Research Square

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Elevated stroke risk in socially isolated adults with high cardiometabolic burden and construction of a LASSO-based predictive nomogram

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Research Article

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Abstract

Background

The cardiometabolic index (CMI) and social isolation are well-established risk factors for stroke. However, the relationship between the modified cardiometabolic index (MCMI) and stroke risk in socially isolated populations remains uninvestigated. This study examined whether MCMI constitutes an independent risk factor for stroke among socially isolated individuals.

Methods

Data from four waves of CHARLS were analyzed, focusing on socially isolated participants aged ≥ 45 years (n = 977; mean age = 63.75 ± 9.16 years; stroke incidence = 9.52%). Social isolation was defined as a composite score ≥ 2 out of 4 items. Multiple logistic regression, LASSO regression with 5-fold cross-validation, and generalized additive models were applied. A nomogram was constructed based on LASSO-selected variables and validated using 200 bootstrap replications, with both calibration and discrimination assessed.

Results

Stroke cases exhibited significantly higher baseline MCMI than non-stroke participants (3.02 vs. 2.85, $P < 0.05$). Married participants had a significantly lower stroke incidence than unmarried participants (41.94% vs. 58.06%, $P < 0.05$). A significant positive association between MCMI and stroke was observed exclusively in males (OR: 1.84, 95% CI: 1.08–3.15, $P < 0.05$). LASSO regression identified four predictors: MCMI, marital status, alcohol consumption, and kidney disease. The nomogram demonstrated satisfactory calibration (mean absolute error = 0.005). A nonlinear threshold relationship between MCMI and stroke risk was identified.

Conclusions

MCMI is nonlinearly associated with stroke risk in socially isolated populations, with a significant positive association below the inflection point of 4.06. The LASSO-derived nomogram provides a practical tool for individualized stroke risk assessment.

1. Introduction

According to World Health Organization statistics, stroke is the third leading cause of death globally, resulting in approximately 5 million deaths annually[1], surpassed only by heart disease and cancer[2]. Particularly in low- and middle-income countries, stroke mortality and disability rates are significantly higher. Many patients face long-term functional impairments and reduced quality of life after a stroke[3].

Studies have shown that among survivors, approximately 40% experience disabilities of varying degrees, severely affecting their daily living and social participation[4]. The pathogenesis of stroke is complex. Beyond traditional risk factors such as hypertension, diabetes, and hypercholesterolemia, an increasing body of research is focusing on the impact of social factors on stroke risk.

Social isolation refers to a reduction in an individual's connection with their social environment, manifested as a lack of social interaction and support. In modern society, social isolation is becoming increasingly prevalent, especially among the elderly population. Loneliness and social isolation may lead to higher health risks, including mental health issues and psychosomatic disorders[5]. Research indicates that social isolation not only affects mental health but is also closely linked to serious health problems like cardiovascular disease and stroke[6].

The modified Cardiac Metabolic Index (MCMI) is emerging as a novel biomarker with promising potential for assessing cardiovascular health and stroke risk. The Cardiac Metabolic Index (CMI) evaluates an individual's cardiometabolic health status. CMI is typically calculated by combining measures of abdominal obesity and lipid levels, reflecting an individual's cardiometabolic risk. Studies have demonstrated that CMI is closely associated with the risk of developing cardiovascular disease (CVD), particularly among middle-aged and older adults[7]. High CMI values are generally correlated with an increased risk of cardiovascular events, highlighting its importance in cardiometabolic health assessment. Furthermore, changes in CMI are also linked to improvements in cardiac function and reductions in cardiovascular risk, underscoring its potential value in clinical applications[8].

In recent years, an increasing number of epidemiological studies have begun to examine the role of social isolation in stroke incidence. Their findings indicate a significant correlation between social isolation and stroke risk. Some research has found that individuals experiencing social isolation have a 64% increased risk of stroke[1]. Additionally, social isolation may indirectly elevate stroke risk by affecting mental health, such as contributing to depression[9]. Therefore, investigating the relationship between the modified Cardiac Metabolic Index and stroke among socially isolated populations can provide scientific evidence for formulating public health policies and intervention strategies. This not only contributes to understanding the pathogenesis of stroke but may also offer new avenues for stroke prevention and intervention.

2. Method

2.1. Study Design and Population

The China Health and Retirement Longitudinal Study (CHARLS) is a nationally representative interdisciplinary cohort study conducted by the National School of Development at Peking University. Its primary objective is to collect high-quality longitudinal microdata on households and individuals aged 45 years and older in China, facilitating research into health, socioeconomic status, and their dynamic changes in the context of population aging. Initiated in 2011, the baseline survey employed a multistage

stratified probability-proportional-to-size (PPS) sampling design, encompassing 150 county-level units and 450 villages/communities across 28 provinces. CHARLS collects comprehensive data across multiple domains, including: health status (self-rated health, chronic conditions, physical/cognitive/psychological function, biomarkers, healthcare utilization); socioeconomic characteristics (household structure, income/expenditure, assets, pensions, insurance coverage, employment/retirement status, intergenerational transfers); work and retirement patterns; and community-level environments. Follow-up surveys have been conducted in 2013, 2015, 2018, and 2020 (with additional waves planned), forming a longitudinal panel dataset invaluable for investigating healthy aging, retirement behaviors, social security systems, intergenerational relationships, and health disparities. The study protocol received approval from the Biomedical Ethics Review Committee of Peking University (IRB approval number: IRB00001052-11015), and all participants provided written informed consent.

