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Development and Validation of a Clinical Prediction Model for Acupuncture Response in Community-Dwelling Patients with Chronic Low Back Pain: A Retrospective Cohort Study

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Abstract

Objectives: To identify independent risk and protective factors for acupuncture response in community-dwelling patients with chronic low back pain, and to develop and validate a clinical prediction model incorporating traditional Chinese medicine (TCM) diagnostic components, thereby providing a tool for individualized clinical decision-making and risk stratification in community acupuncture practice.

Methods: A total of 500 patients with chronic non-specific low back pain who received acupuncture treatment at the Ningbo Jiangbei Zhuangqiao Community Health Service Center between January 2023 and November 2025 were retrospectively enrolled. Patients were randomly split into a training cohort (n=350) for model development and a test cohort (n=150) for internal temporal validation using a 7:3 ratio. Predictors were selected via LASSO regression, and a multivariable logistic regression model was constructed and presented as a clinical nomogram. SHapley Additive exPlanations (SHAP) analysis was employed to quantify the global importance of features and their directional association with the outcome. Model performance was comprehensively evaluated by assessing discrimination (receiver operating characteristic curve), calibration (calibration curve), clinical utility (decision curve analysis), and generalizability (performance in the internal/external validation sets).

Results: Multivariable analysis identified longer disease duration (OR=1.170), radiating leg pain (OR=1.998), and the Qi-Stagnation-Blood-Stasis syndrome pattern (OR=3.701) as independent risk factors for poor acupuncture response (all $P<0.05$), while acupoint Weizhong (BL40) selection (OR=0.267) and combined therapy (OR=0.214) were independent protective factors. SHAP analysis confirmed disease duration and the Qi-Stagnation-Blood-Stasis pattern as the top contributors to the prediction. The developed nomogram demonstrated excellent discrimination in the training (AUC=0.819), test (AUC=0.828), and external validation (AUC=0.788) cohorts. The model showed good calibration (Hosmer-Lemeshow test $P>0.05$) and provided a clear clinical net benefit across a wide threshold probability range (25%-90%).

Conclusions: This study pioneers the identification of a TCM syndrome pattern (Qi-Stagnation-Blood-Stasis) and acupoint selection as independent predictors for acupuncture response in community-based low back pain management. The developed nomogram, integrating TCM and clinical features, demonstrates robust predictive performance and clinical utility upon rigorous validation. It facilitates personalized treatment strategies, suggesting early intensified intervention (e.g., combined therapy) for high-risk patients characterized by longer disease duration, radiating pain, or specific TCM patterns to optimize outcomes.

Keywords: Chronic Low Back Pain; Acupuncture; Prediction Model; Traditional Chinese Medicine Syndrome Pattern; Nomogram

Introduction

Chronic low back pain (CLBP) is a leading cause of disability worldwide, imposing a substantial burden on patients' quality of life and socioeconomic systems [1]. With its direct and indirect costs estimated to exceed \$100 billion annually in major economies [2], this burden underscores the urgency for efficient treatment strategies. Acupuncture is recommended as a first-line non-pharmacological therapy in evidence-based medicine and is widely used in community healthcare settings [3,4]. Furthermore, the integration of traditional and complementary medicine, including acupuncture, into national healthcare systems aligns with strategic initiatives such as China's Healthy China 2030, which emphasizes holistic and preventive care [5]. However, treatment responses exhibit significant inter-individual heterogeneity, with a considerable proportion of patients failing to achieve clinically meaningful pain relief [6], leading to inefficient resource allocation and diminished patient satisfaction. Specifically, the response rate to acupuncture for CLBP has been reported to be approximately 60% in clinical practice [7]. Current clinical practice largely relies on practitioner experience, lacking quantitative tools for the early and objective identification of potential non-responders [8, 9]. To bridge this gap and enhance personalized care, this study aimed to develop and validate a clinical prediction nomogram for acupuncture response in community-dwelling CLBP patients (PICO: Population = CLBP patients, Intervention = acupuncture, Comparison = N/A, Outcome = $\geq 30\%$ reduction in VAS score).

The application of predictive models in personalized medical decision-making has gained increasing traction [10, 11]. In pain management, studies have explored using clinical characteristics, imaging, or biomarkers to predict outcomes of pharmacological or surgical interventions [12, 13]. Nevertheless, predictive research specifically targeting acupuncture efficacy in community-based CLBP remains scarce. A significant gap exists in developing predictive tools that incorporate characteristic elements of Traditional Chinese Medicine (TCM), such as syndrome differentiation (bianzheng) and acupoint selection principles. TCM theory emphasizes holism and treatment based on syndrome differentiation, considering syndrome patterns and acupoint selection as core factors influencing therapeutic efficacy [14]; however, their quantitative value within modern predictive methodologies has not been sufficiently validated.

This study aims to address this critical gap. Based on a large-scale community acupuncture cohort, we endeavored to develop and validate a predictive model for acupuncture response in CLBP that integrates conventional clinical indicators with TCM diagnostic elements. By employing LASSO regression for high-dimensional variable selection and SHapley Additive exPlanations (SHAP) to enhance model interpretability [15], we sought to overcome limitations inherent in traditional efficacy research, such as inadequate control for confounders and insufficient mechanistic explanation. The resulting nomogram not only retains the statistical rigor of multivariable logistic regression [16] but also offers clinical visualizability and usability. It is intended to provide community TCM practitioners with a practical tool for identifying high-risk non-responders prior to treatment initiation and for guiding individualized intervention strategies, thereby advancing acupuncture practice towards precision and enhanced efficiency.

Materials and methods

Study population

Study subjects: This retrospective cohort study was conducted at the Ningbo Jiangbei Zhuangqiao Community Health Service Center. A total of 723 patients with chronic low back pain were initially assessed for eligibility between January 2023 and November 2025. The patient screening and enrollment process is detailed in Figure 1. Briefly, after applying the inclusion and exclusion criteria, 500 patients diagnosed with chronic nonspecific low back pain (CNLBP) who completed the standardized treatment were ultimately enrolled. These participants were then randomly divided into a training set (n=350) and a test set (n=150) at a ratio of 7:3 for model development and validation, respectively.

Inclusion criteria:

1. Confirmed diagnosis of CNLBP (defined as pain lasting ≥ 3 months without a specific identifiable cause such as infection, tumor, or fracture) [17].
2. Completion of a standardized community acupuncture regimen comprising ≥ 6 treatment sessions.
3. Availability of complete data, including pre- and post-treatment Visual Analogue Scale (VAS) pain scores and baseline clinical characteristics.
4. Age ≥ 18 years.

Exclusion criteria:

1. Presence of specific underlying pathologies causing low back pain (e.g., lumbar disc herniation with radiculopathy, spinal stenosis, spinal infection, or tumor).
2. Failure to complete the defined acupuncture course (< 6 sessions) or absence of key follow-up assessments.
3. Severe comorbidities (e.g., major cardiovascular, cerebrovascular, renal, or psychiatric diseases) that could interfere with treatment compliance or outcome assessment.
4. Concurrent participation in other systematic therapeutic interventions during the study period (e.g., surgery, long-term oral corticosteroid or opioid therapy).

