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ARTICLE

Development and Validation of a GULP-Based Predictive Model for Dehydration in Elderly Patients with Post-Stroke Dysphagia

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Abstract

Aims/Background The background for establishing and verifying a dehydration prediction model for elderly patients with post-stroke dysphagia (PSD) based on General Utility for Latent Process (GULP) is as follows: For elderly patients with PSD, GULP technology is utilized to build a dehydration prediction model. This aims to improve the accuracy of dehydration risk assessment and provide clinical intervention, thereby offering a scientific basis and enhancing patient prognosis. This research highlights the innovative application of GULP technology in constructing complex medical prediction models and addresses the special health needs of elderly stroke patients. Based on GULP criteria, the study aims to establish and validate a dehydration prediction model for elderly patients with dysphagia following a stroke.

Methods Two hundred patients with post-stroke dysphagia treated at Beijing Rehabilitation Hospital Affiliated with Capital Medical University, from January 2020 to December 2023, were selected retrospectively. The patients were randomly matched at a ratio of 1:4 to establish a verification group (n = 40) and a modelling group (n = 160). Based on the occurrence of dehydration, the modelling group patients were divided into two groups: the dehydration group (n = 55) and the non-dehydration group (n = 105). Univariate and multivariate logistic regression analyses were used to identify the influencing factors of dehydration in elderly patients with dysphagia after a stroke, and to establish a predictive model based on GULP. The predictive value of the model was evaluated using receiver operating characteristic (ROC) curve analysis.

Results The results of univariate and multivariate logistic regression analyses showed significant differences in age, lesion location, muscle strength grade, homocysteine (Hcy), and swallowing function score ($p < 0.05$). When these influencing factors were included in the model, the slope of the calibration curve in both the training set and the validation set was close to 1, indicating that the predicted dehydration risk was consistent with the actual risk. ROC analysis results revealed that in the training set, the model predicted dehydration in elderly post-stroke patients with dysphagia with an area under the curve (AUC) of 0.934, a standard error of 0.034, and a 95% confidence interval (CI) of 0.916 to 0.981. The optimal cutoff value was 0.78, yielding a sensitivity of 88.84% and a specificity of 90.00%. In the validation set, the AUC was 0.867 with a standard error of 0.025 and a 95% CI of 0.694 to 0.934. The optimal cutoff value here was 0.66, with a sensitivity of 80.16% and a specificity of 85.94%.

Conclusion This study successfully established and validated a GULP-based dehydration prediction model for elderly patients with dysphagia following a stroke, demonstrating high application value.

Key words: GULP; stroke; dysphagia; predictive model

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Introduction

Dehydration is a common complication among elderly patients with post-stroke dysphagia. With continual advancements in medical technology and an increasingly ageing population, the number of elderly stroke patients is rising annually. Dysphagia not only affects the patient's nutritional intake and quality of life but may also lead to serious complications such as aspiration pneumonia and malnutrition, which can be life-threatening (Estai et al, 2021). Due to impaired swallowing function, patients may not be able to effectively intake sufficient fluids and nutrients, leading to dehydration (Güleç et al, 2021).

Early prediction and identification of dehydration risks in elderly post-stroke patients with dysphagia are crucial. Accurately recognizing these risks allows doctors to provide timely and effective interventions, thereby improving the patient's prognosis and quality of life (Labeit et al, 2023). However, current methods for predicting and assessing dehydration in these patients are still limited and lack accurate, effective predictive models. This limitation hinders timely clinical detection of dehydration risks, missing the optimal timing for intervention (Li et al, 2022). The General Utility for Latent Process (GULP) is a machine learning-based method for building predictive models. GULP possesses robust data processing and analysis capabilities, capable of uncovering latent relationships and patterns through deep data mining, thus constructing predictive models (Li et al, 2023; Liu et al, 2022). In the medical field, GULP has been widely used for disease prediction and risk assessment, achieving significant application results (Martino et al, 2005).

This study aims to develop and validate a GULP-based predictive model for dehydration in elderly patients with post-stroke dysphagia, providing a reference for clinical practice.