For this retrospective cohort analysis, we utilized data from four waves (2011 baseline, 2013, 2015, and 2018) of the CHARLS study. The initial cohort comprised 17,705 participants. Participants were excluded according to the following criteria:(1) age < 45 years or missing baseline age data;(2) missing critical baseline variables (gender, educational attainment, marital status, residential status, smoking/alcohol consumption history, or medical history of diabetes/liver/kidney disease);(3) prevalent stroke at baseline (2011) or missing follow-up data during 2013–2018;(4) missing baseline MCMI (Mild Cognitive Impairment) assessment data;(5) absence of social isolation or missing social isolation metrics. After applying exclusion criteria—individuals aged < 45 years (n = 602), missing age data (n = 173), baseline stroke history (n = 633), missing MCMI data (n = 4,801), absence of social isolation/missing isolation data (n = 5,293), and loss to follow-up (n = 5,226)—the analytical sample consisted of 977 participants (see Fig. 1 for participant flow diagram).

2.2. Definitions of MCMI

The Modified Cardiometabolic Index (MCMI) was calculated as: ln [TG (mg/dL) × fasting blood glucose (mg/dL) / HDL-C (mg/dL)] × WC (cm) / height (cm). The Cardiometabolic Index (CMI) was calculated using: TG (mmol/L) / HDL-C (mmol/L) × WC (cm) / height (cm).

2.3. Assessment of Social Isolation

Social isolation was assessed using self-reported baseline questionnaires within the CHARLS survey. Participants received one point for each of the following criteria met: (1) unmarried status (including separated, divorced, widowed, or never married), (2) living alone, (3) contacting children less than once per week (via phone, in-person, or email), or (4) reporting no participation in social activities during the preceding month (e.g., interactions with friends, games, sports, or social clubs). A composite isolation index (range: 0–4 points) quantified severity, with scores ≥ 2 defining the socially isolated group.

2.4. Covariates

The following baseline covariates were included: age, gender (male, female), educational attainment (illiterate, middle school and below, bachelor degree or above), marital status (married or living with a partner, living alone), family residence (rural village, urban community), smoking, drinking, diabetes, liver disease and kidney disease.

2.5. Outcome

Acute stroke was identified through follow-up surveys conducted in 2013, 2015, and 2018. Participants were asked: "Has a doctor ever diagnosed you with a stroke (including cerebral infarction or intracerebral hemorrhage)?" A participant was classified as an incident stroke case upon reporting a new physician-diagnosed stroke during any follow-up wave. Individuals with a self-reported stroke diagnosis prior to the 2011 baseline were retrospectively excluded.

2.6. Statistical Analysis

Continuous variables were presented as mean ± standard deviation (SD); categorical variables were reported as frequencies and percentages. Baseline characteristics were compared using independent samples *t*-tests (continuous variables) or chi-square tests (categorical variables). We constructed multivariate linear regression models to evaluate the association between MCMI and stroke. Three statistical models were established: Model 1, Unadjusted; Model 2, adjusted for age, gender, residence, marital status, and education; Model 3, additionally adjusted for smoking status, alcohol consumption, diabetes, and history of liver or kidney disease. A smooth curve fitting plot explored potential nonlinearity in the relationship between MCMI and stroke probability. Subsequent threshold effect analysis identified potential inflection points. Segmental linear regression was then performed: Model I estimated the linear effect size across the entire MCMI range, while Model II derived segment-specific effect sizes above and below the identified inflection point. Statistical significance was defined as a p-values < 0.05. Least absolute shrinkage and selection operator (LASSO) regression was employed for candidate predictor selection. The optimal penalty parameter λ (lambda.1se) was determined via 5-fold cross-validation. An L1 penalty was applied to 11 candidate variables (MCMI, age, gender, family residence, marital status, education level, smoking, alcohol consumption, diabetes, liver disease, and kidney disease), with regression coefficients shrunk toward zero to achieve variable selection. All analyses were performed using EmpowerStats software (version 4.2; http://www.empowerstats.net/analysis) and R (version 4.4.2) statistical software (R - project, Vienna, Austria).

3. Results

3.1. Baseline characteristics and sample description

The final analytical cohort comprised 977 participants. Baseline characteristics stratified by stroke status are presented in Table 1. No statistically significant differences were observed between groups regarding age, gender, family residence, education level, smoking, drinking, diabetes, liver diseases or kidney diseases (p > 0.05). Participants who developed incident stroke demonstrated significantly higher

baseline MCMI compared to those without stroke (3.02 ± SD vs. 2.85 ± SD, $p < 0.05$). Additionally, married participants exhibited a significantly lower incidence of stroke compared to the participants who living alone (41.94% vs. 58.06%, $p < 0.05$).

