Zhao *et al.*
Journal of Health, Population and Nutrition (2025) 44:85
https://doi.org/10.1186/s41043-025-00819-0

Journal of Health, Population and Nutrition

RESEARCH

Open Access

The Naples prognostic score as a nutritional and inflammatory biomarkers of stroke prevalence and all-cause mortality: insights from NHANES

Jin Zhao[1], Xingfu Fan[1], Xiaofang Li[1], Yang Luo[1] and Shiping Liu[1*]

Abstract

Background Stroke is a complex neurological condition characterized by high rates of incidence, recurrence, disability, and mortality, making it one of the leading causes of death and disability worldwide. The Naples prognostic score (NPS), an index that combines markers of inflammation and nutritional status, has demonstrated prognostic value in various diseases. This research investigated the relationships among NPS, stroke prevalence, and overall mortality in stroke individuals, drawing on data from the National Health and Nutrition Examination Survey from 2007 to 2018.

Methods The cross-sectional analysis included 20,798 participants aged beyond 40 years with 1155 persons with stroke analyzed for mortality. Stroke prevalence was self-reported, and the NPS was derived from serum albumin, total cholesterol, the neutrophil-to-lymphocyte ratio, and the lymphocyte-to-monocyte ratio (Galizia et al. in Cancer 60:1273–1284, 2017). Weighted Logistic regression and Cox models assessed associations among NPS, stroke, and mortality, adjusting for demographic and clinical factors.

Results Higher NPS scores were linked to increased stroke prevalence (OR 3.573, 95% CI 2.745–4.652, $P < 0.001$) and elevated all-cause mortality risk (HR 3.281, 95% CI 1.978–5.442, $P < 0.001$) in stroke individuals. The triglyceride-glucose index (TYG) significantly modified the relationship between the NPS and stroke prevalence.

Conclusion This study supports the clinical utility of the NPS as a predictor of both stroke prevalence and all-cause mortality. The NPS may serve as a valuable tool for risk stratification in stroke prevention and long-term prognosis.

Keywords Stroke, Naples prognostic score (NPS), Inflammation, Nutrition, NHANES

Introduction

Stroke is a complex neurological disorder that is typically classified into two main subtypes: ischemic and hemorrhagic, based on its etiology and clinical presentation. When a stroke occurs, it impairs brain function, leading to a range of symptoms such as motor impairments, speech difficulties, and cognitive decline. Stroke has a high incidence, recurrence rate, disability rate, and mortality rate, making it one of the leading causes of death and disability worldwide [1–3]. Especially with the aging population and the dramatic lifestyle changes, the incidence and mortality rates of stroke continue to rise [2, 4]. Moreover, the incidence of stroke is gradually increasing among adults aged 18–50 years, leading to a trend of stroke affecting a younger population [5]. Despite substantial advancements in stroke treatment, identifying high-risk populations and implementing stratified, personalized

*Correspondence:
Shiping Liu
liusp456@163.com
[1] Department of General Medicine, Affiliated Hospital of North Sichuan Medical College, Nanchong 637000, China

management strategies remain key challenges in public health [6, 7].

Previous studies have demonstrated the significant role of the CHA_2DS_2-VASc score and NIHSS (National Institutes of Health Stroke Scale) in assessing the prognosis of stroke patients. Specifically, the CHA_2DS_2-VASc score is widely used in patients with atrial fibrillation to evaluate stroke risk based on clinical factors such as congestive heart failure, hypertension, age, diabetes, a history of stroke or transient ischemic attack, vascular disease, and gender [8–10]. NIHSS, on the other hand, is used in the acute phase of stroke to assess the severity of neurological deficits. By quantifying consciousness, language, motor function, and sensory loss, it helps predict patient outcomes [11–13].

However, despite their significance, traditional risk scores have limitations. First, these tools primarily focus on specific populations, such as CHA_2DS_2-VASc for atrial fibrillation patients and NIHSS for those with neurological impairments, which limits their applicability. Additionally, these scores mainly emphasize cardiovascular risk factors and acute neurological damage, neglecting other factors like inflammation and nutritional status that affect long-term recovery and prognosis. Thus, there is a need for more comprehensive predictive markers.

The Naples prognostic score (NPS), developed by Galizia et al., integrates several clinical parameters, including neutrophil-to-lymphocyte ratio (NLR), lymphocyte-to-monocyte ratio (LMR), serum albumin, and total cholesterol, to provide a comprehensive reflection of systemic inflammation and nutritional status [14]. NPS has been shown to be an independent prognostic factor for various diseases, including liver cancer [15], gastric cancer [16, 17], triple-negative breast cancer [18], as well as non-cancer diseases like acute pulmonary embolism [19], non-alcoholic fatty liver disease [20], and heart failure [21]. However, the relationship between NPS and stroke has yet to be explored.

Compared to traditional stroke prediction models, NPS provides a more holistic assessment by incorporating both systemic inflammation and nutritional status, allowing the identification of high-risk individuals in the general population. This comprehensive approach not only addresses the limitations of traditional models but also offers a more accurate understanding of stroke prognosis, leading to more personalized treatment strategies and improved prognostic accuracy.

To fill this knowledge gap, we conducted a cross-sectional and cohort analysis using the comprehensive data from the NHANES (2007–2018). This study aimed to systematically assess the relationship between NPS and stroke while also exploring its potential association with all-cause mortality in stroke individuals, providing valuable insights for its prognostic application.

Materials and methods

Study population

THE NHANES is a nationwide study conducted by the National Center for Health Statistics (NCHS), a division of the Centers for Disease Control and Prevention (CDC). It collects nationally representative health data, including anthropometric measurements, biochemical test results, and related medical questionnaire information. All laboratory examinations are performed by trained medical personnel in mobile examination centers (MECs). The data are publicly available for download on the official website (www.cdc.gov/nchs/nhanes). The NCHS Research Ethics Review Board approved the study protocol, and informed consent was obtained from all participants.

Inclusion and exclusion criteria

The NHANES datasets (2007–2018) originally comprised 59,842 participants. Informed by the findings of prior studies and the specific design of the current research, the exclusion criteria for this study were delineated as follows [22–24]: (1) individuals with missing stroke diagnosis data were excluded (N = 25,073); (2) participants under 40 years of age were removed (N = 11,543); (3) those with incomplete data for the NPS components, including serum albumin, total cholesterol (TC), and complete blood count, were excluded (N = 2383); and (4) individuals lacking follow-up information were omitted (N = 45). After implementing these criteria, 20,798 participants were retained for cross-sectional analysis, and 1155 were included in the cohort analysis, as illustrated in Fig. 1. To ensure the national representativeness of the hematological variables, Mobile Examination Center (MEC) weights were applied.