Methods

Study Subjects

A retrospective selection of 200 patients with post-stroke dysphagia (PSD) treated at Beijing Rehabilitation Hospital Affiliated with Capital Medical University, from January 2020 to December 2023, was conducted. Patients were randomly matched at a 1:4 ratio into a validation group (n = 40) and a modelling group (n = 160), with the latter divided based on dehydration occurrence into a dehydration group (n = 55) and a non-dehydration group (n = 105). Dehydration was diagnosed using the calculated plasma osmolarity method: Plasma osmolarity = 1.86 $\times$ (sodium + potassium) + 1.15 $\times$ glucose + urea nitrogen + 14. The states of hydration were classified as follows: normal hydration state (275 to $<$296 mmol/L), dehydration tendency (296 to $<$300 mmol/L), and dehydration ($\geq$300 mmol/L). Inclusion criteria included: (1) Clinical diagnosis of post-stroke dysphagia. The diagnosis was conducted using the Watian drinking water test: the patient sits upright and drinks 30 mL of warm water, and the time from water entering the oropharynx to swallowing is observed and recorded (based on laryngeal movement). Two tests are conducted, and the shortest time is recorded. Dysphagia severity is classified into five grades: Grade I: Swallowing smoothly within 5 seconds without choking. Grade II: Swallowing without choking but coughing more than twice in 5 to 10 seconds. Grade III: Swallowing once but accompanied by coughing. Grade IV: Swallowing more than twice with coughing. Grade V: Frequent coughing and inability to swallow completely. Grades III, IV, and V are considered abnormal, indicating dysphagia. (2) Age $>$60 years. (3) Stable vital signs. Exclusion criteria included: (1) Severe heart or lung diseases. (2) Pre-stroke swallowing dysfunctions. (3) Oropharyngeal diseases.

This study complies with the Declaration of Helsinki. Informed consent was obtained from the patient or a family member.

General Data Collection

General data such as gender, Body Mass Index (BMI), High-Density Lipoprotein Cholesterol (HDL-C), Low-Density Lipoprotein Cholesterol (LDL-C), Hematocrit Value (HCT), hypertension, diabetes, type of stroke, duration of disease, alcohol consumption, smoking, age, lesion location, muscle strength grading, homocysteine (Hcy), and swallowing function score were collected.

Swallowing Function Scoring

Using the Standard Swallowing Assessment (SSA) score, we evaluated several aspects including the patient's level of consciousness, head and trunk control, respiratory function, lip closure, soft palate movement, laryngeal function, pharyngeal reflex, and voluntary coughing ability.

During the 5 mL water swallowing test, patients were asked to swallow 5 mL of water three times after an initial normal examination. We observed the laryngeal movements during swallowing, checked for repetitive swallowing actions, any stridor during swallowing, and the recovery of laryngeal function post-swallow. The total score for this part ranges from 5 to 11 points, with lower scores indicating better swallowing function.

In the 60 mL water swallowing test, if the previous tests were normal, a third test was conducted where patients were asked to swallow 60 mL of water in one go. This test focuses on observing the time required for swallowing and any adverse reactions such as coughing. The total score ranges from 5 to 12 points, with lower scores indicating smoother swallowing.

The overall score ranges from 18 to 46 points, with lower scores indicating better swallowing function.

Statistical Analysis

The collected data were analyzed using SPSS 27.0 (IBM Corp., Armonk, NY, USA). Quantitative data fitting a normal distribution are expressed as mean $\pm$ standard deviation and compared using independent sample t-tests. Count data are expressed as numbers or rates and compared using chi-squared tests. Factors affecting dehydration in elderly post-stroke patients with dysphagia were analyzed using univariate and multivariate logistic regression analyses. The predictive value of the model for dehydration was assessed using the receiver operating characteristic (ROC) curve, with a p-value of less than 0.05 considered statistically significant.

Results

Comparison of General Data between the Validation Group and the Modelling Group

No significant difference was observed between the validation and modelling groups ($p > 0.05$), as shown in Table 1.

Table 1. Comparison of general data between the validation group and the modelling group.

Indicator	Validation group (n = 40)	Modelling group (n = 160)	t/χ^2 value	p-value
Age (years)	64.45 ± 2.15	65.01 ± 1.63	1.816	0.071
Sex			0.021	0.885
Male	24	98		
Female	16	62		
BMI (kg/m^2)	23.16 ± 1.26	23.42 ± 1.51	1.005	0.316
Lesion site			0.033	0.984
Brainstem	16	64		
Multiple lesions	24	96		
Grading of muscle strength			0.322	0.570
≤Grade 3	20	88		
>Grade 3	20	72		
HDL-C (mmol/L)	1.30 ± 0.22	1.27 ± 0.31	0.576	0.565
LDL-C (mmol/L)	2.81 ± 0.43	2.77 ± 0.43	0.526	0.599
HCT (%)	49.21 ± 2.51	49.00 ± 1.98	0.567	0.571
Hcy (µmol/L)	16.41 ± 2.55	16.54 ± 2.87	0.262	0.794
Hypertension			0.724	0.395
Yes	19	88		
N/A	21	72		
Diabetes			0.781	0.377
Yes	10	30		
N/A	30	130		
Swallowing function score (points)	42.46 ± 2.16	43.11 ± 2.45	1.535	0.126
Type of stroke			0.005	0.942
Ischemic	25	99		
Hemorrhagic	15	61		
Course of disease (months)	3.05 ± 1.51	2.87 ± 1.62	0.637	0.525
Alcohol use			2.915	0.088
Yes	13	76		
N/A	27	84		
Smoking			0.512	0.475
Yes	15	70		
N/A	25	90		

BMI, Body Mass Index; HDL-C, High-Density Lipoprotein Cholesterol; LDL-C, Low-Density Lipoprotein Cholesterol; HCT, Hematocrit Value; Hcy, homocysteine.