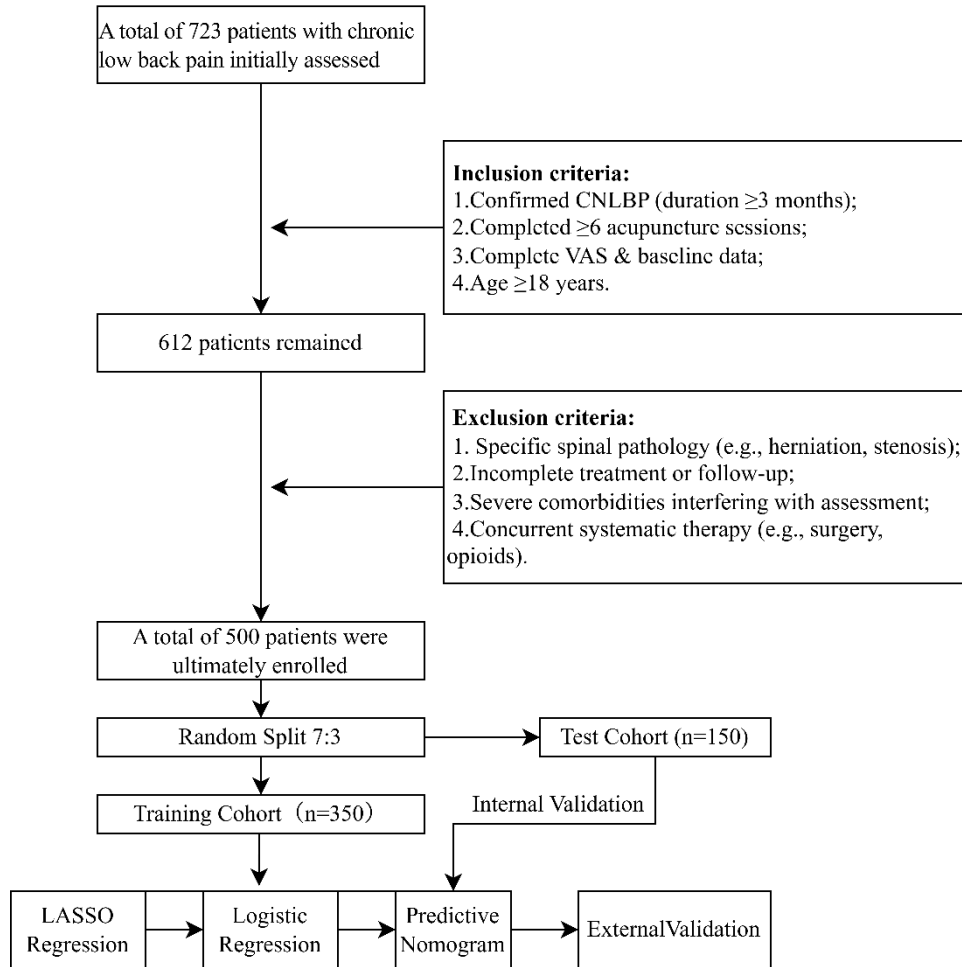


Figure 1. Patient flow and model development diagram according to TRIPOD.

Ethics

This retrospective cohort study was conducted using de-identified data from patients who received treatment at the Zhuangqiao Community Health Service Center, Jiangbei District, Ningbo, between January 2023 and November 2025. The study protocol was reviewed and approved by the Ethics Committee of the Zhuangqiao Community Health Service Center, with the approval number IRB-ZHQ-S-20251215-001, with a waiver of the requirement for informed consent due to the retrospective nature of the study and the use of anonymized data. The study was performed in accordance with the ethical standards outlined in the Declaration of Helsinki and the national ethical guidelines for biomedical research involving human subjects in China. To ensure data security, all analyses were conducted on password-protected computers within a secure hospital network. Data accuracy was ensured by having two researchers independently perform data entry and verification, with any inconsistencies reviewed and resolved by a senior clinician.

Clinical data

A comprehensive set of clinical and traditional Chinese medicine (TCM) diagnostic data was retrospectively collected from 500 patients with chronic nonspecific low back pain who completed

a standardized acupuncture course at the Zhuangqiao Community Health Service Center. The data encompassed the following domains:

1.Demographic and Basic Characteristics: Age, sex, height, body weight, and body mass index (BMI).

2.Clinical Profiles of Low Back Pain: Duration of illness (months), baseline pain intensity measured by the Visual Analogue Scale (VAS, scored 0–10), presence of radiating pain to the lower limb (yes/no), and previous treatment history for low back pain (yes/no).

3. TCM Diagnosis and Treatment Parameters:

- Syndrome Differentiation: TCM pattern diagnosis (categorized as Cold-Dampness Obstruction, Qi-Stagnation and Blood-Stasis, or Liver-Kidney Deficiency), tongue body characteristics, and tongue coating.

- Acupuncture Prescription: Primary acupoints utilized (Shenshu BL23, Dachangshu BL25, Weizhong BL40, Yaoyangguan GV3, Ashi points, Huantiao GB30, Chengshan BL57, each recorded as yes/no), use of electroacupuncture (yes/no), and application of combined therapies (e.g., Tuina, cupping, or moxibustion) during the treatment course (yes/no).

- Treatment Protocol: Total number of acupuncture sessions and treatment frequency (sessions per week).

- Definition of Combined Therapy: For the purpose of this study, “combined therapy” was specifically defined as acupuncture administered in conjunction with one or more of the following adjunctive TCM modalities: Tuina (therapeutic massage), cupping, or moxibustion.

4. Treatment Protocol: The standardized community acupuncture protocol was consistently applied. The primary acupoints included Shenshu (BL23), Dachangshu (BL25), Weizhong (BL40), Yaoyangguan (GV3), Ashi points, Huantiao (GB30), and Chengshan (BL57), with selection guided by syndrome differentiation and meridian theory. For patients receiving electroacupuncture, the following parameters were used: a continuous wave (dense wave) at a frequency of 2-5 Hz. The intensity was individually adjusted to elicit a local *deqisensation* (soreness, distension, numbness, or radiation) accompanied by mild muscle fasciculation, without causing sharp pain. This low-frequency stimulation is supported by evidence for endogenous opioid-mediated analgesia in chronic pain. The treatment course comprised a minimum of 6 sessions. Combined therapy, when applied, consisted of Tuina (using relaxing maneuvers and acupressure on specific points) and/or stationary cupping. These adjuncts were administered according to a fixed schedule of 2-3 sessions per week, with each Tuina session lasting 20 minutes and cupping retention for 8-10 minutes, aligning with the patient's acupuncture sessions.

5. Acupoint Selection Rationale: Acupoint selection followed a standardized protocol based on Traditional Chinese Medicine (TCM) principles to ensure reproducibility. Points were chosen through an integrated strategy: first, according to TCM syndrome differentiation (e.g., Shenshu BL23 for Liver-Kidney Deficiency); second, from meridians traversing the low back, primarily the Bladder and Governor Vessel channels; and third, by including standard local points and tender Ashipoints to address local pain. This approach aimed to treat both the root (*ben*) and branch (*biao*) of the disorder, translating classical theory into a consistent community practice.

6.Outcome Assessment: Post-treatment pain intensity was measured by the Visual Analogue Scale (VAS, 0 – 10). The pre-treatment (baseline) VAS assessment was conducted immediately before the first acupuncture session. The post-treatment VAS assessment was performed at a standardized follow-up visit scheduled within one week after completion of the final treatment

session, to evaluate the immediate treatment effect. The primary outcome was defined as a clinical responder, characterized by a reduction in VAS score of $\geq 30\%$ from baseline upon completion of the treatment course.

Statistical analysis

The overall analytical strategy proceeded sequentially: (1) univariate screening of candidate variables; (2) variable selection via least absolute shrinkage and selection operator (LASSO) regression with 10-fold cross-validation; (3) construction of a multivariable logistic regression model; (4) development and visualization of a clinical nomogram; (5) internal validation using bootstrap resampling; and (6) performance evaluation assessing discrimination, calibration, and clinical utility. All analyses were conducted using SPSS (version 22.0) and R (version 4.2.0). As the complete-case dataset contained no missing values for variables of interest, no imputation was performed. Continuous non-normally distributed variables are reported as median (interquartile range) and compared using the Mann-Whitney U test; categorical variables are presented as counts (percentages) and compared using the Chi-square test. The dataset was randomly split into a training set (70%) and a test set (30%). After confirming negligible multicollinearity (variance inflation factor < 5 for all variables), independent predictors were identified via multivariable logistic regression, with results expressed as odds ratios (ORs) and 95% confidence intervals (CIs). Model discrimination was evaluated using the area under the receiver operating characteristic curve (AUC), calibration was assessed via calibration plots and the Hosmer-Lemeshow test, and clinical utility was quantified via decision curve analysis (DCA). SHapley Additive exPlanations (SHAP) analysis was further employed to interpret feature importance and effect direction. A two-sided p-value < 0.05 was considered statistically significant.

Results

To develop and validate the prediction model, the full dataset was randomly partitioned into a training set (70%, n=350) for model derivation and an independent test set (30%, n=150) for performance evaluation. Baseline demographic, clinical, and treatment characteristics were compared between the two cohorts, confirming no statistically significant differences for any of the assessed variables (all $p > 0.05$; Table 1). The balanced distribution of all key predictors and the primary outcome across the training and test sets establishes a robust foundation for the subsequent modeling analyses and supports the generalizability of the developed model.

