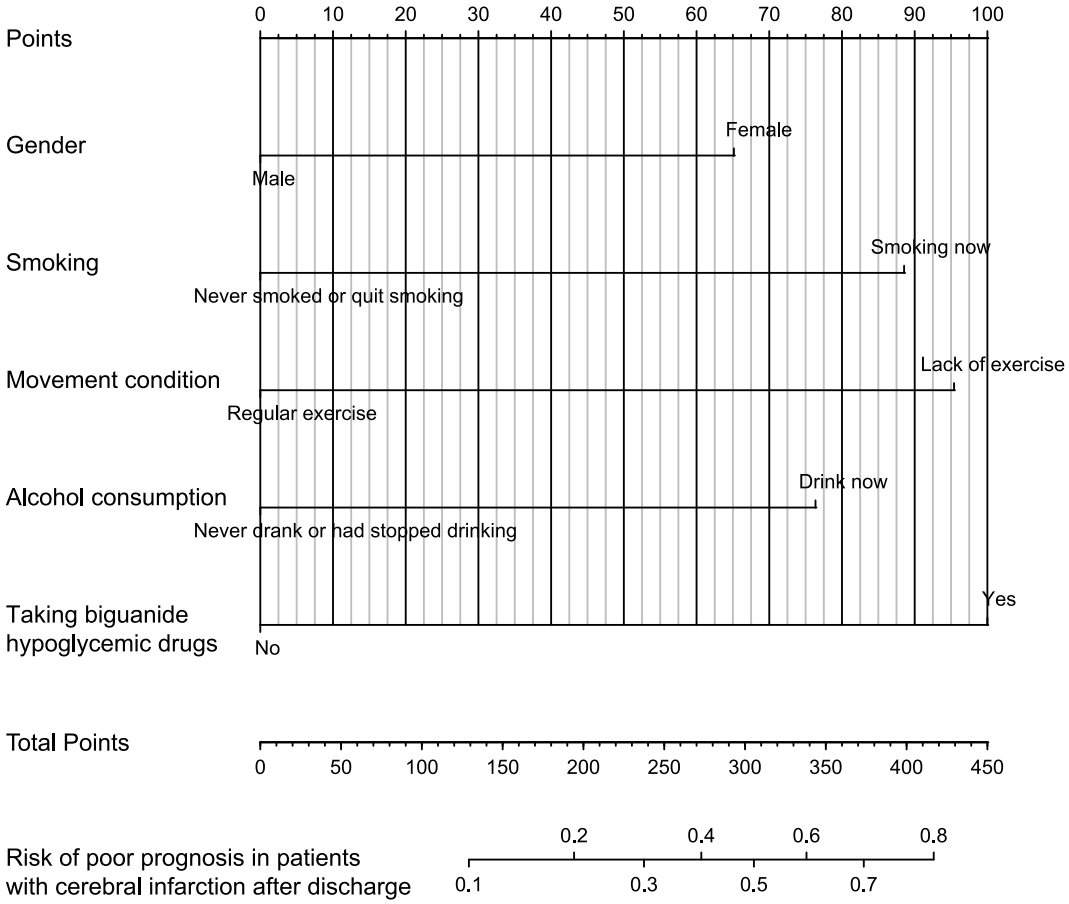

Fig. 1. Nomogram prediction model for the risk of poor prognosis in patients with cerebral infarction
This nomogram presents a visual representation of the risk factors that contribute to poor prognosis in patients with cerebral infarction by illustrating the statistical model used for predicting outcomes.