Assessment of stroke

Following previous studies [23, 25], participants were classified as having a history of stroke if they responded affirmatively to the following question: "Has a doctor or other healthcare professional ever informed you that you have had a stroke?" Conversely, individuals who provided a negative response were designated as the control group.

Assessment of NPS

Following the method established by Galizia et al. [14], NPS was calculated using four clinical parameters: serum albumin, TC, NLR, and LMR. For each parameter, thresholds were assigned as follows: serum albumin $\geq$ 40 g/L, TC > 180 mg/dL, NLR $\leq$ 2.96, or LMR > 4.44 scored 0; levels outside these thresholds scored 1. The

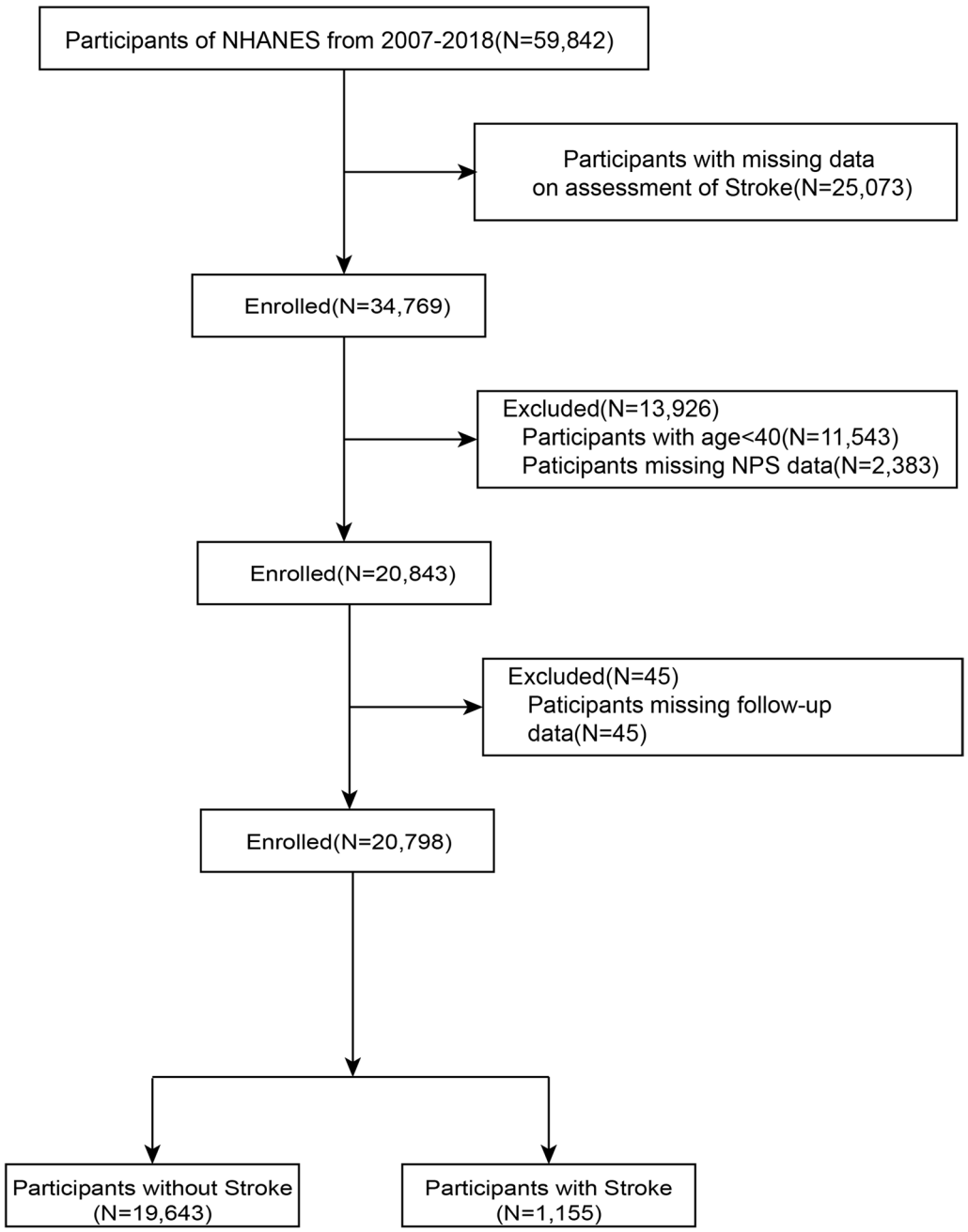

Fig. 1 Flowchart of participants in this study

NPS score (0–4) was the sum of these four components (Table 1). According to the previous study [26–28], participants were stratified into three distinct groups according to their total score distribution: Group 1 (NPS score = 0), Group 2 (NPS score = 1–2), and Group 3 (NPS score = 3–4).

Table 1 The standard of NPS

Points	ALB (g/dL)	TC (mg/dL)	NLR	LMR
NPS score				
0	≥ 4	> 180	≤ 2.96	> 4.44
1	< 4	≤ 180	> 2.96	≤ 4.44

Assessment of mortality

Deceased participants in this study were identified by linking the NHANES dataset with the National Death Index (NDI). Mortality data, including all-cause mortality as of December 31, 2019, were obtained from the 2019 Linked Mortality File (LMF). These records were matched with NHANES data and are publicly accessible online at www.cdc.gov/nchs/data-linkage/mortality.htm.

Covariates

Based on a comprehensive review of the existing literature, we identified several key potential covariates that may influence the outcomes, including age, sex, race, educational attainment, smoking status, body mass index (BMI, kg/m^2), poverty income ratio (PIR), triglyceride, fasting glucose, glycohemoglobin, marriage status, diabetes, triglyceride-glucose index (TYG) and average alcohol consumption per day over the past 12 months. Demographic data such as age, gender, race, PIR, educational level, marital status, diabetes status, and alcohol consumption were self-reported by the participants. Smoking status was dichotomized into two distinct categories: smokers and nonsmokers. Individuals were classified as smokers if they reported consuming at least 100 cigarettes over their lifetime, whereas those who had smoked fewer than 100 cigarettes were categorized as nonsmokers. BMI was stratified into three discrete groups: normal weight (BMI < 25 kg/m^2), overweight (BMI ≥ 25 to < 30 kg/m^2), and obese (BMI ≥ 30 kg/m^2). The PIR was divided into three levels to reflect socioeconomic status: low (< 1.3), medium (1.3 to < 3.5), and high (≥ 3.5). Diabetes status was determined based on self-reported diagnosis, with individuals classified as "yes" if they reported a prior diagnosis and "no" otherwise. Marital status was dichotomized into "married" and "unmarried" based on responses to standardized questionnaire items. Finally, TYG index levels were categorized into quartiles, providing a nuanced stratification for further analyses.