Table 1 Comparison of Baseline Characteristics Between Training and Testing Sets

Variable	Training Cohort (n=350)	Test Cohort (n=150)	χ^2/z -value	p-value
Clinical Responder, n (%)			1.008	0.315
Yes	157(44.86)	60(40.00)		
No	193(55.14)	90(60.00)		
Age, years, mean $\pm$ SD	63.12 $\pm$ 12.39	61.95 $\pm$ 11.42	0.993	0.321
Sex, n (%)			1.175	0.278
Male	156(44.57)	59(39.33)		

Female	194(55.43)	91(60.67)		
BMI, median (IQR)	24.13(21.72,25.95)	23.5(21.51,25.95)	-0.517	0.605
Duration, months, median (IQR)	12(6,12)	12(8,16)	-1.000	0.317
Radiating Leg Pain, n (%)			1.866	0.172
No	100(28.57)	34(22.67)		
Yes	250(71.43)	116(77.33)		
Inducing Factor, n (%)			1.731	0.421
Overexertion	327(93.43)	135(90.00)		
Catching Cold	21(6.00)	14(9.33)		
No Obvious Cause	2(0.57)	1(0.67)		
Previous Treatment History, n (%)			0.588	0.443
No	4(1.14)	0(0)		
Yes	346(98.86)	150(100)		
TCM Syndrome Pattern, n (%)			3.552	0.169
Cold-Dampness Obstruction	26(7.43)	19(12.67)		
Qi-Stagnation and Blood-Stasis	196(56)	78(52)		
Liver-Kidney Deficiency	128(36.57)	53(35.33)		
Tongue Body, n (%)			0.024	0.876
Pale	180(51.43)	76(50.67)		
Purplish	170(48.57)	74(49.33)		
Tongue Coating, n (%)			0.699	0.705
Thin White	159(45.43)	63(42.00)		
White Greasy	111(31.71)	53(35.33)		
Yellow Greasy	80(22.86)	34(22.67)		
Acupoint Shenshu (BL23), n (%)			-	0.558
No	3(0.86)	0(0)		
Yes	347(99.14)	150(100)		
Acupoint Dachangshu (BL25), n (%)			1.793	0.181
No	11(3.14)	1(0.67)		
Yes	339(96.86)	149(99.33)		
Acupoint Weizhong (BL40), n (%)			0.122	0.727
No	36(10.29)	17(11.33)		
Yes	314(89.71)	133(88.67)		
Acupoint Yaoyangguan (GV3), n (%)			0.072	0.788
No	5(1.43)	1(0.67)		
Yes	345(98.57)	149(99.33)		
Acupoint Ashi, n (%)			0.363	0.547
No	39(11.14)	14(9.33)		
Yes	311(88.86)	136(90.67)		
Acupoint Huantiao (GB30), n (%)			0.926	0.336
No	64(18.29)	33(22.00)		
Yes	286(81.71)	117(78.00)		
Acupoint Chengshan (BL57), n (%)			2.962	0.085
No	20(5.71)	15(10.00)		

Yes	330(94.29)	135(90.00)		
Electroacupuncture, n (%)			0.000	1.000
No	6(1.71)	3(2.00)		
Yes	344(98.29)	147(98.00)		
Combined Therapy, n (%)			0.129	0.719
No	27(7.71)	13(8.67)		
Yes	323(92.29)	137(91.33)		
Total Sessions, median (IQR)	10(10,12)	10(10,10)	-0.925	0.355
Frequency, sessions/week, median (IQR)	3(3,3)	3(3,3)	-0.283	0.777
Pre-treatment VAS score (IQR)	4(4,5)	4(4,5)	-0.791	0.429
Post-treatment VAS score (IQR)	3(3,3)	3(3,3)	-0.626	0.532

Predictor Selection and Model Development

Univariate Screening of Candidate Predictors

Univariate analysis of the training cohort identified several baseline and treatment-related variables significantly associated with clinical response to acupuncture (all $p < 0.05$; Table 2). The pre-treatment VAS score was significantly lower in responders than in non-responders ($p < 0.001$), and the post-treatment VAS score showed the expected significant reduction in responders ($p < 0.001$). Patient sex was a significant factor ($p = 0.005$), with a higher proportion of females observed in the responder group (63.69%) compared to non-responders (48.7%). Key clinical factors associated with a positive treatment response included a shorter disease duration ($p < 0.001$) and the absence of radiating leg pain ($p = 0.002$). Regarding TCM-specific parameters, the TCM syndrome pattern was a significant predictor overall ($p < 0.001$), with responders showing a distinct profile characterized by a lower proportion of the Qi-Stagnation-Blood-Stasis pattern. Furthermore, treatment parameters including the selection of the Weizhong (BL40) acupoint ($p < 0.001$) and the application of combined therapy ($p < 0.001$) were strongly associated with a positive outcome. In contrast, other demographic characteristics such as age and BMI, along with most other acupoints and treatment parameters, did not show statistically significant univariate associations. This initial screening provided a set of candidate predictors for subsequent analysis.

Table 2 Univariate Comparison of Baseline Characteristics Between Responders and Non-Responders in the Training Cohort

Variable	Clinical Responder (n=157)	Clinical Responder (n=157)	χ^2/z - value	p - value
Age, years, mean $\pm$ SD	63.47 $\pm$ 12.61	62.83 $\pm$ 12.24	0.478	0.633
Sex, n (%)			7.874	0.005
Male	57(36.31)	99(51.3)		
Female	100(63.69)	94(48.7)		
BMI, median (IQR)	24.22(21.76,25.95)	24.03(21.64,25.95)	-0.104	0.917
Duration, months, median (IQR)	7(5,12)	12(10,23)	-8.952	<0.001
Radiating Leg Pain, n (%)			9.777	0.002
No	58(36.94)	42(21.76)		
Yes	99(63.06)	151(78.24)		

Inducing Factor, n (%)			0.436	0.804
Overexertion	148(94.27)	179(92.75)		
Catching Cold	8(5.1)	13(6.74)		
No Obvious Cause	1(0.64)	1(0.52)		
Previous Treatment History, n (%)			0.089	0.766
No	1(0.64)	3(1.55)		
Yes	156(99.36)	190(98.45)		
TCM Syndrome Pattern, n (%)			18.52	<0.001
Cold-Dampness Obstruction	19(12.1)	7(3.63)		
Qi-Stagnation and Blood-Stasis	70(44.59)	126(65.28)		
Liver-Kidney Deficiency	68(43.31)	60(31.09)		
Tongue Body, n (%)			1.278	0.258
Pale	86(54.78)	94(48.70)		
Purplish	71(45.22)	99(51.30)		
Tongue Coating, n (%)			2.042	0.360
Thin White	77(49.04)	82(42.49)		
White Greasy	44(28.03)	67(34.72)		
Yellow Greasy	36(22.93)	44(22.80)		
Acupoint Shenshu (BL23), n (%)			0.000	1.000
No	1(0.64)	2(1.04)		
Yes	156(99.36)	191(98.96)		
Acupoint Dachangshu (BL25), n (%)			0.072	0.789
No	4(2.55)	7(3.63)		
Yes	153(97.45)	186(96.37)		
Acupoint Weizhong (BL40), n (%)			18.474	<0.001
No	4(2.55)	32(16.58)		
Yes	153(97.45)	161(83.42)		
Acupoint Yaoyangguan (GV3), n (%)			0.453	0.501
No	1(0.64)	4(2.07)		
Yes	156(99.36)	189(97.93)		
Acupoint Ashi, n (%)			0.726	0.394
No	15(9.55)	24(12.44)		
Yes	142(90.45)	169(87.56)		
Acupoint Huantiao (GB30), n (%)			0.226	0.635
No	27(17.2)	37(19.17)		
Yes	130(82.8)	156(80.83)		
Acupoint Chengshan (BL57), n (%)			1.966	0.161
No	12(7.64)	8(4.15)		
Yes	145(92.36)	185(95.85)		
Electroacupuncture, n (%)			0.025	0.874
No	2(1.27)	4(2.07)		
Yes	155(98.73)	189(97.93)		
Combined Therapy, n (%)			13.470	<0.001
No	3(1.91)	24(12.44)		