Table 2. Univariate analysis of the influencing factors of swallowing dysfunction after stroke in the elderly.

Indicator	Swallowing dysfunction (n = 55)	Non-swallowing dysfunction (n = 105)	t/χ^2 value	p-value
Age (years)	68.53 ± 3.53	63.17 ± 3.18	9.747	<0.001
Sex			0.055	0.814
Male	33	65		
Female	22	40		
BMI (kg/m^2)	23.15 ± 2.17	23.56 ± 2.56	1.012	0.313
Lesion site			16.621	<0.001
Brainstem	10	54		
Multiple lesions	45	51		
Grading of muscle strength			26.031	<0.001
≤Grade 3	15	73		
>Grade 3	40	32		
HDL-C (mmol/L)	1.25 ± 0.20	1.28 ± 0.25	0.770	0.443
LDL-C (mmol/L)	2.80 ± 0.35	2.75 ± 0.30	0.945	0.346
HCT (%)	48.79 ± 1.58	49.11 ± 1.70	1.158	0.249
Hcy (µmol/L)	17.25 ± 2.38	16.17 ± 2.16	3.366	<0.001
Hypertension			2.526	0.112
Yes	35	53		
N/A	20	52		
Diabetes			0.018	0.894
Yes	10	20		
N/A	45	85		
Swallowing function score (points)	45.57 ± 2.26	41.82 ± 2.09	10.481	<0.001
Type of stroke			0.001	0.992
Ischemic	34	65		
Hemorrhagic	21	40		
Course of disease (months)	2.80 ± 0.43	2.91 ± 0.46	1.469	0.144
Alcohol use			0.002	0.967
Yes	26	50		
N/A	29	55		
Smoking			1.858	0.173
Yes	20	50		
N/A	35	55		

BMI, Body Mass Index; HDL-C, High-Density Lipoprotein Cholesterol; LDL-C, Low-Density Lipoprotein Cholesterol; HCT, Hematocrit Value; Hcy, homocysteine.

Univariate and Multivariate Logistic Regression Analysis of Influencing Factors in the Training Group

Univariate analysis revealed no significant differences in patient gender, BMI, HDL-C, LDL-C, HCT, hypertension, diabetes, stroke type, duration of illness, alcohol consumption, and smoking ($p > 0.05$). However, significant differences were observed in age, lesion location, muscle strength grading, homocysteine levels, and

Table 3. Logistic regression analysis of influencing factors in the modelling group.

Risk factors	OR	95% CI	p-value	β	SE	Wald
Age	3.841	2.232–6.610	<0.001	1.346	0.277	23.602
Lesion site (Multiple lesions vs Brainstem)	3.151	1.893–5.245	<0.001	1.148	0.260	19.486
Grading of muscle strength (>Grade 3 vs ≤Grade 3)	3.812	2.228–6.522	<0.001	1.338	0.274	23.851
Hcy	2.482	1.527–4.034	<0.001	0.909	0.248	13.437
Swallowing function score	4.054	2.328–7.060	<0.001	1.400	0.283	24.462

Hcy, homocysteine; OR, odds ratio; CI, confidence interval; SE, standard error.

swallowing function scores ($p < 0.05$), as shown in Table 2. These significant variables were subsequently included in a multivariate logistic regression analysis. After assigning actual values (dehydration = 1, no dehydration = 0), the analysis indicated that age, lesion location, muscle strength grading, homocysteine levels, and swallowing function scores are independent factors influencing dehydration in these patients ($p < 0.05$), as shown in Table 3.

Development of a Gulp-Based Predictive Model for Dehydration in Elderly Post-Stroke Dysphagia Patients

According to the results of the logistic regression analysis, age, lesion site, muscle strength grade, Hcy levels, and swallowing function score were included in the model for predicting dehydration in elderly patients with dysphagia following a stroke. The weights assigned to these factors were: age (8), lesion site (15), muscle strength grade (10), Hcy level (25), and swallowing function score (42), corresponding to different percentages.

The term “net benefit rate” refers to the trade-off between high-risk patients with dehydration and low-risk patients who do not require treatment. The Y-axis represents the net benefit rate of using the model to guide clinical decision-making. The red curve represents the Decision Curve Analysis (DCA) curve, which predicts dehydration in the target population. The black and grey horizontal lines represent extreme cases: the black line (none) indicates the assumption that no patients have dehydration, resulting in a net benefit rate of 0; the all-black line assumes that all patients have dehydration, resulting in a negative net benefit rate. The closer the distance between the DCA curve and the black-grey straight line, the higher the clinical application value of the model. The model shows the highest benefit when the prediction probability ranges from 0.6 to 0.9 (see Fig. 1).

The slope of the calibration curve of the model is close to 1 in both the training set and the validation set. These results indicate that the model’s predictions of dehydration risk in elderly patients with dysphagia after stroke are well-aligned with actual risk, as shown in Figs. 2,3.