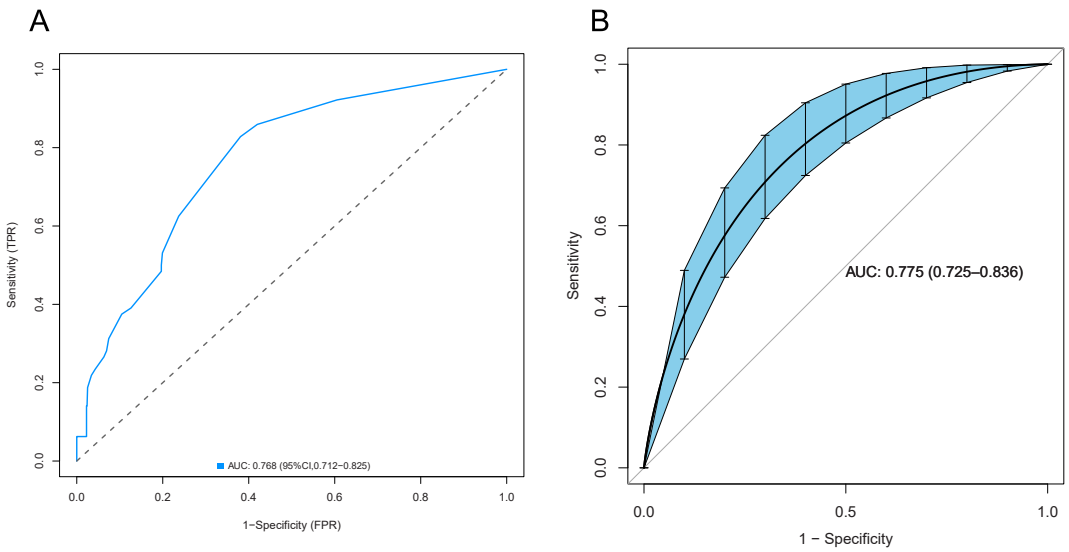

Fig. 2. ROC curve of nomogram model. Note: A. before internal validation; B. after internal validation
This ROC curve of the nomogram model demonstrates its performance in terms of sensitivity and specificity before and after internal validation. The two curves represent the model's predictive accuracy before and after validation.

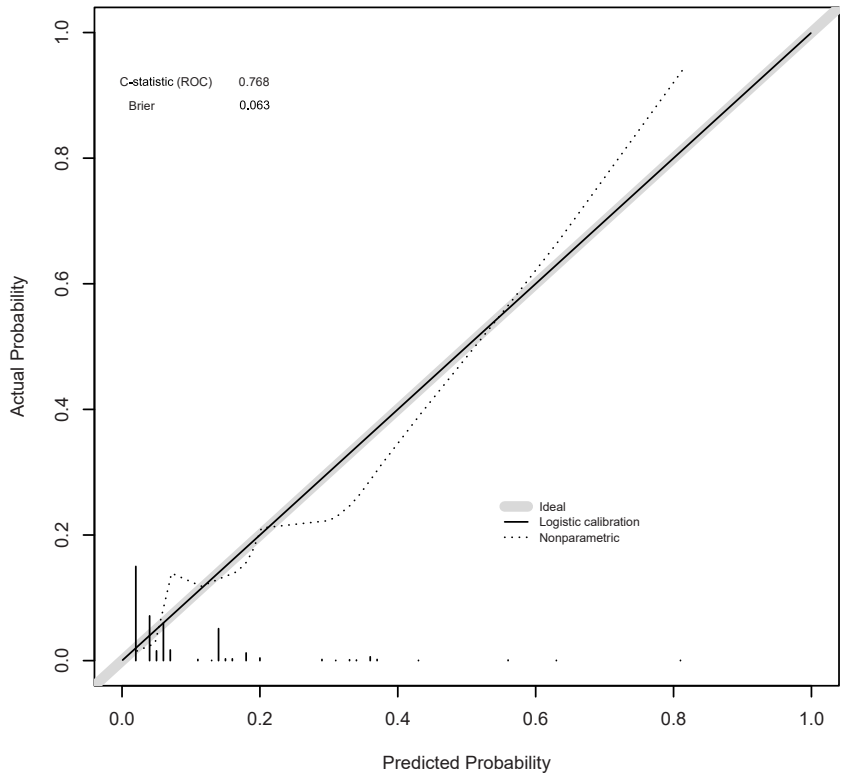

Fig. 3. Calibration curve of nomogram model. **Note:** The C-statistic (ROC) AUC is a vital metric used to assess the predictive accuracy of a model. It ranges between 0.5 and 1, where 0.5 indicates that the model's predictions are comparable to random guessing and 1 indicates perfect predictive ability. A C-statistic close to 1 signifies good predictive ability, whereas a value close to 0.5 denotes weak predictive ability, slightly better than random guessing. Brier refers to the Brier score, a statistical metric used to assess the calibration of probabilistic prediction models. Specifically, the Brier score is the average of the sum of the squares of the differences between the observations and the model's predicted probabilities, reflecting the model's prediction error. A lower Brier score indicates more accurate probabilistic predictions, whereas a higher Brier score implies that the probabilistic predictions are significantly biased. The Brier score is often used in conjunction with other metrics to provide a comprehensive assessment of a predictive model's performance.
The calibration curve of the nomogram model provides a visual demonstration of the agreement between the predicted probabilities of poor prognosis and the observed outcomes in patients with cerebral infarction.