Statistical analysis

To ensure the representativeness of the national population, sampling weights were employed in accordance with the NHANES Analytic Guidelines, which account for the survey's sophisticated multistage probability sampling framework. Participant characteristics are summarized as the means ± standard deviations (SDs) for continuous variables and as proportions for categorical variables. Individuals were stratified into three groups based on their NPS scores. Group differences in continuous variables were analyzed using the analysis of Variance, while the weighted chi-square test was utilized to compare categorical variables. To address missing data, multiple imputation was performed via the "mice" package in R, and the random forest algorithm was used to ensure robust and reliable data estimation.

In the cross-sectional analysis, weighted multivariable logistic regression was used to evaluate the association between NPS and the odds of stroke. The results were expressed as odds ratios (ORs) with 95% confidence intervals (CIs). The logistic regression models were adjusted progressively: the crude model had no adjustments, Model 1 included adjustments for Age, Gender, and Race, and meantime Model 2 further accounted for Gender, Age, Race, Triglyceride, Fasting Glucose, Glycohemoglobin, Marriage, PIR, BMI, Smoke, Education, Diabetes, and TYG.

The cohort study analysis investigated the association between NPS and overall survival in Stroke individuals via Kaplan–Meier (KM) survival curves, with statistical comparisons made through a two-sided log-rank test. To further evaluate the relationship between NPS and all-cause mortality among Stroke individuals, weighted multivariate Cox regression analysis was performed, and the results were presented as hazard ratios (HRs) with 95% confidence intervals (CIs). Stepwise adjustments were incorporated into the Cox regression models: the crude model included no adjustments, Model 1 was adjusted for Age, Gender, and Race, and Model 2 incorporated additional adjustments for diabetes, marriage, PIR, TYG, and Triglycerides. Nonlinear relationships between NPS and all-cause mortality risk were also systematically explored.

In the concluding phase of the analysis, the data were stratified by different covariates. Interaction effects among these variables were examined through the inclusion of interaction terms in the models. Pearson's correlation analysis was used to evaluate the correlation coefficients between the NPS and its components. The statistical procedures were carried out via R Studio (version 4.2.2) and STATA (version 15.1), applying a two-tailed significance criterion of $P < 0.05$.

Results

Basic characteristics of the participants

The baseline characteristics of the study population are presented in Table 2 and Supplement Material 1. A total of 20,798 participants were included in this study and categorized into three groups based on NPS scores: Group 1 (N = 3759, 18.074%), Group 2 (N = 13,892, 66.795%), and Group 3 (N = 3147, 15.131%). The overall mean age was 57.905 ± 11.719 years. Significant differences were observed across multiple covariates among the three groups ($P < 0.05$), with Group 3 displaying distinct characteristics compared with the other groups.

The mean age in Group 3 was 62.704 ± 12.667 years, making it the oldest group. Additionally, Group 3 had

Table 2 Characteristics of participants

Characteristic	Total N = 20,798	Group1 N = 3759 (18.074%)	Group2 N = 13,892 (66.795%)	Group3 N = 3147 (15.131%)	*P* value
M ± SD					
Age (years)	57.905 ± 11.719	54.630 ± 9.979	57.725 ± 11.596	62.704 ± 12.667	*< 0.001*
Gender, n%					*< 0.001*
Male	10,141 (47.568%)	1337 (32.968%)	7044 (49.754%)	1760 (54.289%)	
Female	10,657 (52.432%)	2422 (67.032%)	6848 (50.246%)	1387 (45.711%)	
Education, n%					*0.040*
< High school	5655 (16.632%)	1022 (17.302%)	3721 (15.885%)	912 (19.500%)	
High school	4778 (23.445%)	857 (23.731%)	3176 (23.111%)	745 (24.741%)	
> High school	10,365 (59.923%)	1880 (58.967%)	6995 (61.004%)	1490 (55.758%)	
Marriage, n%					*< 0.001*
Married	11,943 (63.212%)	2209 (64.153%)	8060 (63.821%)	1674 (59.096%)	
Non-married	8855 (36.788%)	1550 (35.847%)	5832 (36.179%)	1473 (40.904%)	
PIR, n%					*< 0.001*
Low < 1.3	5596 (16.666%)	1007 (17.078%)	3698 (16.125%)	891 (18.829%)	
Medium1.3 ≥, < 3.5	9172 (39.620%)	1659 (40.802%)	6019 (38.380%)	1494 (44.296%)	
High ≥ 3.5	6030 (43.714%)	1093 (42.121%)	4175 (45.495%)	762 (36.875%)	
BMI (kg/m^2), n%					*< 0.001*
Normal (< 25 kg/m^2)	5089 (24.992%)	980 (27.274%)	3388 (24.829%)	721 (23.067%)	
Overweight (≥ 25, < 30 kg/m^2)	7333 (35.336%)	1374 (36.412%)	5008 (36.208%)	951 (29.772%)	
Obese (≥ 30 kg/m^2)	8376 (39.672%)	1405 (36.314%)	5496 (38.963%)	1475 (47.161%)	
Diabetes, n%					*< 0.001*
Yes	3885 (14.257%)	470 (9.486%)	2433 (12.847%)	982 (26.876%)	
No	16,913 (85.743%)	3289 (90.514%)	11,459 (87.153%)	2165 (73.124%)	
Smoke, n%					*< 0.001*
Smoker	9880 (47.286%)	1579 (44.036%)	6588 (47.189%)	1713 (51.647%)	
Non-smoker	10,918 (52.714%)	2180 (55.964%)	7304 (52.811%)	1434 (48.353%)	
Quartiles of TYG, n%					*< 0.001*
Q1 (5.848–8.450)	5200 (26.823%)	795 (22.321%)	3483 (27.254%)	922 (30.093%)	
Q2 (8.450–8.772)	5198 (25.458%)	842 (23.633%)	3534 (25.898%)	822 (25.483%)	
Q3 (8.772–9.196)	5198 (24.153%)	989 (26.047%)	3429 (23.563%)	780 (24.786%)	
Q4 (9.196–22.144)	5202 (23.566%)	1133 (27.999%)	3446 (23.286%)	623 (19.639%)	
Stroke, n%					*< 0.001*
No	19,643 (95.699%)	3635 (97.365%)	13,201 (96.212%)	2807 (91.184%)	
Yes	1155 (4.301%)	124 (2.635%)	691 (3.788%)	340 (8.816%)	

Italicized values indicate statistically significant *P*-values (e.g., $P < 0.05$)

the highest proportion of males (54.289%). Racial distribution analysis revealed that non-Hispanic Whites were most prevalent in Group 3 (73.845%). In contrast, the proportion of non-Hispanic Blacks in this group was 10.073%, surpassing that in Group 2 (9.168%) but falling short of that in Group 1 (12.349%). Compared with the other groups, the other racial groups were less represented in Group 3.