Yes	154(98.09)	169(87.56)		
Total Sessions, median (IQR)	10(10,12)	10(10,10)	-1.414	0.157
Frequency, sessions/week, median (IQR)	3(3,3)	3(3,3)	-1.618	0.106
Pre-treatment VAS score (IQR)	5(4,5)	4(4,5)	-8.436	<0.001
Post-treatment VAS score (IQR)	3(2,3)	3(3,4)	-10.911	<0.001

Variable Selection via LASSO Regression

To refine the candidate predictors identified by univariate analysis and mitigate potential overfitting from the initial set of variables, we performed variable selection using Least Absolute Shrinkage and Selection Operator (LASSO) regression. The results of this analysis are presented in Figure 2. This approach applies a penalty to the regression coefficients, effectively shrinking less contributory variables to zero and retaining a more parsimonious set of robust predictors. Figure 2a shows the LASSO coefficient paths, illustrating the trajectories of the standardized coefficients for the 26 candidate variables as the regularization penalty (λ) increases. The numbers at the top indicate the count of variables retained with non-zero coefficients at specific λ thresholds. Figure 2b displays the ten-fold cross-validation curve for binomial deviance, which was used to determine the optimal λ value. The mean deviance is plotted against $\log(\lambda)$, with the vertical dotted lines corresponding to the λ values achieving the minimum deviance (left) and the largest λ within one standard error of the minimum (right). The lambda.1se criterion ($\lambda = 0.04618$) was selected to favor model generalizability. This process retained six variables with non-zero coefficients for inclusion in the subsequent multivariable model: disease duration, presence of radiating leg pain, the TCM syndrome pattern of Qi-Stagnation and Blood-Stasis, selection of the Weizhong (BL40) acupoint, and application of combined therapy.

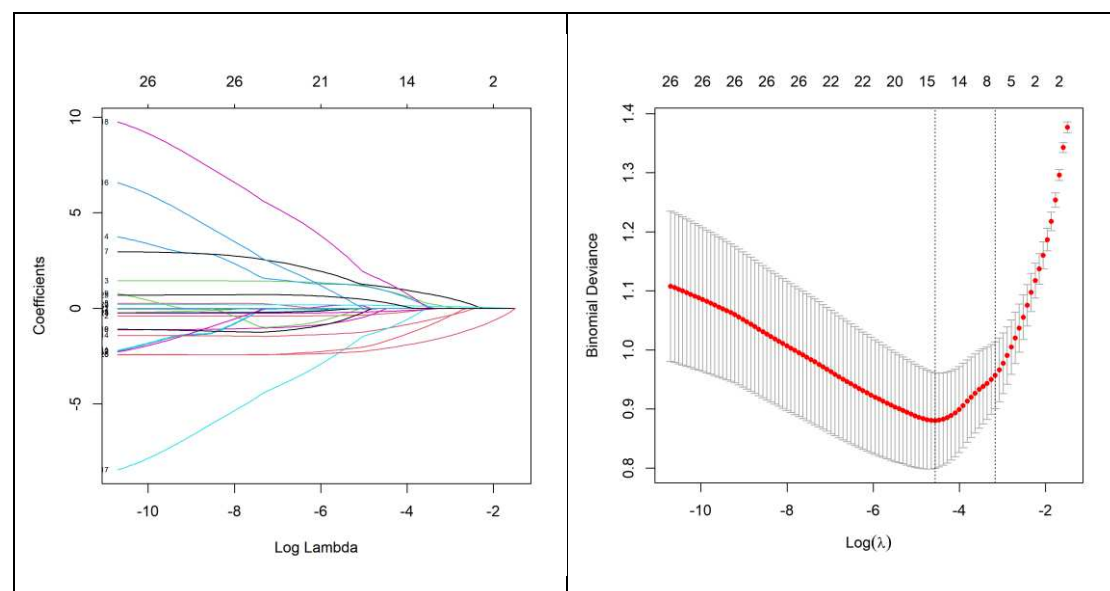


Figure 2a

Figure 2b

Figure 2. Variable Selection and Parameter Tuning via LASSO Regression.

Independent Predictors Identified by Multivariable Analysis

Multivariable logistic regression analysis, performed on the six variables selected by LASSO regression, identified five independent predictors of clinical response to acupuncture in the training cohort (Table 3). The model revealed that for each additional month of disease duration, the odds of being a non-responder increased by 17.0% (OR=1.170, 95% CI: 1.116-1.228, $p<0.001$). The presence of radiating leg pain nearly doubled the odds of poor response (OR=1.998, 95% CI: 1.123-3.552, $p=0.018$). From a TCM perspective, patients with the Qi-Stagnation and Blood-Stasis syndrome pattern had 3.7 times higher odds of being non-responders compared to those with the Cold-Dampness Obstruction pattern (OR=3.701, 95% CI: 1.283-10.670, $p=0.015$). Conversely, the selection of the Weizhong (BL40) acupoint reduced the odds of non-response by 73.3% (OR=0.267, 95% CI: 0.081-0.886, $p=0.031$), and the application of combined therapy reduced the odds by 78.6% (OR=0.214, 95% CI: 0.050-0.917, $p=0.038$). Notably, while sex was significantly associated with outcome in the univariate analysis ($p=0.005$), it was not an independent predictor in the multivariable model after adjusting for other factors (OR=0.635, 95% CI: 0.381-1.060, $p=0.082$). This suggests that the apparent association between sex and treatment response observed initially may have been confounded by its relationship with other variables in the model, such as disease duration or TCM syndrome patterns. Similarly, the Liver-Kidney Deficiency syndrome pattern did not show an independent association with the outcome ($p=0.334$).

Table 3 Multivariable Logistic Regression Analysis for Independent Predictors of Acupuncture Response in the Training Cohort

Variable	B	S.E.	Wald	<i>p</i> -value	OR	95%CI	
						Lower Limit (LL)	Upper Limit (UL)
Sex (Ref: Female)	-0.454	0.261	3.022	0.082	0.635	0.381	1.06
Duration of illness (months)	0.157	0.024	41.625	0.000	1.170	1.116	1.228
Radiating leg pain (Ref: No)	0.692	0.294	5.551	0.018	1.998	1.123	3.552
TCM Syndrome Pattern							
Cold-Dampness Obstruction					1.000		
Qi-Stagnation and Blood-Stasis	1.308	0.5400	5.865	0.015	3.701	1.283	10.67
Liver-Kidney Deficiency	0.531	0.549	0.933	0.334	1.700	0.579	4.99
Acupoint Weizhong (BL40) selected (Ref: No)	-1.319	0.611	4.66	0.031	0.267	0.081	0.886
Combined therapy applied (Ref: No)	-1.544	0.743	4.31	0.038	0.214	0.050	0.917
Constant	0.436	1.122	0.151	0.698	1.546		

Model Interpretation and Clinical Translation

SHAP Analysis for Model Interpretability

To elucidate the decision-making process of the final prediction model, we employed SHapley Additive exPlanations (SHAP) analysis based on the predictors selected by the LASSO regression. The analysis treated the multi-category TCM syndrome pattern as a single, integral feature to assess its overall importance. The resulting summary plot quantifies the relative contribution and directional influence of these predictors (Figure 3).

Disease duration was the most influential feature, accounting for 47.4% of the total predictive contribution, with a high positive SHAP correlation ($r=0.884$), aligning with its role as the

strongest risk factor (OR>1). The TCM syndrome pattern was the second most important contributor (20.0%). Decomposition of its effect revealed that the Qi-Stagnation and Blood-Stasis subcategory exhibited a strong positive association ($r=0.95$), consistent with its significant risk effect in the regression model, while the Liver-Kidney Deficiency subcategory showed a minimal and non-significant influence, corroborating its lack of independent association in the final model. In contrast, features associated with a lower predicted risk of non-response—absence of radiating leg pain ($r=-0.905$, 13.4%), selection of the Weizhong (BL40) acupoint ($r=-0.956$, 9.0%), and application of combined therapy ($r=-0.941$, 8.7%)—showed high negative correlations, visually reinforcing their protective roles (OR<1). Thus, the SHAP analysis not only ranks the global importance of predictors but also, for composite features like TCM syndromes, clarifies the contribution of individual categories, enhancing the interpretability of the model.