ROC Curve Analysis to Assess the Predictive Value of the Model for Dehydration in Elderly Post-Stroke Dysphagia Patients

ROC analysis results indicate that in the training set, the model predicts dehydration in elderly post-stroke patients with dysphagia with an area under the curve (AUC) of 0.934, a standard error of 0.034, and a 95% confidence interval (CI) rang-

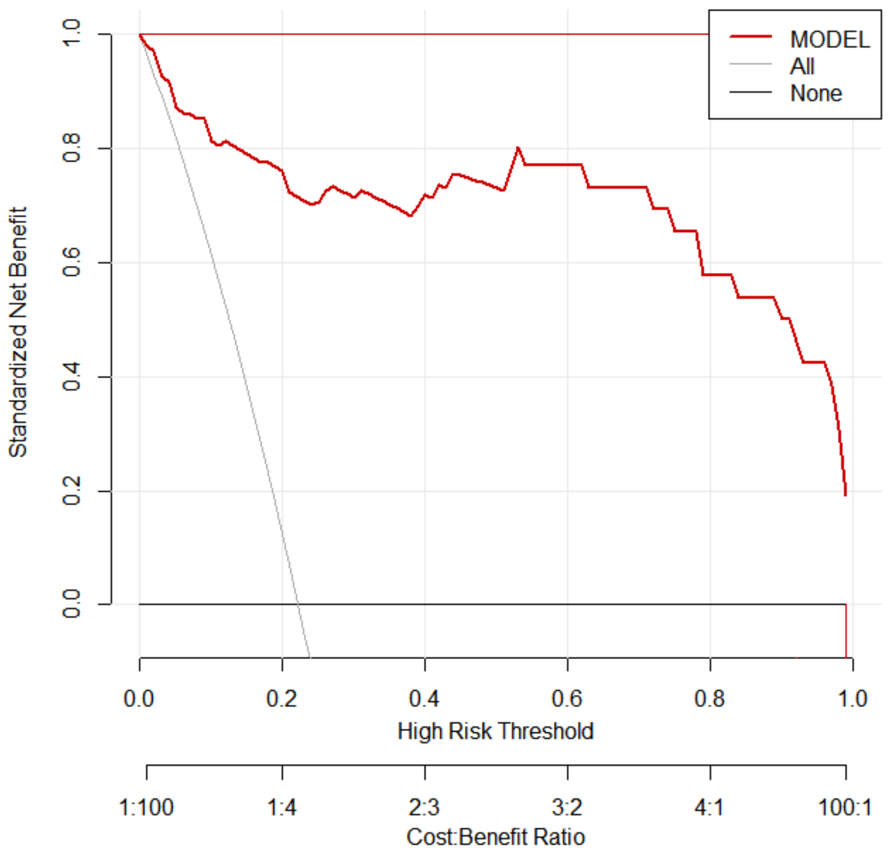

Fig. 1. Predictive model. Note: Successful establishment of prediction model.

ing from 0.916 to 0.981. The optimal cutoff value is 0.78, which yields a sensitivity of 88.84% and a specificity of 90.00% (see Fig. 4). In the validation set, the AUC is 0.867 with a standard error of 0.025 and a 95% CI from 0.694 to 0.934. The optimal cutoff value in this set is 0.66, with a sensitivity of 80.16% and a specificity of 85.94% (see Fig. 5).

Discussion

Applicable to binary classification problems, logistic regression is a classic method for handling such cases. It maps the output of linear regression to the [0,1] interval using a sigmoid function, allowing for the prediction of the probability that data belongs to a particular category. This method has significant application value in fields such as healthcare, finance, and marketing, especially in scenarios requiring a binary decision, such as disease diagnosis, credit evaluation, and marketing response prediction.

Strong Explanatory Power

The results of the logistic regression model are straightforward and easy to interpret, allowing for a clear understanding of how each independent variable influences the dependent variable (i.e., the classification results). This clarity is crucial for interpreting model predictions and making informed decisions.