Health-related indicators exhibited remarkable disparities. Group 3 had significantly elevated levels of HbA1c and fasting glucose. This group also had recorded the highest prevalence of diabetes. Markers of inflammation further emphasized these differences, with Group 3 presenting the highest NLR and the lowest albumin level. When stratified by TYG quartiles, Group 3 participants were disproportionately represented in Q1 but underrepresented in Q4, with both distributions being statistically significant.

The behavioral characteristics also highlighted significant variations. Group 3 presented the highest smoking prevalence and the greatest obesity rate. Conversely,

the proportion of individuals with a normal BMI was the lowest in this group.

The socioeconomic parameters further distinguished Group 3. This group had the highest proportion of individuals with low income (PIR < 1.3) and the greatest percentage of participants with less than a high school education.

The prevalence of Stroke, a key outcome of the study, was significantly elevated in Group 3. Among the 1155 participants who experienced a stroke, Group 3 demonstrated the highest prevalence (8.82%) compared with Group 1 (2.635%) and Group 2 (3.778%) ($P < 0.001$).

Finally, to avoid selection bias, we further excluded individuals with missing values, resulting in a sample population with complete data. The characteristics of this population are presented in Supplementary Material 2. In addition, we performed further testing between the included and excluded groups to explore the potential impact of selection bias on the study results, with the findings presented in Supplementary Material 3.

Associations between NPS and stroke prevalence

Weighted logistic regression analyses were performed to investigate the relationship between NPS and stroke prevalence among the 20,798 participants as shown in Fig. 2. The results consistently demonstrated a positive association between higher NPS scores and an increased odds of stroke. In the unadjusted model, participants in group 3 had a 257.3% higher likelihood of experiencing a stroke than did those in the reference group (group 1) (OR 3.573, 95% CI 2.745–4.652, $P < 0.001$). After adjusting for gender, age, and race (Model 1), participants in Group 3 had a 128.5% higher likelihood of experiencing a stroke compared to the reference group (OR 2.285, 95% CI 1.732–3.028, $P < 0.001$). After further adjustment for gender, age, race, triglyceride levels, fasting glucose, glycohemoglobin, marital status, PIR, BMI, smoking status, education, diabetes, and TYG (Model 2), the association remained statistically significant, with participants in Group 3 having a 89.1% higher likelihood of experiencing a stroke compared to the reference group (OR 1.891, 95% CI 1.413–2.531, $P < 0.001$). Across all the models, group 3 consistently exhibited a significant positive correlation with stroke prevalence when compared to the reference group (group 1).

We also conducted weighted logistic regression analysis on individuals with complete data to further investigate the relationship between NPS and stroke, with the results presented in Supplementary Material 4. After individuals with missing data were excluded, we still observed a significant increase in stroke prevalence with increasing NPS scores.

Associations between NPS and stroke all-cause mortality

To further investigate the association between NPS and all-cause mortality in stroke patients, we conducted a cohort study. In this cohort study, a total of 1155 stroke participants with available mortality data were included. In the mortality analysis, the follow-up period began with the initiation of MEC and continued until December 31, 2019. The total follow-up duration ranged from 1 to 156 months. The mean follow-up time was 65.205 months, with a standard deviation of 39.513 months. The median follow-up time was 57.00 months. A total of 389 individuals (30.032%) experienced all-cause mortality during the follow-up period. The baseline characteristics of the stroke cohort are summarized in Table 3 and Supplement Material 5. Group 3 exhibited the highest mean age (70.046 ± 10.655 years), which significantly exceeded that of the other groups.