favorable outcomes at three months compared to men [16]. Furthermore, the study by Shen et al. [17] shows that the proportion of alcohol consumption and smoking history in patients with CI is significantly higher compared to those without the condition ($\chi^2 =$ 4.810, 5.041, $P < 0.05$). Multiple studies [18,19] have suggested that alcohol consumption may contribute to the narrowing and severity of intracranial and extracranial vessels. Nicotine in tobacco can increase carbon monoxide, reduce oxygen content, lead to vascular hypoxia, affect vascular elasticity, promote necrosis, and further increase the risk of CI [20]. A study by Shi [21] confirmed that exercise therapy can improve autonomic nervous function, reduce the risk of cardiovascular events, and improve the quality of life of patients with CI.

Patients with CI who take biguanide antidiabetic drugs often have concurrent diabetes. Compared to individuals without diabetes, those with diabetes have a significantly increased risk of CI and poor prognoses. These patients are more likely to have permanent neurological dysfunction and prolonged hospitalization after CI. Additionally, diabetes increases the risk of further cerebrovascular events, as well as the incidence, disability, and mortality rates associated with CI [22].

Four kinds of hypoglycemic drugs were analyzed in this study, namely glycosidase inhibitors, biguanides, sulfonylureas, and insulin. Notably, biguanides emerged as a factor contributing to the poor prognosis of stroke, whereas other antidiabetic drugs did not show this association. As can be seen from Table 1, the proportion of patients who used glycosidase inhibitors, biguanides, sulfonylureas, and insulin in the group with good prognosis was 8.70 %, 10.84 %, 5.04 %, and 6.31 % respectively, whereas the proportion of patients who used glycosidase inhibitors, biguanides, sulfonylureas, and insulin in the group with poor prognosis was 7.81 %, 28.13 %, and 6.31 %, respectively. Compared to the good prognosis group, the number of patients who used glycosidase inhibitors decreased by 0.89 %, biguanides increased by 17.29 %, sulfonylureas decreased by 0.35 %, and insulin increased by 7.75 %. The most significant difference in drug usage between the two groups was seen with biguanides, followed by insulin. This difference was statistically significant, as shown in Table 1 ($P < 0.05$). In Table 2, after further controlling the confounding factors, insulin was no longer considered a risk factor, whereas biguanides remained an independent risk factor for poor prognosis.

It is particularly necessary to take targeted prevention and control measures against the independent risk factors mentioned above. Firstly, for female patients, enhancing awareness through targeted health education is essential. Women have special physiological and psychological needs that require attention with adjustments in diet, lifestyle habits, and other aspects. Regular comprehensive physical examinations are also important for the early identification of potential diseases and the implementation of appropriate treatment measures. Secondly, it is necessary to promote cessation of smoking and alcohol consumption. Medical professionals can educate patients and their families about the health risks associated with these habits through individual or group counseling and supportive treatments as necessary. Thirdly, patients can be encouraged to engage in moderate physical exercise, which not only increases physical resistance but also improves mental health. Finally, medical staff should establish a scientific medication plan that involves strict monitoring of medication quality and dosage, along with continuous observation and documentation of the patient's physical condition and responses, in order to promptly adjust the medication dosage and plans.