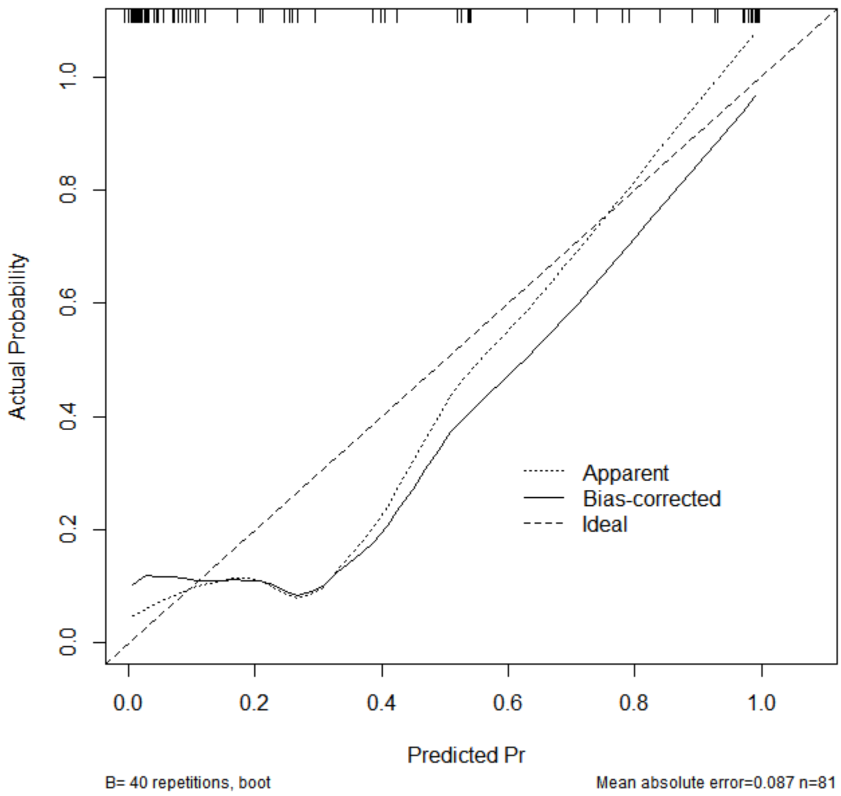

Fig. 2. Calibration curve for the training set. Note: The slope of the calibration curve is close to 1, indicating that the risk is in good agreement with the actual risk.

High Computational Efficiency

Compared to more complex classification algorithms such as support vector machines (SVM) and neural networks, logistic regression is computationally efficient. This efficiency becomes particularly advantageous when processing large-scale datasets.

Other Potential Statistical Methods

In addition to logistic regression, several other statistical methods can address classification problems, including linear discriminant analysis (LDA), naive Bayes classifiers, decision trees, and random forests. Each method has its own strengths and weaknesses and is suited to different scenarios.

Comparison Results

- Linear Discriminant Analysis (LDA): Logistic regression does not require strict assumptions about data distribution, making it more flexible in practical applications compared to LDA.

- Naive Bayes Classifiers: These perform well in tasks like text classification but may struggle with datasets involving complex relationships.

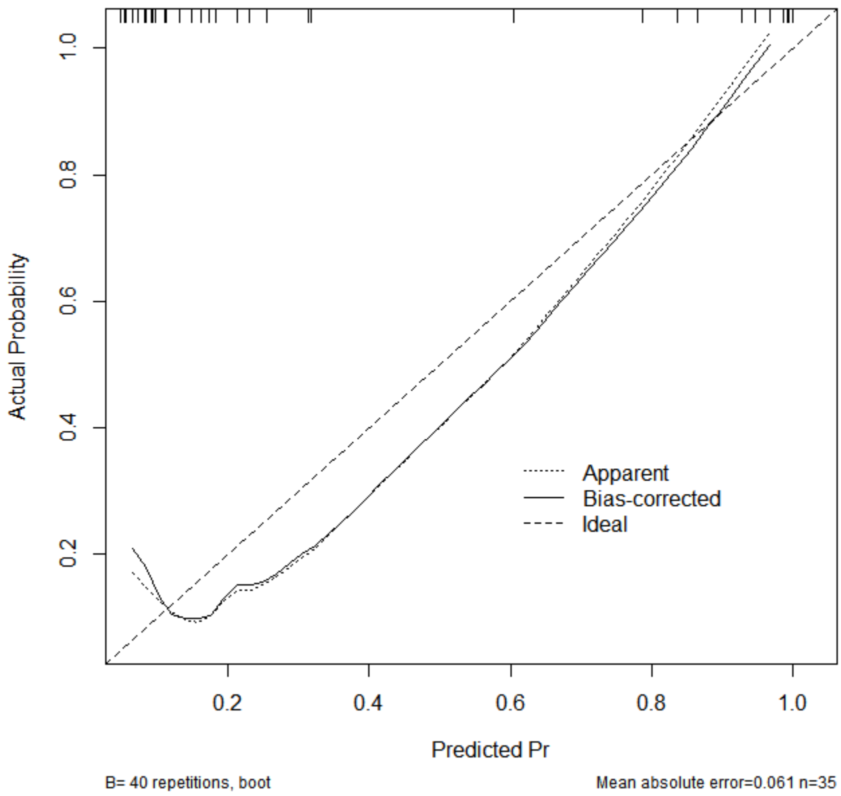

Fig. 3. Calibration curve for the validation set. Note: The slope of the calibration curve is close to 1, indicating that the risk is in good agreement with the actual risk.

- Ensemble Methods: Decision trees and random forests can handle nonlinear relationships and multiple classification problems effectively. However, they tend to be less interpretable than logistic regression.

Elderly patients with post-stroke dysphagia frequently face the risk of dehydration, which poses a serious threat to their rehabilitation and quality of life. To accurately predict and manage this risk, this study employs the GULP method to develop a predictive model for dehydration in these patients. The study investigates factors influencing dehydration risk through comparisons of general data between the modelling and validation groups, as well as through univariate and multivariate analyses.