Table 1
Baseline characteristics of the non-stroke and stroke participants

Variable		Overall	Non-stroke	Stroke	95%CI	P-value
N		**977**	**884**	**93**		
Age (Mean ± SD)		63.75 ± 9.16	63.60 ± 9.29	65.18 ± 7.74	0.18(-0.03,0.40)	0.114
Gender (%)					0.02(-0.19,0.23)	0.863
	Male1	412 (42.17%)	372(42.08%)	40(43.01%)		
	Female 0	565(57.83%)	512(57.92%)	53(56.99%)		
MCMI (Mean ± SD)		2.87 ± 0.68	2.85 ± 0.68	3.02 ± 0.68	0.24(0.03,0.46)	0.026
Family residence (%)	Rural Village	723(74.00%)	658(74.43%)	65(69.89%)		0.342
	Urban Community	254(26.00%)	226(25.57%)	28(30.11%)		
Marital (%)					0.27(0.05,0.48)	0.015
	married or living with a partner	527(53.94%)	488(55.20%)	39(41.94%)		
	living alone	450(46.06%)	396(44.80%)	54(58.06%)		
Education level (%)					0.08(-0.13,0.30)	0.743
	illiterate	627(64.18%)	564(63.80%)	63(67.74%)		
	Middle school and below	340(34.80%)	311(35.18%)	29(31.18%)		
	bachelor degree or above	10(1.02%)	9 (1.02%)	1(1.08%)		
Smoking (%)					0.06(-0.15,0.27)	0.576

Abbreviations: OR, Odds ratio; CI, confidence interval.

Variable		Overall	Non-stroke	Stroke	95%CI	P-value
N		**977**	**884**	**93**		
	No	604(61.82%)	549(62.10%)	55(59.14%)		
	Yes	373(38.18%)	335(37.90%)	38(40.86%)		
Drinking (%)					0.13(-0.09,0.34)	0.238
	No	622(63.66%)	568(64.25%)	54(58.06%)		
	Yes	355(36.34%)	316(35.75%)	39(41.94%)		
Diabetes (%)					0.01(-0.21,0.22)	0.943
	No	926(94.78%)	838(94.80%)	88(94.62%)		
	Yes	51(5.22%)	46(5.20%)	5 (5.38%)		
Liver disease (%)					0.07(-0.15,0.28)	0.514
	No	946(96.83%)	857(96.95%)	89(95.70%)		
	Yes	31(3.17%)	27(3.05%)	4 (4.30%)		
Kidney disease (%)					0.18(-0.03,0.40)	0.059
	No	916(93.76%)	833(94.23%)	83(89.25%)		
	Yes	61(6.24%)	51(5.77%)	10(10.75%)		

Abbreviations: OR, Odds ratio; CI, confidence interval.

3.2. Association between MCMI and stroke

Unadjusted analysis showed significantly higher MCMI in stroke cases, with a strong positive correlation between stroke and elevated MCMI ($p < 0.05$). After adjusting for age, gender, family residence, marital status, and education level (Model 2), the positive association remained significant ($p < 0.05$). Further adjustment for smoking, drinking, diabetes, liver diseases and kidney diseases (Model 3) stabilized the association, with enhanced statistical significance ($p < 0.05$) (Table 2).

Table 2
Relationship between MCMI and Stroke

Variables	Model1		Model2		Model3	
	OR (95%CI)	P-value	OR (95%CI)	P-value	OR (95%CI)	P-value
Non-stroke	0		0		0	
Stroke	0.17(0.02.0.31)	0.0256	0.16(0.02,0.29)	0.0275	0.16(0.02.0.29)	0.0221
Abbreviations: OR, Odds ratio; CI, confidence interval.						
Model1: didn't adjust for confounding factors						
Model2: adjusted for age, gender, family residence, marital, education level.						
Model3: adjusted for age, gender, family residence, marital, education level, smoking, drinking, diabetes, liver disease, kidney disease.						

3.3. Subgroup analysis by gender

Significant gender differences were observed in the MCMI-stroke association (Table 3). Among males, higher baseline MCMI was significantly associated with increased stroke risk in both unadjusted (OR: 1.84; 95% CI: 1.08–3.15; $p < 0.05$) and fully adjusted models (OR:2.01; 95% CI: 1.13–3.56; $p < 0.05$). In contrast, no significant association was observed among females (OR: 1.30; 95% CI: 0.88–1.92; $p = 0.19$).

Table 3
Relationship between MCMI and Stroke by gender groups

Variables	Gender							
	Male				Female			
	Model1		Model2		Model1		Model2	
	OR (95%CI)	P-value	OR (95%CI)	P-value	OR (95%CI)	P-value	OR (95%CI)	P-value
MCMI	1.84(1.08–3.15)	0.0252	2.01 (1.13–3.56)	0.0169	1.30 (0.88–1.92)	0.1899	1.30 (0.84–1.99)	0.2380
Abbreviations: OR, Odds ratio; CI, confidence interval.								
Model1: didn't adjust for confounding factors								
Model2: adjusted for age, family residence, marital, education level, smoking, drinking, diabetes, liver disease, kidney disease.								