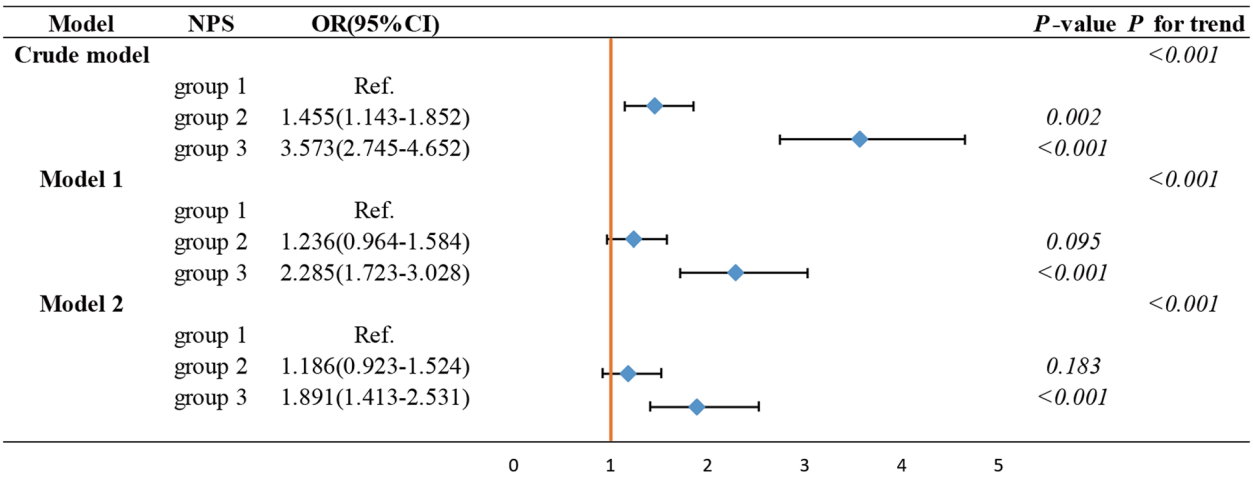

Fig. 2 ORs (95%CIs) of the prevalence of stroke according to the NPS

Table 3 Characteristics of stroke participants

Characteristic	Total N = 1155	Group1 N = 124 (N = 10.736%)	Group2 N = 691 (N = 59.827%)	Group3 N = 340 (N = 29.437%)	*P* value
M ± SD					
Age (years)	66.635 ± 11.335	61.370 ± 11.081	65.909 ± 11.215	70.046 ± 10.655	*< 0.001*
Follow-up time (months)	65.205 ± 39.513	81.853 ± 43.527	68.519 ± 38.636	52.267 ± 36.017	*< 0.001*
Gender, n%					*< 0.001*
Male	562 (43.373%)	35 (22.944%)	344 (45.781%)	183 (45.591%)	
Female	593 (56.627%)	89 (77.056%)	347 (54.219%)	157 (54.409%)	
Marriage, n%					*0.008*
Married	551 (52.340%)	54 (40.572%)	337 (55.289%)	160 (50.324%)	
Non-married	604 (47.660%)	70 (59.428%)	354 (44.711%)	180 (49.676%)	
PIR, n%					*0.046*
Low < 1.3	421 (28.174%)	53 (35.324%)	261 (27.703%)	107 (26.616%)	
Medium1.3 ≥, < 3.5	543 (49.349%)	57 (51.249%)	316 (47.638%)	170 (52.277%)	
High ≥ 3.5	191 (22.477%)	14 (13.427%)	114 (24.659%)	63 (21.107%)	
Diabetes, n%					*< 0.001*
Yes	397 (31.493%)	35 (23.139%)	218 (28.821%)	144 (40.115%)	
No	758 (68.507%)	89 (76.861%)	473 (71.179%)	196 (59.885%)	
Quartiles of TYG, n%					*< 0.001*
Q1 (7.349–8.494)	289 (25.320%)	19 (13.934%)	171 (25.270%)	99 (29.491%)	
Q2 (8.494–8.810)	288 (24.140%)	28 (22.995%)	167 (22.659%)	93 (27.674%)	
Q3 (8.810–9.241)	289 (26.187%)	29 (24.358%)	180 (27.423%)	80 (24.231%)	
Q4 (9.241–13.183)	289 (24.354%)	48 (38.713%)	173 (24.648%)	68 (18.604%)	
All-cause mortality					*< 0.001*
Survival	766 (69.968%)	100 (78.113%)	482 (73.692%)	184 (59.205%)	
Death	389 (30.032%)	24 (21.887%)	209 (26.308%)	156 (40.795%)	

Italicized values indicate statistically significant *P*-values (e.g., $P < 0.05$)

In terms of biochemical markers, Group 3 demonstrated the lowest albumin levels (3.863 ± 0.349 g/dL), while triglyceride levels (134.897 ± 74.967 mg/dL) and lymphocyte counts ($1.606 \pm 0.595 \times 10^3$ cells/μL) were also markedly lower compared to the other groups. Conversely, neutrophil count was highest in Group 3 ($5.255 \pm 1.810 \times 10^3$ cells/μL). Regarding diabetes prevalence, Group 3 showed a significantly higher proportion of affected individuals, reaching 40.115%. Analysis of economic status revealed that the proportion of participants with high income in Group 3 was relatively low, at 21.107%. For marital status, the percentage of married individuals in Group 3 was 50.32%, which was significantly lower than that in Group 2. Most notably, Group 3 exhibited the highest all-cause mortality rate, with only 59.205% of participants surviving during the follow-up period.

The Kaplan–Meier (KM) survival curve (Fig. 3) depicts the all-cause mortality rates within the stroke cohort, highlighting a notably poorer overall survival in individuals in group 3. The associations were statistically significant, as indicated by the log-rank test ($P < 0.001$). We conducted a stratified analysis of several important subgroups via Kaplan–Meier survival curves, and the results are shown in Supplementary Material 6. In terms of gender, the analysis revealed that females had significantly lower survival probabilities than males did (log-rank $P = 0.005$), suggesting that gender may have a certain impact on patient survival. Regarding education level, the analysis indicated that individuals with at least a high school education had a lower survival probability than compared to those who did not complete high school (log-rank $P = 0.038$). The analysis of marital status did not reveal significant differences (log-rank $P = 0.951$). Groups with a lower poverty index demonstrated a lower survival probability (log-rank $P = 0.018$). Lastly, the analysis of smoking status did not reveal significant differences (log-rank $P = 0.065$).

The results of the weighted Cox proportional hazards regression analysis investigating the association between NPS and all-cause mortality in stroke individuals are presented in Fig. 4. In the crude model, compared to the reference group (Group 1), Group 2 had a 51.4% higher risk of all-cause mortality, although this was not