A dehydration prediction model based on GULP (or other advanced data analysis methods) for elderly post-stroke patients with swallowing dysfunction is highly significant for improving patient care and prognosis assessment. By integrating multiple data sources—such as clinical information, swallowing function assessments, and imaging examinations—this model can accurately predict the risk of dehydration during rehabilitation, enabling timely and effective intervention measures.

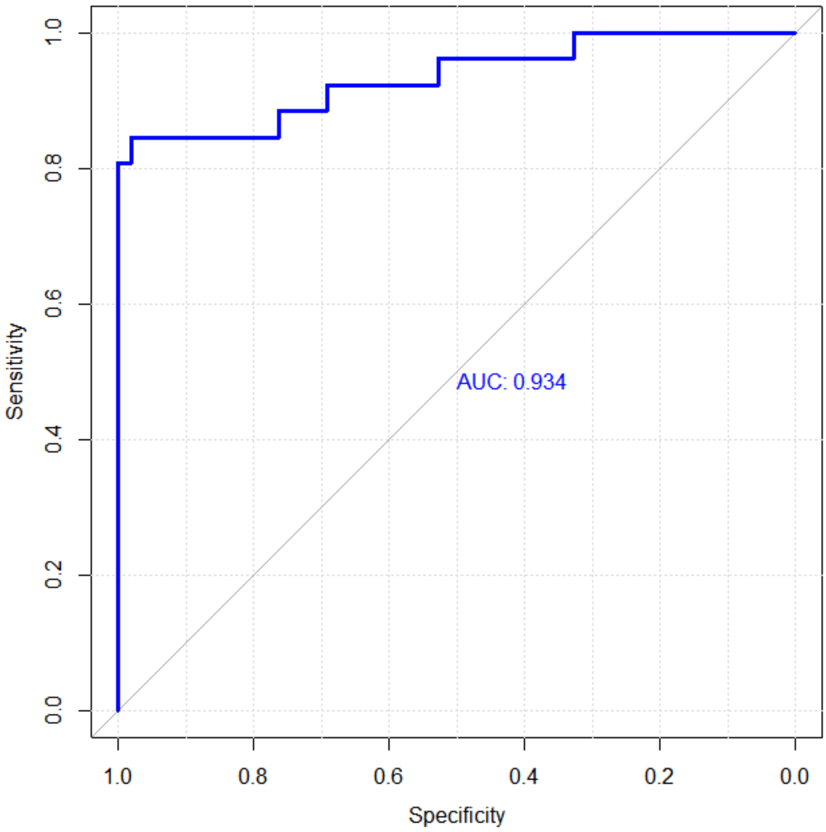

Fig. 4. Receiver operating characteristic (ROC) curve of the training set. Note: The area under the ROC curve is approximately one, indicating that the prediction value is good. AUC, area under the curve.

Mechanism Analysis

Swallowing dysfunction is a common complication following a stroke, impacting patients' food and water intake and increasing the risk of dehydration. Dehydration not only disrupts physiological functions but may also exacerbate neurological damage post-stroke. The model provides a scientific basis for predicting dehydration by elucidating the complex relationship between swallowing disorders and dehydration, and by integrating pathophysiological changes such as decreased saliva secretion and delayed swallowing.

Research Limitations

First, the sample size may be limited, which could restrict the generalizability of the model. Second, the single-centre design might result in a relatively homogeneous patient population, affecting the model's applicability across different medical environments. Additionally, biases and errors in the data collection process could influence the model's accuracy.

Future Research Directions

To enhance the representativeness and generalizability of the model, future research should focus on expanding the sample size and incorporating multi-centre