3.4. Nonlinear relationship exploration

A significant nonlinear relationship between baseline MCMI and stroke risk was identified (log-likelihood ratio test, $p = 0.027$), with a piecewise regression model demonstrating superior fit compared to a simple linear model (Table 4). A two-segment linear regression model was fitted, identifying an inflection point at 4.06 via recursive analysis. Bootstrap resampling confirmed the threshold confidence interval. The relationship exhibited a reverse U-shaped curve, with a threshold effect at MCMI = 4.06(Fig. 2). Below the inflection point (MCMI < 4.06), each unit increase in MCMI was associated with an 84% increased risk of stroke (OR: 1.84; 95% CI: 1.23–2.74; $p = 0.0028$). Above the inflection point (MCMI>4.06), the association was non-significant and reversed in direction (OR: 0.10; 95% CI: 0.00–3.18; $p = 0.1933$), corresponding to a 90% relative risk reduction per unit increase, though this did not reach statistical significance.

Table 4
The results of the two-piecewise linear regression model (Independent variable is MCMI; the dependent variable is Stroke)

Outcome	**Stroke**	
	OR (95%CI)	**P-value**
Fitting by weighted linear regression model	1.48(1.06–2.07)	0.0223
Fitting by the weighted two-piecewise linear regression model		
Inflection point	4.06	
<4.06	1.84(1.23–2.74)	0.0028
>4.06	0.10 (0.00, 3.18)	0.1933
log-likelihood ratio test	0.027	
Abbreviations: OR, Odds ratio; CI, confidence interval.		

3.5. LASSO Regression Variable Selection and Nomogram Development

LASSO regression was applied to screen 11 candidate variables, with lambda.1se selected as the optimal penalty parameter. Of the 11 variables, 8 had their coefficients shrunk to zero, and 3 independent predictors were retained: MCMI (coefficient = 0.120), marital status (coefficient = − 0.220), and kidney disease (coefficient = 0.217). The coefficient for alcohol consumption was negligible (0.007) and contributed minimally to the model. Based on these selected variables, a nomogram prediction model was developed using logistic regression (Fig. 3). The nomogram demonstrated that MCMI contributed the greatest number of points, followed by kidney disease and marital status. The total point range was 0 to 160, corresponding to predicted stroke probabilities of 5% to 30%. Bootstrap internal validation (B = 200 repetitions) showed that the bias-corrected calibration curve closely approximated the ideal diagonal, with a mean absolute error of 0.005, indicating satisfactory calibration performance of the model (Fig. 4).

4. Discussion

This study documented that 93 participants (9.5%) experienced a stroke during the 7-year follow-up period. Notably, among socially isolated individuals, the Modified Cardiometabolic Index (MCMI) showed a significant positive association with stroke incidence, while married participants exhibited a lower stroke risk. Stratified analysis revealed a particularly strong correlation between MCMI and stroke in male participants, with an unadjusted odds ratio (OR) of 1.84 [95% confidence interval (CI): 1.08–3.15]. This association remained statistically significant after adjusting for relevant covariates, with an adjusted OR of 2.01 [95% CI: 1.13–3.56]. A key innovation of this research was the identification of a significant non-linear relationship between MCMI and stroke risk (log-likelihood ratio test P = 0.027), demonstrating that a piecewise regression model better captures this association than a simple linear model. Specifically, within the lower range of MCMI values, there was a pronounced positive correlation between MCMI and stroke risk, providing a critical foundation for developing early clinical intervention strategies.

Stroke continues to rank among the leading causes of global mortality and disability, characterized by a complex pathogenesis involving multiple risk factors. Established major risk factors—including hypertension, hypercholesterolemia, diabetes, and smoking—have demonstrated consistent associations with stroke across diverse populations[10, 11]. Hypertension elevates stroke risk through multiple mechanisms, such as promoting arterial stiffness, vascular wall thickening, and endothelial dysfunction[10]. The strength of its association with stroke increases with advancing age[12]. Diabetes mellitus acts as an independent risk factor, elevating stroke risk by 1.5 to 3 times compared to non-diabetic individuals[13], via mechanisms including accelerated atherosclerosis, increased blood viscosity, and impaired endothelial function[14]. Notably, diabetic patients exhibit poorer post-stroke outcomes, with higher rates of recurrence and mortality than non-diabetic counterparts [15]. Elevated cholesterol levels not only exacerbate atherosclerotic burden but also potentiate stroke risk through inflammatory pathways and endothelial dysfunction. Smoking has been firmly linked to increased stroke incidence and unfavorable post-stroke prognosis[16].