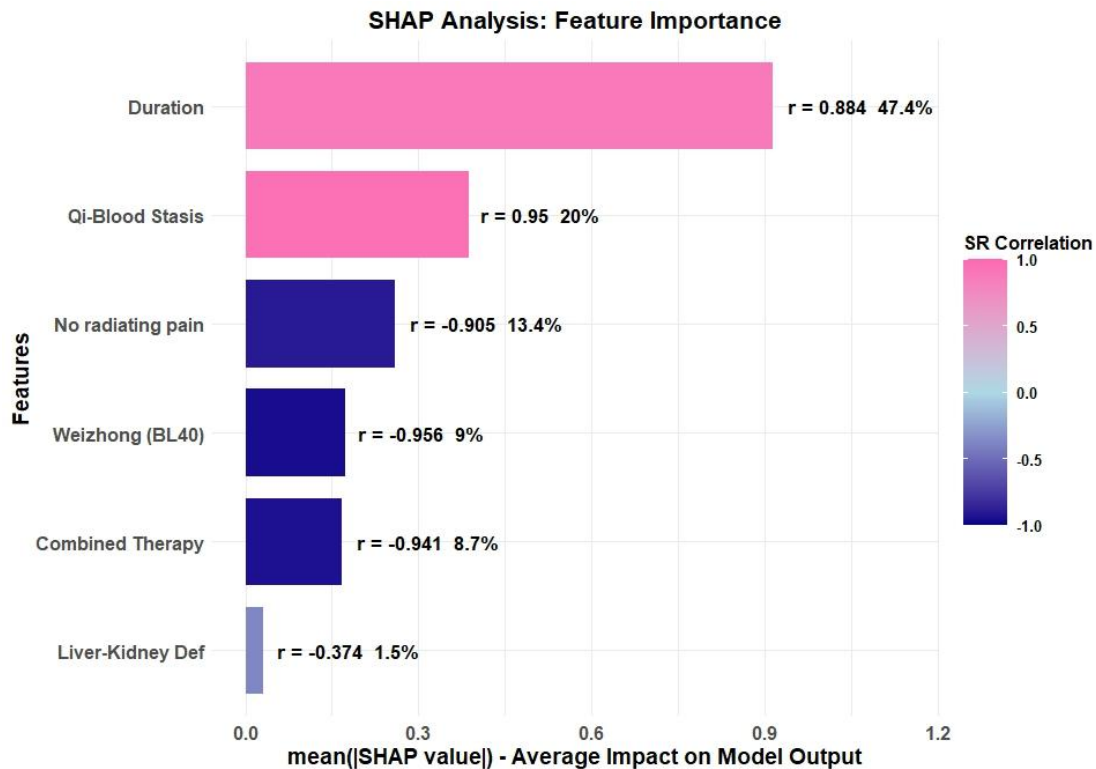


Figure 3. SHAP Feature Importance Analysis for the Acupuncture Response Prediction Model.

Figure 3. SHAP analysis for the acupuncture response prediction model. Bar length represents the mean absolute SHAP value, indicating each predictor's average impact on the model output. Color denotes the direction and strength of the correlation (Spearman's r) between the predictor and the SHAP value: pink for positive (risk) and blue for negative (protective) associations.

Development of a Clinical Nomogram

Based on the five independent predictors identified and interpreted above, we constructed a clinically applicable nomogram to facilitate individualized risk assessment at the point of care (Figure 4). The nomogram visually integrates the predictors in proportion to their relative importance, as quantified by the preceding SHAP analysis. Specifically, it includes: radiating leg

pain (No/Yes), the TCM syndrome pattern (with levels: Liver-Kidney Deficiency, Cold-Dampness Obstruction, Qi-Stagnation-Blood-Stasis), selection of the Weizhong (BL40) acupoint (No/Yes), application of combined therapy (No/Yes), and disease duration (range: 0-40 months). The length of each predictor's scale in the nomogram approximates its contribution to the final risk score, with disease duration—the most influential predictor per SHAP analysis—occupying the longest scale.

To use the nomogram, a clinician locates the patient's status for each predictor on its corresponding axis and draws a line upward to the top “Points” axis to read the assigned score. The sum of these scores yields a “Total Points” (ranging from 0 to approximately 180 on the nomogram). This aggregate score is then projected downward onto the bottom axis, labeled “Risk of Being a Non-Responder,” to obtain the individualized predicted probability, which spans from 0.05 to >0.999. This tool effectively translates the multivariate logistic regression model into a rapid, visual scoring system, enabling pre-treatment identification of patients at high risk for a poor acupuncture outcome.

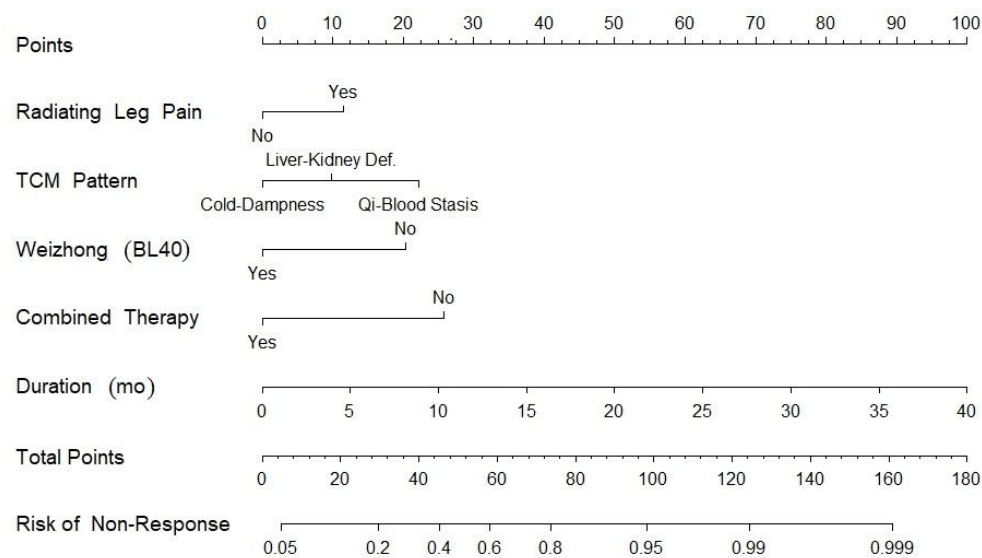


Figure 4. Nomogram for predicting the risk of being a clinical non-responder to acupuncture.

Internal Validation of the Predictive Model

Discriminative Ability (ROC Analysis)

The predictive performance of the nomogram was evaluated using receiver operating characteristic (ROC) analysis (Figure 5) in both the training (Figure 5a) and test (Figure 5b) sets. In the training set, the model demonstrated excellent discriminative ability with an area under the curve (AUC) of 0.819 (95% CI: 0.775-0.863). The test set validation yielded a comparable and robust performance, achieving an AUC of 0.828 (95% CI: 0.762-0.893). Both ROC curves are

accompanied by bootstrap confidence intervals (light blue shading), indicating stable estimation of model performance. The diagonal dashed line represents the reference for a non-informative model (AUC = 0.5). The close agreement between the training and test AUC values confirms the model's robust predictive capability and its generalizability.

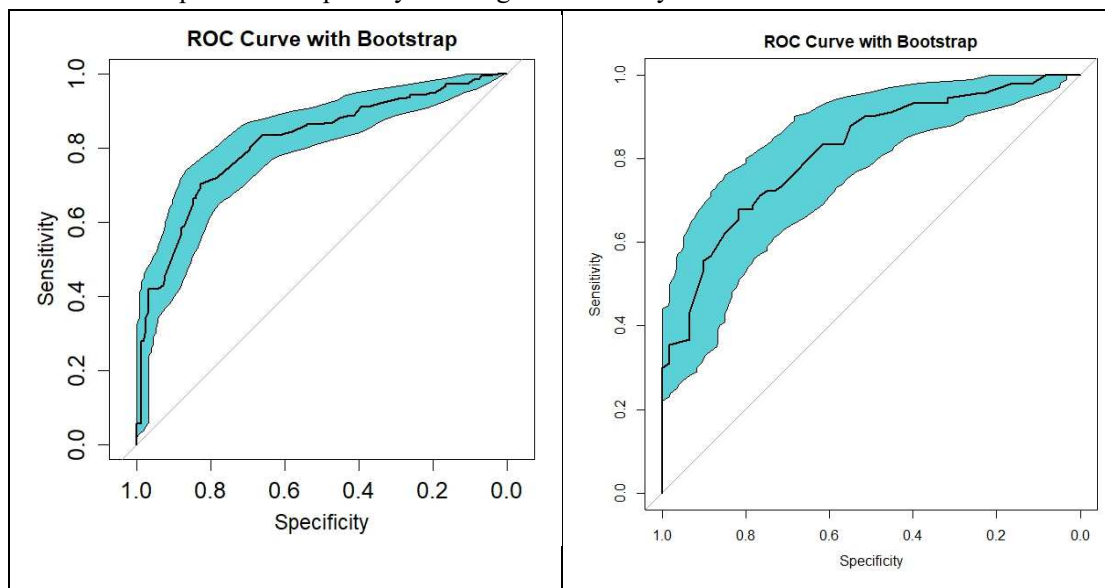


Figure 5a

Figure 5b

Figure 5. Bootstrap-validated ROC curve analysis of the predictive model (training set: 5a; test set: 5b)