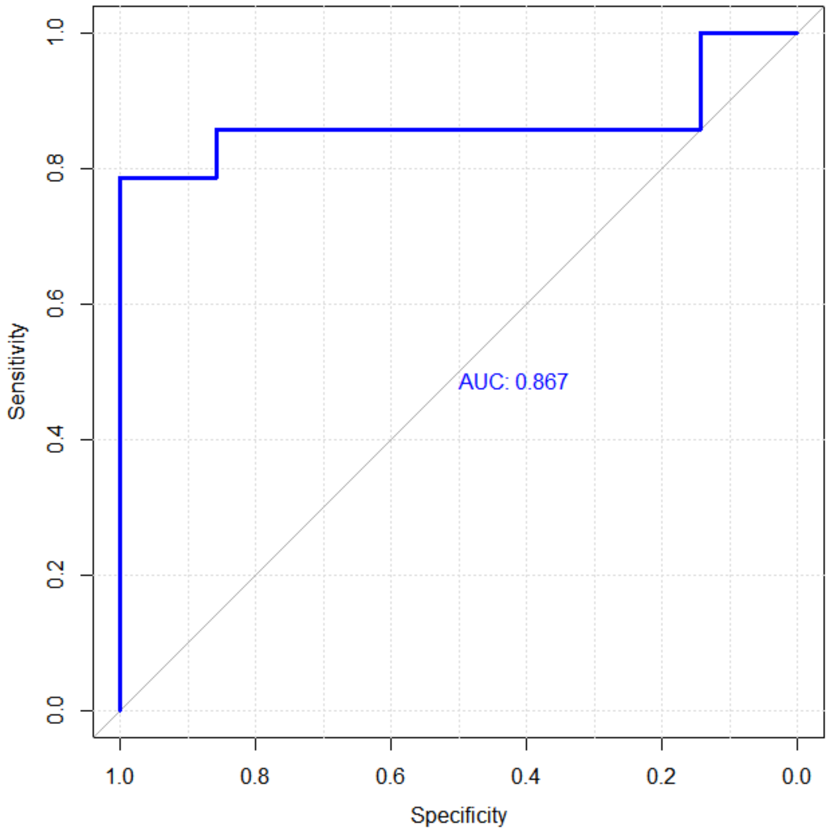

Fig. 5. ROC curve of the validation set. Note: The area under the ROC curve is approximately one, indicating that the prediction value is good.

data. Additionally, employing more advanced data processing technologies and machine learning algorithms can further optimize model performance. Attention should also be given to individual patient differences and dynamic changes, with the development of more personalized prediction models.

Clinical Application Recommendations

The research findings can be directly applied to clinical practice to assist doctors in swiftly identifying high-risk patients and formulating personalized hydration plans and dehydration prevention strategies. Early intervention can help reduce the incidence of dehydration complications, thereby improving patients' quality of life and rehabilitation outcomes. Moreover, this model can serve as a valuable indicator for assessing the recovery and rehabilitation of patients' swallowing function, providing robust support for clinical decision-making.

The results of this study indicated that age, lesion site, muscle strength grade, Hcy levels, and swallowing function score were significantly associated with the risk of dehydration in elderly patients with post-stroke dysphagia, as determined by univariate analysis. This highlights the importance of monitoring these factors when assessing dehydration risk in patients. One reason for these associations may be that, with increasing age, physical functions, including swallowing ability and water metabolism, tend to decline. In older adults, the muscles involved in swallowing, such as those in the mouth, throat, and esophagus, may become weakened, leading to difficulties in swallowing and an increased risk of aspiration and dehydration of food or fluids (Matos et al, 2022). Additionally, decreased kidney function and metabolic rate in the elderly further contribute to a higher susceptibility to water imbalance.

Furthermore, the lesion site and muscle strength grading are crucial indicators for assessing neurological impairment in patients (Tang et al, 2022; Umay et al, 2022). After a stroke, damage to brain areas, particularly those in the brainstem or cerebral cortex that are associated with swallowing, can significantly impact swallowing function (Wang et al, 2022).

In addition, muscle strength grading reflects the degree of neuromuscular impairment in patients. Reduced muscle strength can lead to uncoordinated swallowing movements, resulting in food or liquid retention in the mouth or esophagus, which increases the risk of dehydration (Westendorp et al, 2022; Yang and Pan, 2022). Elevated Hcy levels are often associated with various cardiovascular and cerebrovascular diseases. In elderly patients with post-stroke dysfunction, elevated Hcy levels may indicate the severity and complexity of their condition (Yang and Pan, 2022). High Hcy levels can further exacerbate neurological impairment and swallowing dysfunction by affecting vascular endothelial function, promoting oxidative stress, and triggering inflammatory responses, thereby increasing the risk of dehydration.

Lastly, the swallowing function score is a critical tool for assessing patients' risk of dehydration (Yang et al, 2023). This score directly reflects the status of a patient's swallowing function, including swallowing speed, coordination, and efficiency. A low swallowing score indicates that patients may struggle to effectively transport food or fluids from the mouth to the stomach, leading to inadequate nutrient and water intake and a heightened risk of dehydration (Al Rjoob et al, 2022; Zhuang et al, 2023).

Multivariate logistic regression analysis confirmed that age, lesion location, muscle strength grading, Hcy levels, and swallowing function scores are independent factors influencing dehydration in elderly patients with post-stroke dysphagia. These findings provide a strong foundation for constructing a predictive model.

Model Construction

(1) Variable Selection: The model incorporates age, lesion location, muscle strength grade, Hcy levels, and swallowing function scores.

(2) Weight Scoring: Each variable is assigned a weight score: swallowing function score is the highest (42), Hcy is the second (25), lesion site is the third (15), muscle strength grade is the fourth (10), and age is the lowest (8).

(3) Prediction Mechanism: The model calculates a total score by summing the scores of each variable. This total score corresponds to the probability of poor prognosis (i.e., dehydration).

Clinical Application Value

- Decision Curve Analysis (DCA): The DCA curve (red curve in Fig. 1) evaluates the model's net benefit at various thresholds. The model's clinical application value is indicated by the distance between the red curve and the "none" and "all" lines. A moderate distance suggests the model has some clinical utility.