Recent advances in stroke etiology research have identified a range of emerging risk factors—including psychosocial factors, metabolic syndrome, and biomarkers—that may play pivotal roles in stroke pathogenesis. For example, psychosocial factors such as depression and anxiety have been linked to increased stroke risk, particularly among women and older adults[17]. Concurrently, metabolic syndrome substantially elevates stroke risk, especially in individuals with obesity and dysglycemia[12]. Metabolic syndrome serves as a robust predictor of stroke risk, given that its components (e.g., hypertension, hyperglycemia, dyslipidemia) are each independently associated with stroke. Studies show that patients with metabolic syndrome have significantly higher stroke recurrence rates than those without[18]. The Modified Cardiometabolic Index (MCMI) integrates lipid profiles, glycemic markers, and anthropometric measures to reflect visceral adiposity, insulin resistance, and dyslipidemic processes underlying endothelial dysfunction, atherosclerosis, and thrombosis. By synthesizing clinical indicators such as plasma triglycerides, high-density lipoprotein cholesterol (HDL-C), and waist-to-height ratio (WHtR), it

provides a comprehensive assessment of cardiometabolic health. Recent studies using advanced methodologies like machine learning and multivariate regression have further enhanced the predictive capacity and clinical utility of cardiometabolic indices (CMIs)[19]. Research indicates a strong association between CMI and stroke risk, with higher CMI values correlating with increased stroke incidence—particularly in individuals with metabolic syndrome[20], which aligns with the significant positive association observed between MCMI and stroke risk in this study. CMI monitoring offers critical clinical insights for stroke prevention and early intervention, thereby improving patient outcomes[20, 21]. As such, MCMI serves not only as a vital tool for assessing cardiometabolic health but also as a key indicator for stroke risk management.

The role of other emerging risk factors—including psychological stress, social isolation, sleep disturbances, and dietary habits—in stroke pathogenesis is gaining recognition, though their underlying mechanisms remain under investigation. These factors may indirectly increase stroke risk by activating the sympathetic nervous system and endocrine responses, leading to elevated blood pressure and glycemic fluctuations [22]. Social isolation is defined as an objective lack of social contacts and/or a state of loneliness, characterized by sparse social connections that negatively impact emotional, psychological, and physical health.

Well-documented effects of social isolation on mental health include significant associations with depression, anxiety, and other psychiatric disorders, with increased loneliness strongly linked to declining mental well-being[5]. Additionally, social isolation may adversely affect cognitive function, increasing the risk of cognitive decline—particularly in older adults[23]. Thus, interventions to promote social engagement and support networks are critical for improving mental health[24]. Beyond mental health, social isolation is significantly associated with physical health outcomes. Research has linked it to an increased risk of chronic diseases, including cardiovascular disease and stroke[9], and it may exacerbate health issues by influencing lifestyle behaviors such as physical activity and diet[21]. In older adults, it correlates with declining physical function, increased fall risk, and overall health deterioration[25]. Consequently, enhancing social connections and reducing social isolation are considered key strategies for promoting physical health[26]. A report by the U.S. National Academies of Sciences, Engineering, and Medicine (NASEM) emphasized that social isolation is a major risk factor for premature mortality, with impacts potentially comparable to obesity, hypertension, and smoking[27]. Both social isolation and loneliness are associated with increased cardiovascular disease risk[27, 28], and a recent American Heart Association statement identified them as prevalent, independent risk factors for worsening cardiovascular and brain health—with effect sizes varying by specific health outcome [29]. A systematic review and meta-analysis of longitudinal observational studies by Valtorta et al. showed that poor social relationships are associated with increased incidence of coronary heart disease and stroke[30, 31]. Deteriorating cardiovascular health is closely linked to stroke, given that cardiovascular disease is a primary risk factor[32]. This study found that MCMI independently predicts stroke risk in socially isolated adults (with a threshold effect at 4.06), with heightened susceptibility in males. These findings suggest MCMI could serve as a practical tool for identifying early metabolic management targets, and its robust predictive value highlights metabolic health as a key intervention

focus for this vulnerable population. Future research should explore whether social support can mitigate MCMI-associated stroke risk.

Given the complex and multifactorial nature of stroke pathogenesis, a comprehensive understanding of both traditional and emerging risk factors is essential for effective prevention and treatment. Future studies should prioritize elucidating the mechanisms of emerging factors and their interactions with traditional risk factors, which will not only provide new avenues for stroke prevention but also inform the development of personalized treatment strategies. Concurrently, emphasizing multidisciplinary collaboration will facilitate the creation of more holistic stroke management approaches, thereby enhancing clinical intervention efficacy.

Strengths and Limitations

This study uniquely investigated the association between MCMI and stroke within a socially isolated population, employing a piecewise regression model supported by likelihood ratio testing to avoid underestimating effect modifications. However, as a single-center study, residual confounding from unmeasured variables (e.g., dietary patterns, physical activity) may persist despite covariate adjustment. Additionally, the sample size was limited (only 93 stroke events), particularly within the high MCMI range, resulting in wider confidence intervals that included 1.

Declarations

Competing interests

The authors declare no competing interests.

Competing interests

The authors declare that they have no competing interests.

Clinical trial number

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Author Contribution

All authors met the author standards specified in the uniform requirements for submission of contributions to biomedical journals, and their specific contributions are as follows: Conceptualization and Supervision: Na Li; Data curation and Formal analysis: Na Li, Puheng Hao; Software: Puheng Hao; Validation and Visualization: Dongzi Zhang; Writing – original draft: Puheng Hao, Dongzi Zhang; Writing – review and editing: Na Li. All authors have read and approved the authors' final manuscript.