Calibration Performance

The calibration curves (Figure 6) illustrate the agreement between the predicted probabilities and the observed frequencies of being a clinical non-responder. In the training set (Figure 6a), the bias-corrected curve closely aligns with the ideal reference line, indicating excellent calibration, with a mean absolute error (MAE) of 0.022 (n=350, bootstrap repetitions=1000). The test set (Figure 6b) also shows good calibration, with a bias-corrected curve that closely follows the ideal line, yielding an MAE of 0.019 (n=150, bootstrap repetitions=1000). Hosmer-Lemeshow goodness-of-fit tests confirmed the calibration accuracy, with non-significant results in both the training ($\chi^2=10.792$, $p=0.214$) and test sets ($\chi^2=3.078$, $p=0.929$), indicating no evidence of poor fit and high model goodness-of-fit. These comprehensive assessments demonstrate that the nomogram provides well-calibrated risk predictions, ensuring its reliability in translating predicted probabilities to actual clinical outcomes.

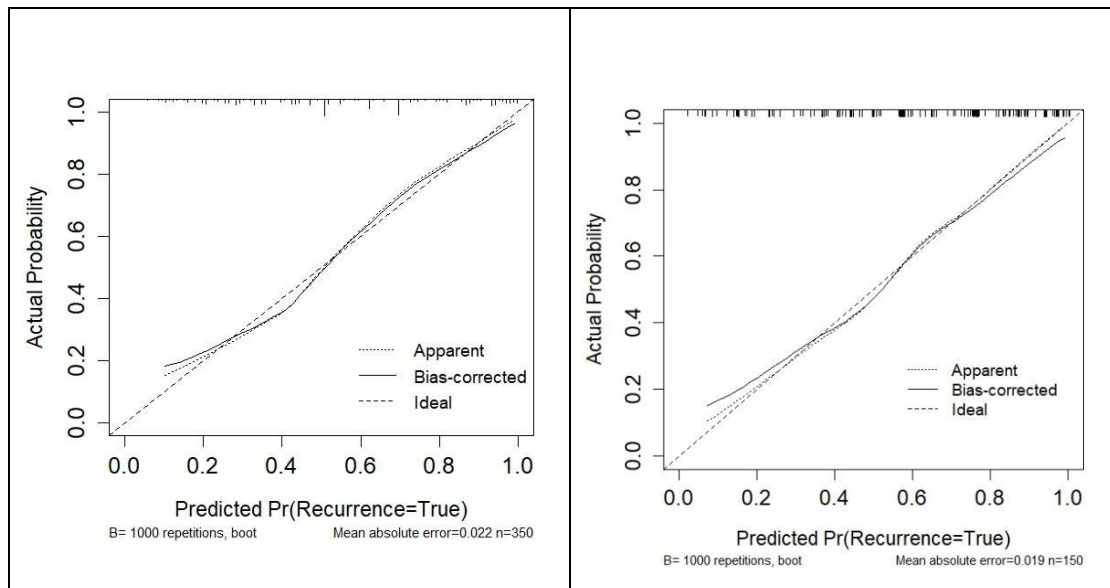


Figure 6a

Figure 6b

Figure 6. Bootstrap-validated Calibration Curve Analysis of the Predictive Model (training set: 6a; test set: 6b)

Clinical Utility (Decision Curve Analysis)

Decision curve analysis (Figure 7) was performed to evaluate the clinical utility of the nomogram across different high-risk thresholds. In the training set (Figure 7a), the nomogram demonstrated superior net benefit compared to the "All" and "None" strategies within a high-risk threshold range of approximately 0.25-0.90. The testing set (Figure 7b) showed consistent performance, with the nomogram maintaining higher net benefit than both reference strategies across a comparable threshold range. In both cohorts, the nomogram's net benefit gradually decreased as the risk threshold increased but remained above the reference curves throughout most intervals. These results indicate that the nomogram provides positive net benefits over a wide range of risk thresholds in both the training and testing populations, supporting its clinical utility for guiding individualized treatment decisions regarding acupuncture for chronic low back pain.

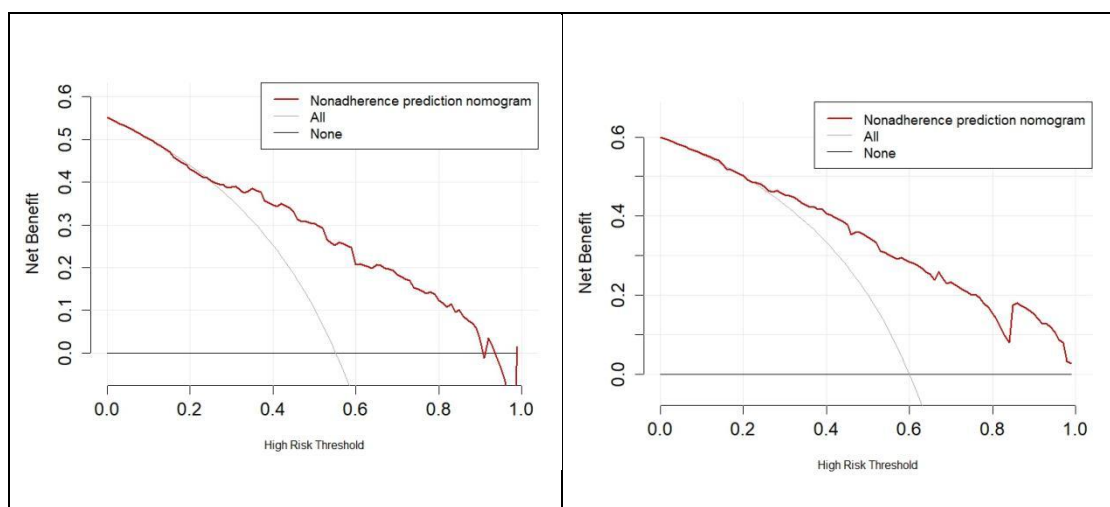


Figure 7a

Figure 7b

Figure 7. Bootstrap-validated Decision Curve Analysis of the Predictive Model (training set: 7a; test set: 7b)

Assessment of Model Robustness via 10-Fold Cross-Validation

The model's stability and generalizability were further evaluated using 10-fold cross-validation. The area under the curve (AUC) for each of the ten folds (Fold01 to Fold10) is presented in Figure 8. The cross-validation procedure yielded a mean AUC of 0.805. The AUC values across all folds were distributed within a narrow range, consistently fluctuating around 0.8. This consistency indicates that the model maintained stable and reliable discriminative performance across different data subsets, demonstrating its robustness without evidence of substantial overfitting or underfitting.