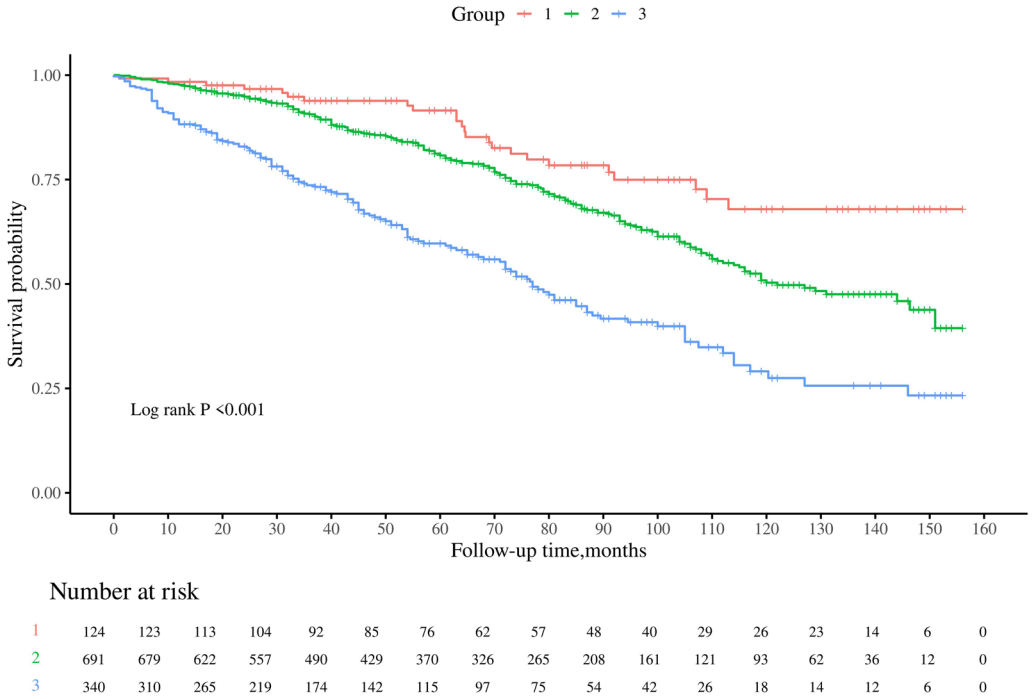

Fig. 3 Kaplan–Meier survival curve of stroke all-cause mortality

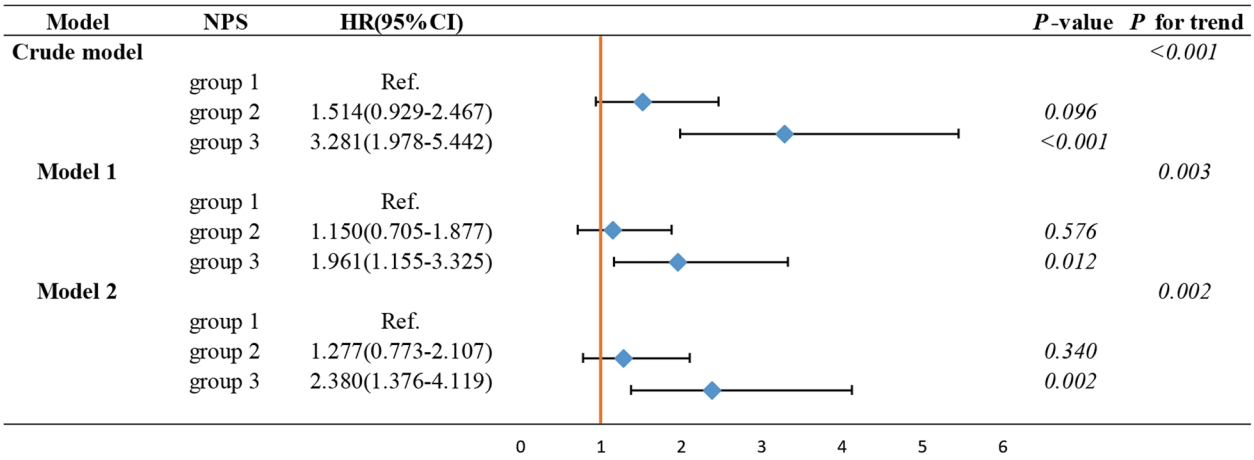

Fig. 4 HRs (95% CIs) of all-cause mortality according to NPS

statistically significant ($P=0.096$), whereas Group 3 had a 228.1% higher risk of all-cause mortality (HR 3.281, 95% CI 1.978–5.442, $P<0.001$), which was statistically significant. After adjusting for gender, age, and race in Model 1, participants in Group 3 had a 96.1% higher risk of all-cause mortality, which remained statistically significant (HR 1.961, 95% CI 1.155–3.325, $P=0.012$), while Group 2 had a 15.0% higher risk, which was not statistically significant ($P=0.576$). In Model 2, after further adjustments for diabetes, marital status, PIR, TYG, and triglycerides, participants in Group 3 had a 138.0% higher risk of all-cause mortality, which remained statistically significant and even higher than in Model 1 (HR 2.380, 95% CI 1.376–4.119, $P=0.002$). However, Group 2 still did not demonstrate a significant association with all-cause mortality ($P=0.340$). Across all the models, the trend analysis (P for trend) consistently indicated a significant upward trend in all-cause mortality risk with increasing NPS group levels. These findings suggest that higher NPS scores, particularly in Group 3, are strongly associated

with increased all-cause mortality risk, even after comprehensive adjustment for potential confounders.

Subgroup analyses

We examined the associations between NPS and the prevalence of stroke across various subgroups, including gender, race, education level, marriage status, PIR, BMI, diabetes status, TYG, and smoking status as demonstrated in Fig. 5 and Supplement Material 7. The findings consistently indicate that individuals in group 3 among most of the subgroups have significantly increased odds of stroke compared with those in group 1.

Among all the subgroups, the TYG subgroup demonstrated the most pronounced interaction between NPS and stroke prevalence (P for interaction = 0.017). In the lowest TYG group (Q1), a significant association was observed in both Group 2 (OR 2.122, 95% CI 1.054–4.273, P = 0.035) and Group 3 (OR 3.248, 95% CI 1.461–7.219, P = 0.004). Similarly, in the second quartile (Q2), a stronger association was found in Group 3 (OR 2.651, 95% CI 1.502–4.679, P = 0.001), whereas no significant association was observed in Group 2 (P = 0.71). For the third quartile (Q3), Group 3 continued to show a significant association (OR 2.22, 95% CI 1.246–3.956, P = 0.007), while Group 2 remained non-significant (P = 0.173). Interestingly, in the highest quartile (Q4), no significant associations were found across either Group 2 (P = 0.342) or Group 3 (P = 0.953). These findings indicate that the relationship between NPS and stroke prevalence is more pronounced in individuals with moderate TYG levels (Q1–Q3), while the effect diminishes at the highest TYG levels (Q4), possibly reflecting a saturation effect. The statistically significant interaction suggests that TYG levels play a modifying role in the association between NPS and stroke prevalence.

To further investigate the associations between NPS and all-cause mortality in stroke individuals, subgroup analyses were performed based on diverse demographic and clinical factors as shown in Fig. 6. The findings revealed that group 3 was significantly linked to an elevated mortality risk in most of the subgroups. Notably, a high NPS emerged as a consistent and independent predictor of all-cause mortality, and was unaffected by variables such as gender, educational background, PIR, BMI, marriage status, diabetes status, TYG, or smoking status, with no significant interaction effects detected (P for interaction > 0.05).

Relationship between NPS and its components

The results of the correlation analysis provide insightful relationships among the components contributing to NPS, as shown in Supplementary material 8. Specifically, NPS exhibited moderate negative correlations with both Albumin (r = −0.36) and Cholesterol (r = −0.43), suggesting that higher levels of these biomarkers may be associated with lower NPS scores. In contrast, NLR showed a moderate positive correlation with NPS (r = 0.44), indicating that higher NLR values tend to correspond with higher NPS scores. The LMR, on the other hand, presented a strong negative correlation with NPS (r = −0.45), further reinforcing the notion that lower LMR levels could be indicative of higher NPS values.