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Data Availability

Detailed information about the acquisition of research data can be queried in the Charls database (http://charls.pku.edu.cn/pages/data /111/zhcn.html).

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Figures

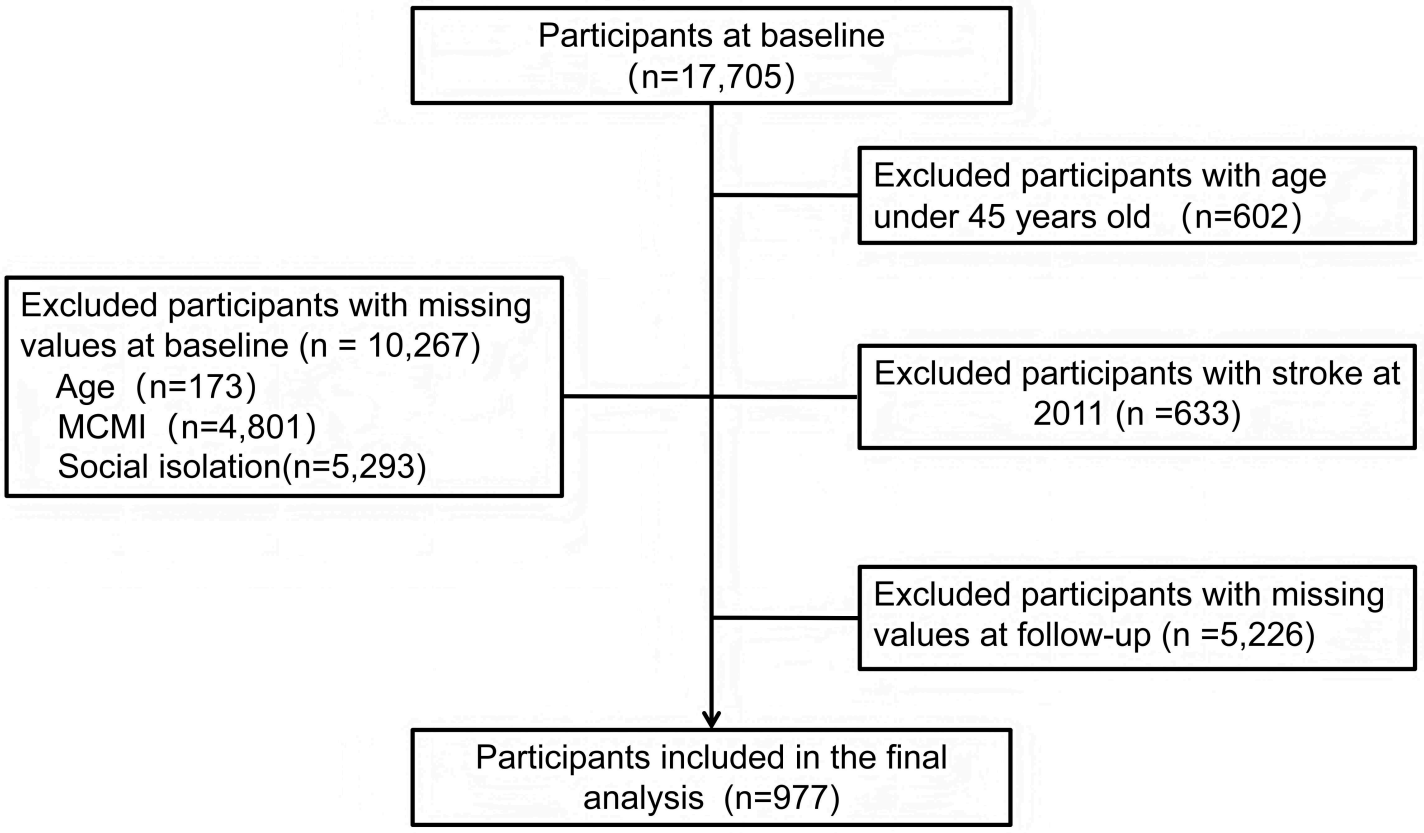


Figure 1

Flow chart of participants selection.