- Calibration Curve Analysis: The calibration curves for both the training and validation sets demonstrate good agreement between the predicted values and actual outcomes. A calibration curve slope near 1 indicates high reliability for clinical use.

- ROC Curve Analysis: The model shows high predictive performance in both datasets. In the training set, the model achieved an AUC of 0.934 (standard error: 0.034; 95% CI: 0.746–0.921), with an optimal cutoff value of 0.78, yielding a sensitivity of 88.84% and specificity of 90.00%. In the validation set, the AUC was 0.867 (SE: 0.025; 95% CI: 0.694–0.934), with a cutoff value of 0.66, resulting in a sensitivity of 80.16% and specificity of 85.94%. These results indicate high predictive accuracy and generalizability, effectively distinguishing dehydration risk in elderly patients with post-stroke dysphagia.

Compared with other similar studies, this study has several advantages over others in the field. It specifically addresses elderly patients with dysphagia after stroke, a group with urgent health needs (Alvarez-Larruy et al, 2023). The research adopts a comprehensive approach, including demographic characteristics, disease history, and dysphagia severity, ensuring model accuracy and reliability. Advanced statistical methods, such as logistic regression, are utilized for scientific rigor, and the model undergoes thorough validation through cross-validation and independent sample verification. Detailed interpretation of the prediction results provides clinicians with clear and intuitive information, enhancing the model's clinical utility (D'Netto et al, 2023).

If this study creatively employs GULP technology for model construction, it represents a significant advantage. GULP's advanced data processing and modelling capabilities can capture complex data relationships and patterns more accurately, resulting in a more precise and reliable predictive model.

This study's predictive model provides a novel approach for assessing dehydration risk in elderly patients with post-stroke dysphagia. By integrating factors such as age, lesion location, muscle strength grading, Hcy levels, and swallowing function scores, the model can accurately predict the risk of dehydration. However, there are limitations to the model.

Firstly, the limited sample size may affect the model's predictive performance. Future research should aim to expand the sample size to improve the model's accuracy and generalizability. Secondly, the current model considers only clinical data and laboratory indicators, excluding psychological, social, or environmental factors that could also influence dehydration risk. Future studies should explore these additional factors to fully understand their role in the predictive model. Lastly, while the model currently focuses on predicting dehydration risk in elderly post-stroke dysphagia patients, future applications could extend to predicting other complications or evaluating patient rehabilitation outcomes.

In conclusion, factors such as age, lesion location, muscle strength grading, Hcy levels, and swallowing function scores are significantly associated with dehydration risk in elderly post-stroke dysphagia patients. These factors should be closely monitored when assessing dehydration risk, and individualized treatment and management strategies should be developed to minimize this risk. The establishment and validation of this predictive model offer valuable insights for clinical practice, and future research could further refine and enhance the model to better support patient rehabilitation and treatment.

Conclusion

The establishment and verification of the GULP-based dehydration prediction model for elderly patients with dysphagia after stroke highlight its focus on the unique needs of this high-risk population. The innovation lies in the use of GULP to develop predictive models, which offers a more accurate and efficient evaluation tool for clinical practice. The model takes into account specific factors related to dysphagia in elderly stroke patients, ensuring that their unique challenges are fully addressed. Verification results demonstrate the model's high accuracy and practical utility in predicting dehydration risk. This makes the model a valuable resource for clinical decision-making and rehabilitation nursing, potentially serving as an important reference for developing targeted interventions.

Key Points

- In-depth special needs: The research focuses on elderly patients with dysphagia after stroke to deeply explore their dehydration risks and meet the special health needs of this high-risk group.
- Technological innovation application: It innovatively uses GULP technology to build predictive models, improving the accuracy and efficiency of prediction tools.
- Comprehensive consideration of factors: The model construction carefully considers multiple factors related to dysphagia in elderly patients to ensure a comprehensive prediction.
- Excellent verification results: Model verification showed high prediction accuracy and practicality, confirming its reliability in clinical application.
- Clinical decision support: The model provides an important reference for clinicians, assisting in precise decision-making and efficient rehabilitation care.

Availability of Data and Materials

The datasets used and/or analyzed during the current study were available from the corresponding author on reasonable request.

Author Contributions

QZ and YL designed the study. QZ, YL, BW, HYJ, JXZ, ZQ and XD conducted the study. BW and HYJ collected and analyzed the data. JXZ, ZQ and XD participated in drafting the manuscript. All authors contributed to the critical revision of the manuscript for important intellectual content. All authors gave final approval of the version to be published. All authors participated fully in the work, took public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or completeness of any part of the work are appropriately investigated and resolved.

Ethics Approval and Consent to Participate

This study has been approved by the Medical Ethics Committee of Beijing Rehabilitation Hospital Affiliated with Capital Medical University (Approval No.: 2023bkkyLW004). The patient or family member signs informed consent.

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Conflict of Interest

The authors declare no conflict of interest.

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