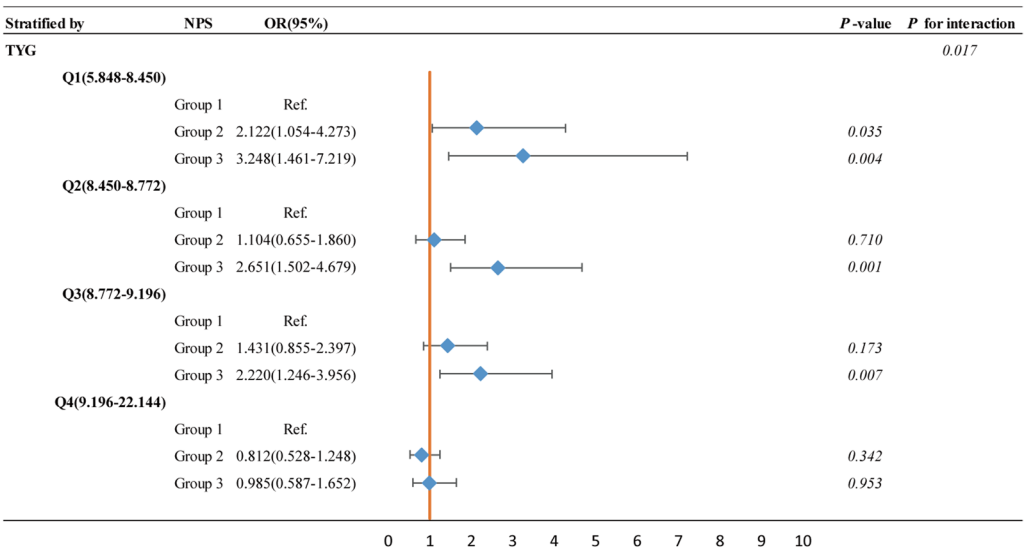

Fig. 5 Subgroup analyses of the association between NPS and stroke prevalence

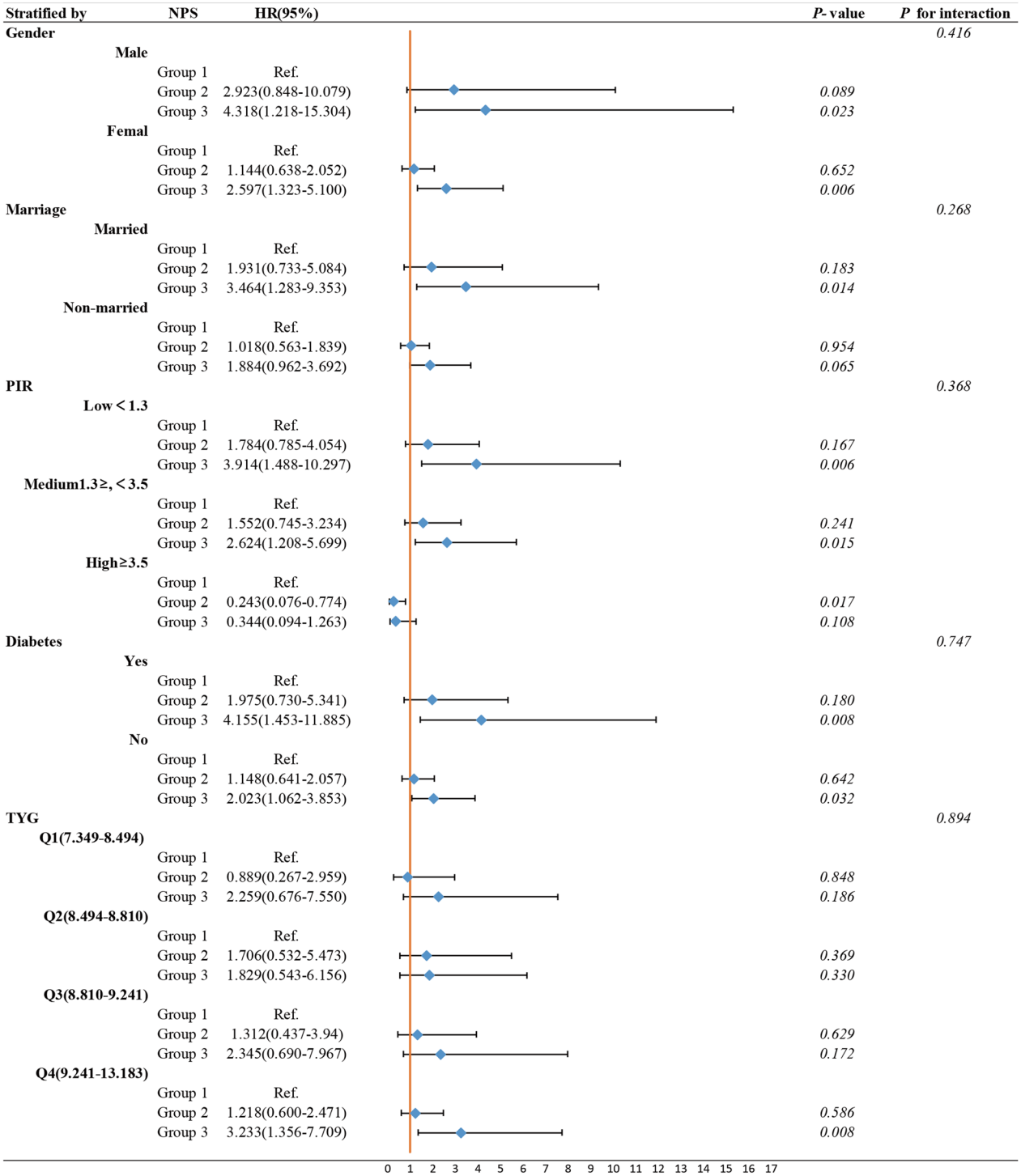

Fig. 6 Subgroup analyses of the association between NPS and all-cause mortality

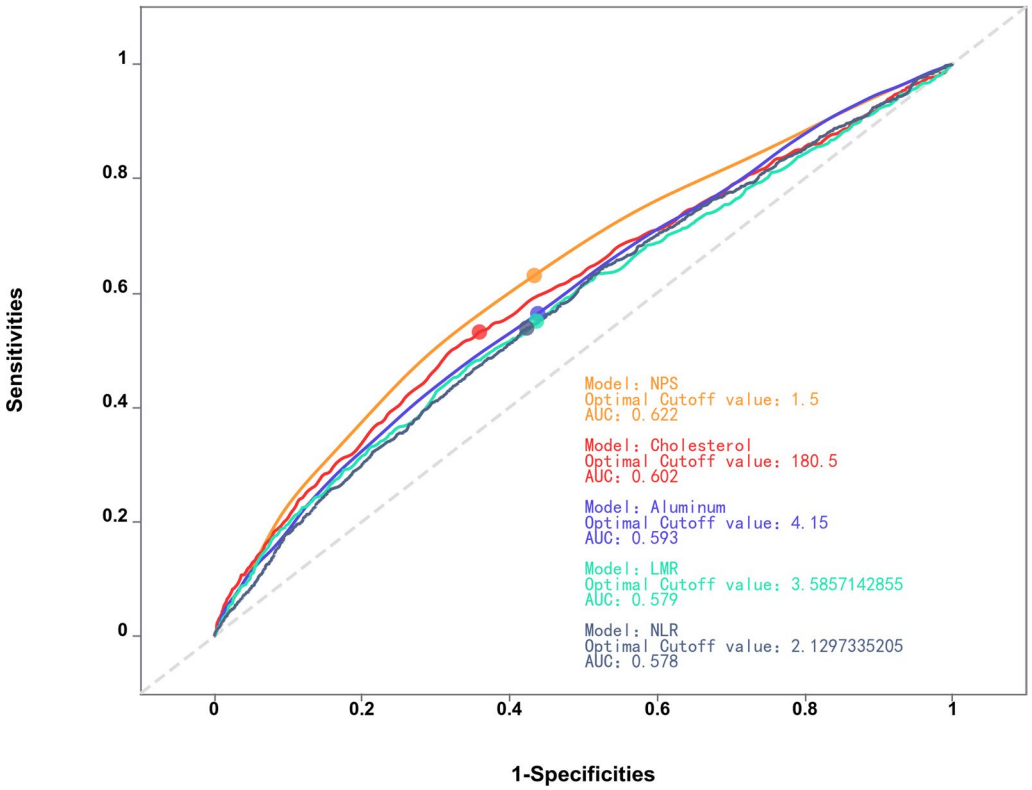

Fig. 7 ROC analysis for stroke prevalence

Table 4 ROC curve analysis of various biomarkers for predicting stroke

	AUC	Ci1	Ci2	Specificity	Sensitivity	PPV	NPV
Aluminum	0.593	0.576	0.611	0.562	0.564	0.930	0.044
Cholesterol	0.602	0.584	0.620	0.641	0.532	0.920	0.041
NLR	0.578	0.561	0.595	0.577	0.534	0.955	0.070
LMR	0.579	0.561	0.597	0.564	0.551	0.931	0.046
NPS	0.622	0.605	0.638	0.567	0.630	0.963	0.079

ROC analysis for stroke prevalence and all-cause mortality

Receiver operating characteristic (ROC) curve analyses were conducted to evaluate the predictive ability of NPS and other biomarkers for stroke prevalence and all-cause mortality in stroke patients.