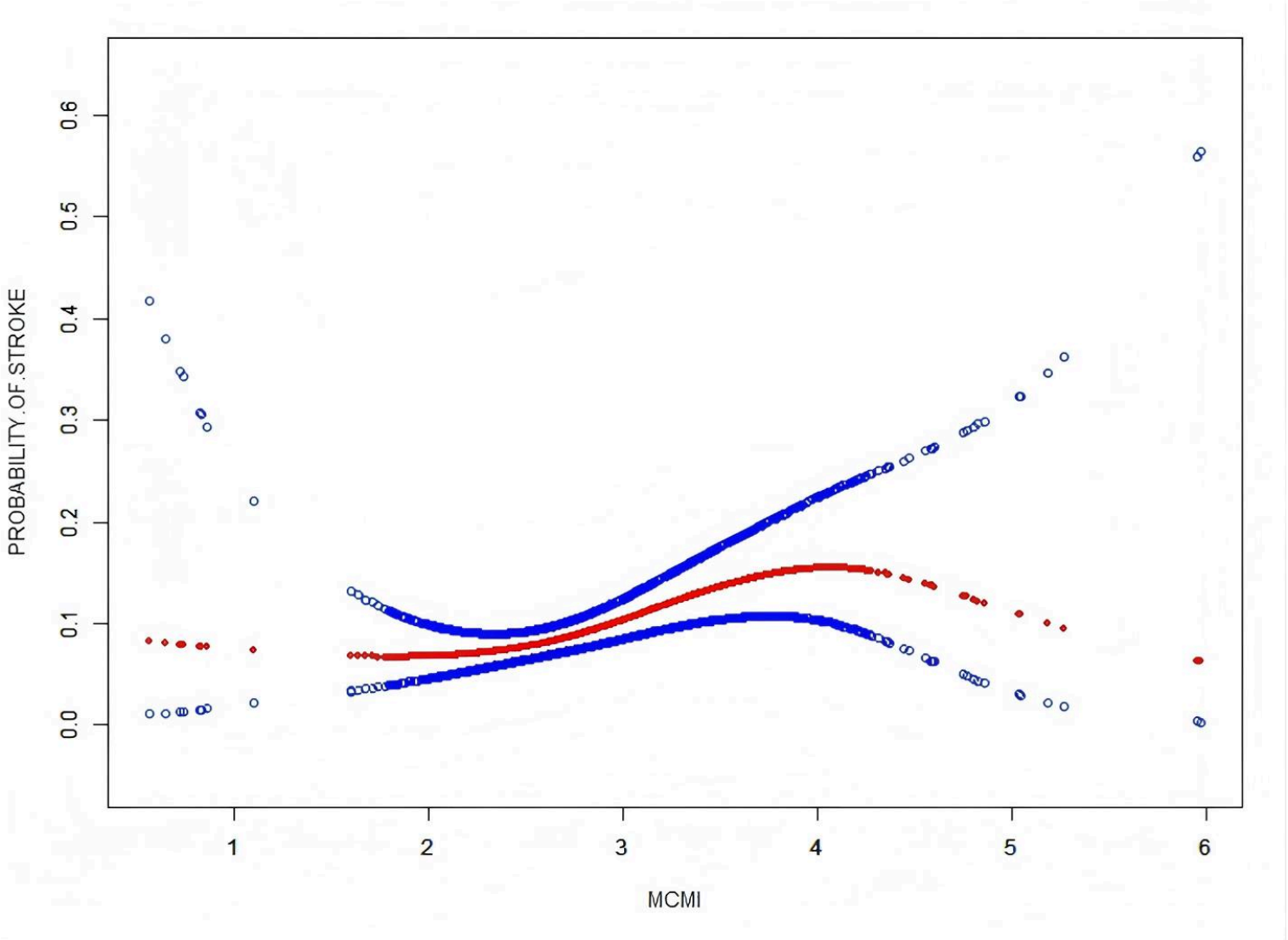


Figure 2

Association between baseline MCMI and stroke risk. Noted: A threshold, nonlinear association between baseline MCMI and stroke risk was found in a generalized additive model (GAM). A solid rad line represents the smooth curve fit between variables. Blue bands represent the 95% of confidence interval from the fit.