In recent years, the use of nomograms to establish prognostic models has been widely recognized. As an intuitive and user-friendly statistical tool, nomograms can consider multiple factors and help healthcare professionals provide personalized evaluations for patients [23]. Previous studies [24–26] have confirmed that the nomogram model has good predictive value in assessing the prognostic risk for different types of tumors such as appendix, gastric, and esophageal cancers. However, to date, there have been no large-scale studies on the use of nomograms for predicting the risk of poor prognosis in patients with CI at both domestic and international levels. The stroke recurrence risk prediction model developed by Yuan et al. [8] primarily targeted a younger demographic as the primary study population, which limited the representativeness and generalizability of the prediction model. Additionally, the nomogram prediction model for prognostic assessment of patients with aortic occlusion-acute ischemic stroke developed by Zeng et al. [9] was based on a sample size of only 243 cases, thereby constraining its representativeness due to the relatively small number of study samples. Based on this, this study retrospectively analyzed the clinical and follow-up data of 857 patients with cerebral infarction and constructed a nomogram model to predict the risk of poor prognosis in patients with cerebral infarction. The research results showed that the AUC before and after internal validation of the nomogram were 0.768 (95 % CI: 0.712–0.825) and 0.775 (95 % CI: 0.725–0.836), respectively, indicating that the nomogram has good discrimination and predictive stability. The calibration curve of the nomogram model indicates that the nomogram has good calibration and predictive consistency ($P = 0.956$).

This study has several limitations. Firstly, it is a retrospective study and may have some selection bias. In addition, the predictive indicators included in this study are relatively limited. Psychological factors and additional laboratory examination indicators, which could enhance the predictive accuracy of the nomogram, were not included. Meanwhile, owing to the retrospective nature of the study, important data such as the type of cerebral infarction (lacuna, cardiogenic, atherothrombotic, etc.) and NIHSS score had a lot of missing information (more than 20 %). To maintain a sufficiently large sample size, these important indicators were not included in this analysis. Further large-sample cohort studies will aim to incorporate these factors to improve the predictive performance of the model. Finally, the construction and validation of the predictive model in this study were all sourced from the research samples of one institute and only internal validation was conducted, which left the extrapolation of the nomogram uncertain. Future studies with multiple centers, large sample sizes, and the inclusion of more risk factors are needed to evaluate the extrapolation and predictive stability of the nomogram. One point that cannot be overlooked is that, owing to the specific focus of this study and data collection limitations, we did not make detailed distinctions between specific causes of deterioration within one year of discharge. These distinctions included whether the deterioration was caused by a relapse or a poor mRS score at discharge without significant improvement. Although these distinctions may be important for individualized treatment and rehabilitation planning, within the scope of this study, our goal was to understand the overall prognosis and inform clinical practice. Because the specific causes of deterioration within one year after discharge may involve a variety of factors, such as patient compliance behavior, treatment efficacy, and rehabilitation measures, more detailed clinical information and long-term follow-up data are needed to make accurate judgments. Therefore, we did not analyze these differences in detail in this study. However, we recognize that these differences are important for the individualization of treatment and rehabilitation plans. Therefore, we plan to study these differences in more detail in future studies with more comprehensive data collection and longer-term follow-up to help physicians better formulate treatment plans for patients and improve their prognosis and quality of life.

5. Conclusion

In conclusion, female gender, post-discharge smoking and alcohol consumption, lack of exercise, and use of biguanide hypoglycemic drugs are independent risk factors for poor prognosis in patients with CI. The nomogram constructed based on these findings shows a strong predictive value for the functional prognosis of these patients and serves as a valuable tool for guiding clinical treatment, rehabilitation, and subsequent decisions regarding continuous nursing care interventions.

Funding

This study was supported by Young Scientists Fund of the National Natural Science Foundation of China (ID: 82001452).

Data availability statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Ethical statement

This study has been approved by the Ethics Committee of the First Affiliated Hospital of University of Science and Technology of China (No.: 2023-RE-141), informed consent of study subjects was waived due to the retrospective nature of the study. The data accessed was de-identified (anonymized) and complied with the data protection and privacy regulations. No other approvals were required for data access.

CRediT authorship contribution statement

Zhenfeng Chen: Conceptualization, Investigation, Methodology, Writing - original draft, Writing - review & editing. **Lixiang Zhang:** Investigation, Methodology, Writing - original draft, Writing - review & editing. **Rui Li:** Data curation, Formal analysis, Funding acquisition, Investigation. **Haiying Hu:** Investigation, Resources, Software, Validation, Visualization. **Qiongdan Hu:** Formal analysis, Resources, Software, Validation, Visualization. **Xia Chen:** Conceptualization, Methodology, Project administration, Supervision, Writing - review & editing.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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