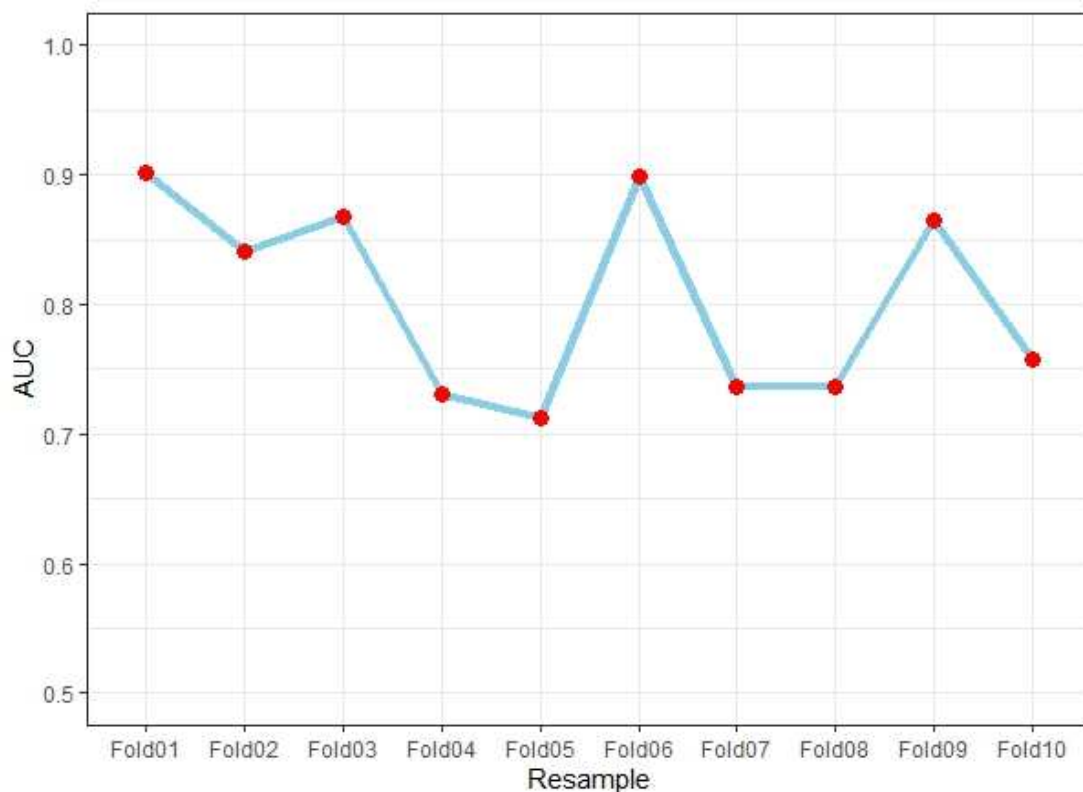


Figure 8: Model accuracy variation across 10-fold cross-validation

External Validation in an Independent Community Cohort

To further assess the generalizability of the developed nomogram, an external validation was performed. We applied the prediction model to an independent cohort of 100 patients with chronic low back pain, who were retrospectively enrolled from two other community health centers, Ningbo Jiangbei Hongtang Community Health Service Center and Ningbo Jiangbei Waitan Community Health Service Center, in the same city according to the same eligibility criteria. All patient data were anonymized prior to analysis. The comprehensive performance of the model in this external cohort is summarized in Figure 9.

Figure 9a presents the receiver operating characteristic (ROC) curve. The model demonstrated good and consistent discriminatory ability, with an area under the curve (AUC) of 0.788 (95% confidence interval: 0.696 to 0.881). The calibration curve (Figure 9b) illustrates the agreement between the predicted probability of being a clinical non-responder and the observed frequency. The bias-corrected curve closely follows the ideal reference line, indicating good calibration. The

Hosmer-Lemeshow goodness-of-fit test showed no evidence of poor fit ($\chi^2 = 12.081$, $p = 0.081$), and the mean absolute error was 0.050, collectively supporting a high level of calibration accuracy. Decision curve analysis (DCA) (Figure 9c) was performed to evaluate clinical utility. The nomogram demonstrated a net benefit superior to the “All” and “None” strategies across a clinically relevant high-risk threshold range of approximately 0.05 to 0.70. Beyond a threshold of approximately 0.8, its net benefit decreased and approached that of the “None” strategy. This indicates that, within a practical decision-making range, using the nomogram provides added clinical value over the strategies of intervening for all or for no patients.

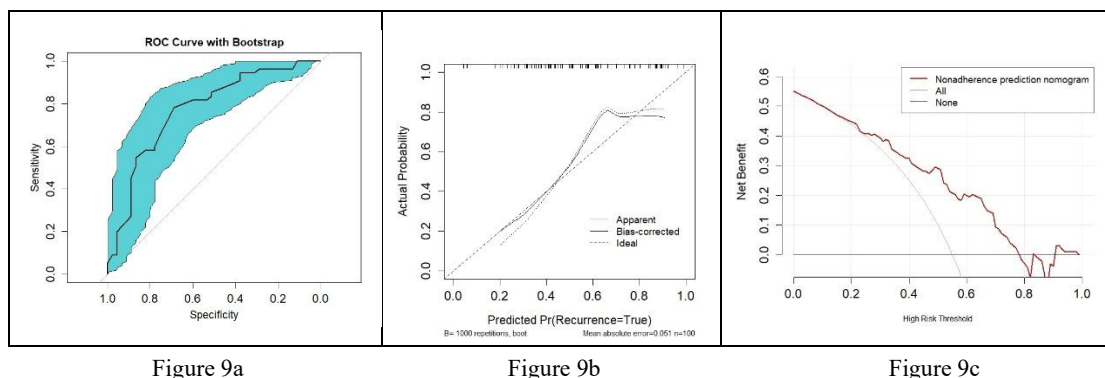


Figure 9. Performance of the nomogram in the external validation cohort. (9a) Receiver operating characteristic (ROC) curve. (9b) Calibration plot. (9c) Decision curve analysis (DCA).

Discussion

Personalized prediction is pivotal for enhancing chronic disease management, with the value of clinical prediction models in this field being widely recognized [18,19]. This first-of-its-kind retrospective cohort study developed and validated a prediction model for acupuncture response in community-dwelling patients with chronic low back pain, utilizing real-world data that integrated TCM diagnostic elements. The model demonstrated excellent discrimination and calibration upon internal validation and was operationalized as a clinical nomogram, effectively translating a complex statistical construct into a practical visual scoring tool [20,21]. Methodologically, the multivariable logistic regression framework was chosen for the final model construction given its optimal suitability for binary outcomes; it provides directly interpretable odds ratios (ORs) for each predictor, which is essential for clinical translation. This choice, following an initial LASSO regression for robust variable selection, balances model parsimony with clinical interpretability. A defining feature of this work is its direct applicability to the community setting, as the cohort was derived solely from routine community health center records, contrasting with most studies based on tertiary hospital populations [22]. This design enhances the relevance and potential implementation of the tool within primary care. Methodologically, the study represents a significant integrative step by quantifying core TCM concepts—specifically, the "Qi-Stagnation and Blood-Stasis" syndrome pattern and the selection of the "Weizhong" (BL40) acupoint—as predictors within a modern modeling framework. These findings align with established TCM theories and provide data-driven validation for their clinical relevance [23,4]. Consequently, this study not only delivers a novel decision-support tool for community acupuncture practice but also

establishes a viable paradigm for conducting integrative, real-world clinical research in traditional medicine.

The clinical and theoretical relevance of the five key predictors identified in this study is well substantiated. Among these, a longer disease duration and the presence of radiating leg pain were independently associated with a poorer response to acupuncture. In the context of chronic pain, increased illness duration is frequently linked to the accumulation of less reversible pathological changes—such as central sensitization and structural tissue alterations—that can diminish the efficacy of monotherapy [24]. Radiating leg pain, often indicative of nerve root involvement, reflects a more complex, likely neuropathic pain mechanism compared with localized back pain; this phenotype is recognized to respond differently to conventional treatments, including acupuncture, and poses a greater therapeutic challenge [25-27]. From a Traditional Chinese Medicine perspective, the "Qi-Stagnation and Blood-Stasis" syndrome pattern, identified as the strongest risk factor, aligns with the classical pathogenesis of "obstruction leads to pain." This pattern signifies significant stagnation of qi and blood with resultant blood stasis, characterizing an excess-type, stubborn condition that typically presents with fixed, pressure-aggravated pain and tends to be chronic and refractory [28-30]. Conversely, the selection of the Weizhong (BL40) acupoint and the use of combined therapy demonstrated clear protective effects. The Weizhong point, a He-Sea point on the Bladder Meridian that traverses the lower back, is historically indicated for back disorders according to the axiom "for back ailments, seek Weizhong." Contemporary evidence supports that stimulation of Weizhong can modulate local circulation and relieve muscular tension, affirming its status as a key point for low back pain [31,32]. Combined therapy, integrating acupuncture with modalities such as tuina or cupping, leverages the holistic principle of TCM, where different interventions act synergistically via multiple pathways—for instance, by releasing adhesions, promoting blood flow, and warming the channels—an effect supported by several studies [33,34]. The confirmation of these two protective factors not only lends empirical support to traditional acupuncture tenets but also offers concrete guidance for refining community-based acupuncture protocols: prioritizing the precise application of efficacious points and advocating for a multimodal treatment strategy.