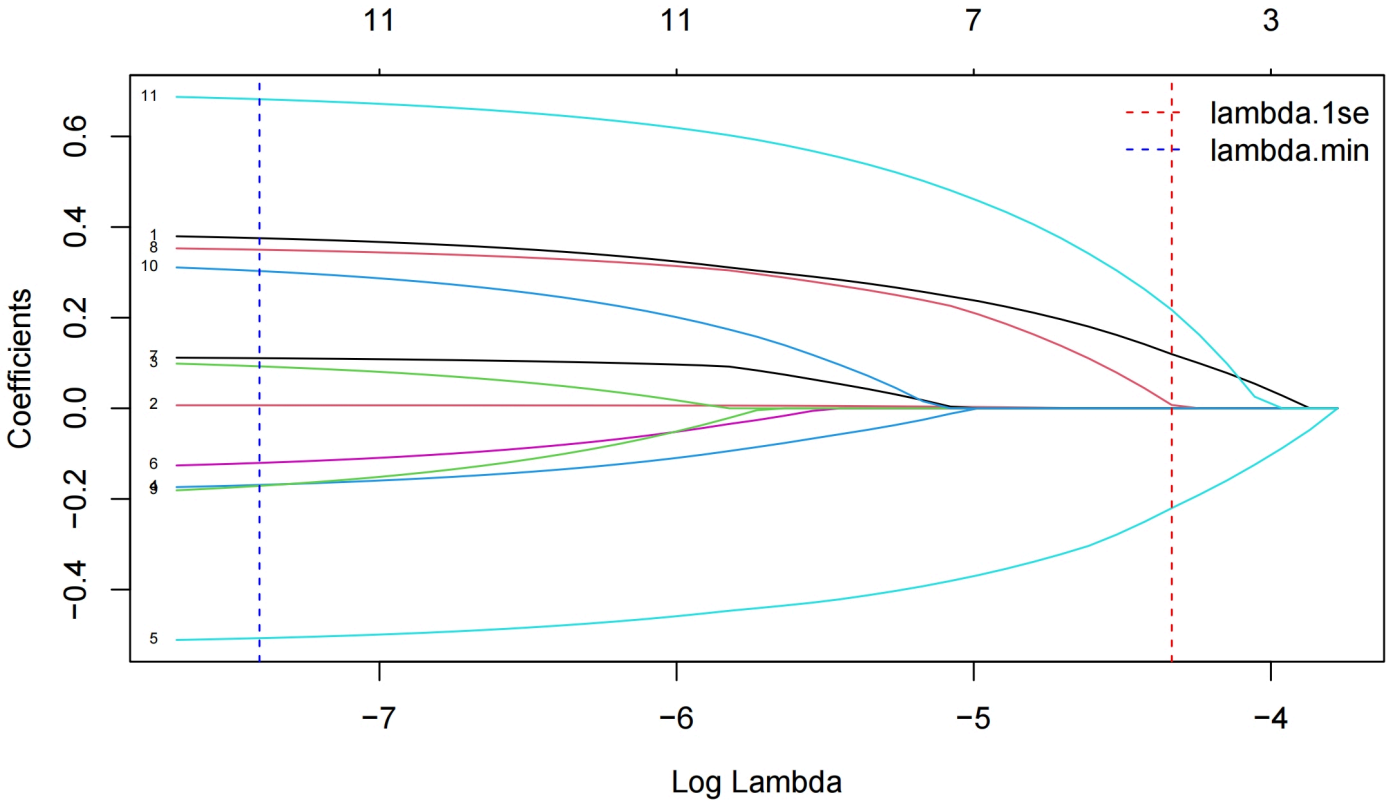


Figure 3

LASSO Coefficient Path for Variable Selection in the Stroke Prediction Model.

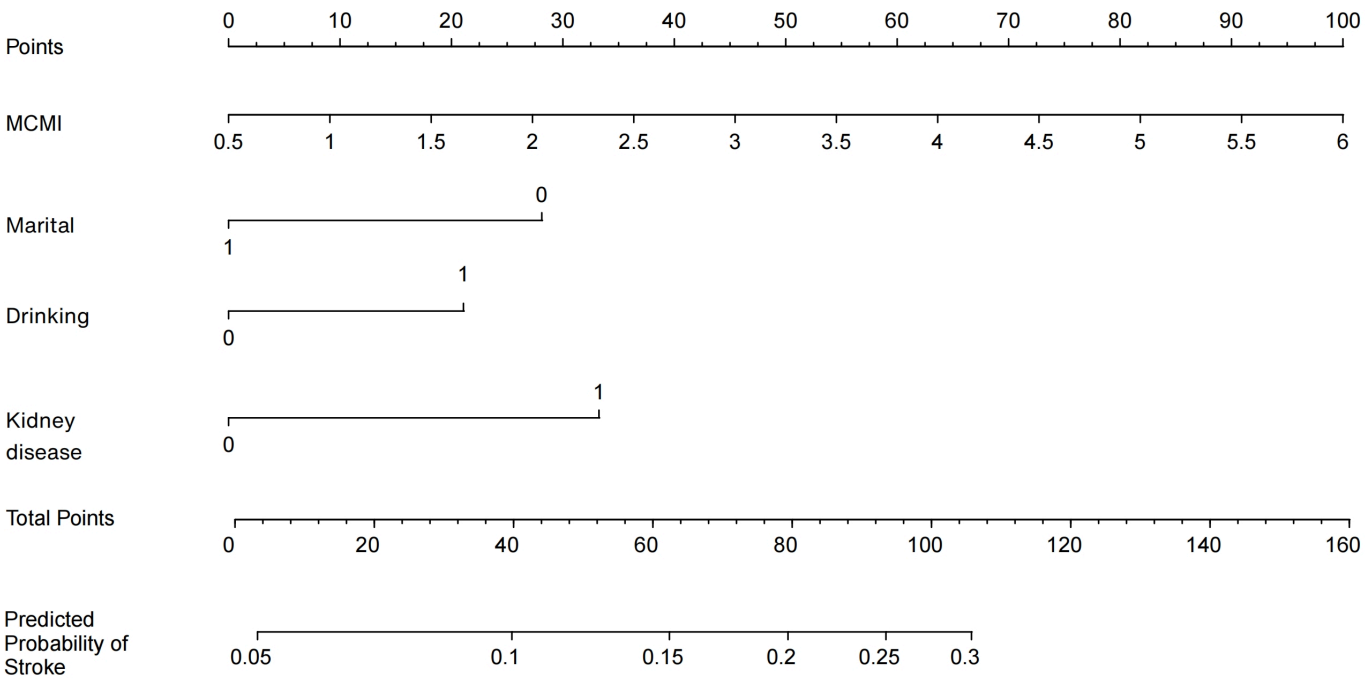


Figure 4

Nomogram for Predicting New-Onset Stroke Risk in the CHARLS Cohort.

Supplementary Files

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- Table2.docx
- Table3.docx
- Table1.docx
- Table4.docx