Beyond the interpretation of key predictors, this study demonstrates clear strengths in its methodological design and clinical translation. First, the analysis is grounded in a real-world community cohort with high ecological validity. All cases were consecutively enrolled from routine outpatient visits, minimizing the referral bias often seen in tertiary care settings where more severe or complex cases are concentrated. This approach enhances the generalizability of the derived prediction rules and ensures that the developed tool is directly applicable to broad primary care practice. Methodologically, the analysis adhered to international reporting standards for clinical prediction model studies and employed robust, transparent analytical strategies [35,36]. The workflow—from handling high-dimensional clinical variables via LASSO regression and constructing a multivariable model, to internal validation using bootstrap resampling and a hold-out test set, and finally to explaining feature contributions with SHAP analysis—was designed to balance predictive performance with interpretability. This comprehensive design ensures the reliability of the conclusions and renders the model's decision logic transparent. A further standout feature is the study's strong orientation toward clinical implementation. Rather than remaining a statistical abstraction, the model was translated into an accessible nomogram for clinicians. Compared to complex algorithms requiring specific computational environments, the nomogram's

intuitive graphical interface allows physicians to perform risk assessment through simple point summation, significantly improving the tool's usability and acceptability in busy community clinics [37,38]. Moreover, preliminary external validation enhances confidence in the model's robustness. Through collaboration with two sister community health centers in the same city, we evaluated the model's performance in an independent patient cohort. Despite the inherent challenges in standardizing community health records, the model maintained good discriminatory ability. This represents an important step beyond internal validation, demonstrating the model's potential generalizability within a similar healthcare context. This cross-institutional validation effort is particularly valuable in the resource-constrained context of primary care research and provides initial evidence to support the future dissemination and application of the tool.

While acknowledging the findings and strengths outlined above, it is important to consider the limitations of this study to appropriately contextualize its conclusions and guide future research. First, the retrospective design inherently determines the level of evidence. Although strict inclusion and exclusion criteria ensured a complete-case dataset with no missing key variables, all data originated from routine clinical documentation. This data source imposes inherent limits on the depth and objectivity of the information captured; for instance, pain scores (VAS) rely on patient self-report, and TCM diagnostic information (e.g., tongue and pulse findings), despite standardized coding, may still be subject to inter-rater variability [39,40]. Second, the model's external validity requires further testing in broader contexts. Although preliminary external validation was conducted through collaboration with two community centers in the same city, all data were sourced from a single municipal healthcare system. The present validation, while supportive, remains retrospective. The model's generalizability and true clinical impact require confirmation through prospective, multi-center studies in diverse healthcare environments—varying in geography, socioeconomic and cultural backgrounds. The model's generalizability across diverse community healthcare environments—varying in geography, socioeconomic and cultural backgrounds, and even health insurance policies—needs to be confirmed by larger, multi-center prospective cohorts. Furthermore, the predictors included in the model are primarily macro-level indicators routinely collected in clinical practice. While this ensures the tool's accessibility and ease of use within current community healthcare settings, it also limits the depth of mechanistic exploration. Future studies that integrate quantitative imaging features of the lumbar spine, objective physiological signals related to pain (e.g., electromyography, infrared thermography), or serum biomarkers could potentially build more powerful integrative models with superior predictive performance and tighter pathophysiological links [41,42]. Finally, this study reflects the common challenges of conducting systematic research in resource-limited community settings. Nonetheless, the successful completion of external validation through cross-institutional collaboration itself represents a valuable experience, contributing to the advancement of clinical research partnerships in primary care practice.

Notwithstanding the aforementioned limitations, the prediction model and its accompanying nomogram developed in this study offer a practical, preliminary pathway toward implementing "precision acupuncture" in resource-constrained community settings. The tool's direct clinical value lies in providing community TCM practitioners with a concise pre-treatment decision-support system. At the initial consultation, clinicians can use it to quickly identify high-risk patients likely to respond poorly to acupuncture alone, thereby enabling the proactive and optimized allocation of limited healthcare resources. For instance, high-risk patients could be

advised to adopt an early, active combination strategy, such as acupuncture integrated with tuina or cupping. Such a risk-stratified, differentiated treatment approach has the potential to enhance the overall efficiency of community acupuncture services and improve patient satisfaction. However, its integration into routine practice should be preceded by prospective validation to confirm its clinical utility and impact.

Looking forward, several clear directions can advance the field. First, a rigorously designed prospective cohort study represents the critical next step to validate and establish the clinical utility of this model, providing a higher level of evidence [43,44]. Second, facilitating the tool's integration into clinical workflow is essential. The current nomogram could be further developed into a mobile application or web-based calculator, or even embedded directly into the electronic health record systems of community hospitals, automating and streamlining the risk assessment process to become a seamless part of routine care [45,46]. Third, efforts to deepen the model's scientific underpinnings are warranted. Building upon the current clinical indicators, future research could incorporate objective functional imaging metrics, such as infrared thermography or surface electromyography, or serum biomarkers associated with pain mechanisms, to construct more powerful multimodal prediction models. This would not only improve predictive performance but also elucidate the biological basis underlying differential responses to acupuncture [47, 48]. Finally, this study underscores both the urgency and the immense potential of strengthening research capacity within community healthcare. Despite numerous challenges, community health institutions are invaluable repositories for generating vast amounts of real-world evidence. By establishing standardized data collection processes, enhancing the research literacy of primary care practitioners, and fostering more cross-institutional collaborations like the one in this study, it is possible to continuously produce high-quality, practice-relevant, localized evidence. This, in turn, can inform and ultimately elevate the overall standard of chronic disease prevention and management at the primary care level [49,50].

Conclusion

This study establishes a clinically actionable framework for predicting acupuncture response in community-dwelling patients with chronic low back pain by integrating five evidence-based predictors—including both conventional clinical factors and core TCM diagnostic elements—into an individualized nomogram. The identification of key risk factors (longer disease duration, radiating leg pain, and the TCM pattern of Qi-Stagnation-Blood-Stasis) and protective factors (selection of the Weizhong acupoint and application of combined therapy) enables pretreatment risk stratification and supports targeted clinical decisions, such as early intervention with multimodal therapy for high-risk individuals. While the model demonstrates robust predictive performance, good calibration, and practical utility in both internal and preliminary external validation, prospective external validation in diverse clinical settings is required to confirm its efficacy and safety before routine clinical implementation. Its broader implementation requires further confirmation through larger, multicenter prospective studies and could be enhanced by the future integration of objective biomarkers. These findings advance the management of chronic low back pain in community acupuncture practice from a standardized, empirical approach toward a more precise, personalized strategy, offering a practical and scalable tool for optimizing treatment protocols in primary care settings.

Declarations

Abbreviations

TCM	Traditional Chinese Medicine
LASSO	Least Absolute Shrinkage and Selection Operator
SHAP	SHapley Additive exPlanations
VAS	Visual Analogue Scale
AUC	Area Under the Curve
OR	Odds Ratio
CI	Confidence Interval
CLBP	Chronic Low Back Pain
CNLBP	Chronic Nonspecific Low Back Pain
BMI	Body Mass Index
DCA	Decision Curve Analysis
ROC	Receiver Operating Characteristic (curve)
IQR	Interquartile Range
SD	Standard Deviation
Ref.	Reference (category)
MAE	Mean Absolute Error
PICO	Population, Intervention, Comparison, Outcome

Ethics approval and consent to participate

This retrospective study was reviewed and approved by the Ethics Committee of the Zhuangqiao Community Health Service Center, Jiangbei District, Ningbo (Approval No. IRB-ZHQ-S-20251215-001). The study was conducted in accordance with the ethical standards of the Declaration of Helsinki and the national ethical guidelines for biomedical research involving human subjects in China. A waiver of written informed consent was granted by the ethics committee due to the retrospective nature of the study and the use of fully anonymized clinical data. All data were analyzed confidentially.

Consent for publication

Not applicable.

Availability of data and materials

All data generated or analysed during this study are included in this published article and its supplementary information files.

Competing Interests

The authors declare no competing interests.

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Authors' contributions

C.W. and J.W. designed the study and wrote the main manuscript text. T.H. and M.Z. curated the data and prepared the figures and tables. All authors reviewed and approved the final manuscript.

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