For stroke prevalence, as shown in Fig. 7 and Table 4, NPS demonstrated the highest predictive value with an AUC of 0.622 and an optimal cutoff value of 1.5. In comparison, total cholesterol (AUC = 0.602), albumin (AUC = 0.593), LMR (AUC = 0.579), and NLR (AUC = 0.578) exhibited relatively lower predictive power. Base on the cutoff value of 1.5, we categorized NPS ≥ 2 as the threshold for high-risk individuals in further discussion.

For all-cause mortality among stroke individuals, as shown in Fig. 8 and Table 5, NPS again exhibited the highest predictive accuracy with an AUC of 0.610 and an optimal cutoff value of 2.5. Other biomarkers, including NLR (AUC = 0.603), LMR (AUC = 0.597), cholesterol (AUC = 0.558), and albumin (AUC = 0.458), showed comparatively lower predictive power. Given this, NPS ≥ 3 was defined as the high-risk threshold for mortality prediction.

Discussion

This study leverages data from the NHANES, which provides a nationally representative sample of the U.S. population spanning 2007–2018. To our knowledge, this is

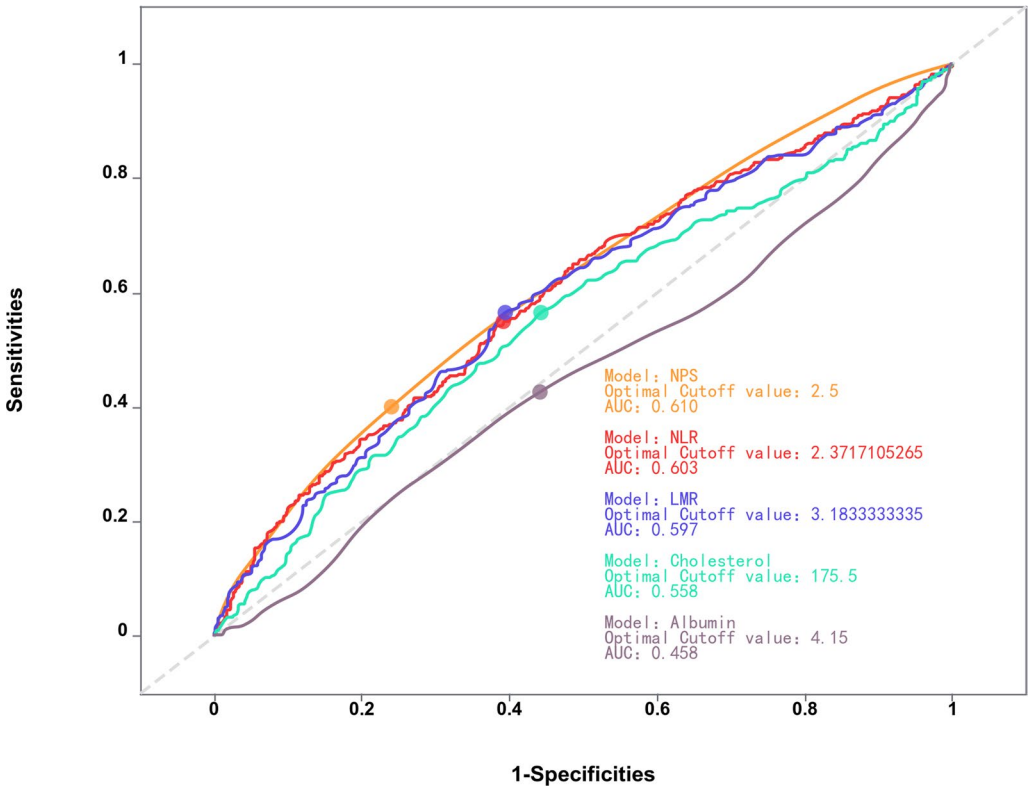

Fig. 8 ROC analysis for all-cause mortality among stroke individuals

Table 5 ROC curve analysis of various biomarkers for predicting all-cause mortality among stroke individuals

	AUC	Ci1	Ci2	Specificity	Sensitivity	PPV	NPV
Albumin	0.458	0.422	0.494	0.559	0.427	0.658	0.329
Cholesterol	0.558	0.522	0.594	0.557	0.566	0.606	0.284
NLR	0.603	0.568	0.638	0.608	0.550	0.727	0.416
LMR	0.597	0.561	0.632	0.606	0.566	0.579	0.267
NPS	0.610	0.576	0.643	0.760	0.401	0.714	0.459

the first comprehensive investigation exploring the relationships among NPS, stroke prevalence, and all-cause mortality. Our study provides some clues supporting the use of NPS as a predictor of both stroke prevalence and all-cause mortality. The results revealed that the NPS outperforms individual inflammatory (NLR, LMR) and nutritional (albumin, cholesterol) biomarkers in both predictive domains.

NPS is primarily composed of four peripheral blood biomarkers: serum albumin, total cholesterol levels, NLR, and LMR. Current research widely recognizes NPS as a novel and comprehensive index reflecting systemic inflammation and nutritional status [26]. Studies on NPS to date have predominantly focused on oncology. For instance, a large-scale study involving 42,582 participants from the general population demonstrated a strong association between NPS and both cancer incidence and prognosis [29]. Similarly, in a cohort of 276 glioblastoma (GBM) patients, researchers observed that NPS exhibited superior predictive power compared to other indices [30]. Furthermore, studies on triple-negative breast cancer (TNBC) have also validated the exceptional prognostic performance of NPS [18].

More recently, the prognostic value of NPS has gained recognition in non-cancerous diseases. For example, NPS has been identified as an effective predictor of outcomes in patients with heart failure [21, 31] and ST-segment elevation myocardial infarction (STEMI) [32]. In chronic

pulmonary diseases, studies have similarly revealed that individuals with higher NPS scores were at an increased risk of developing asthma, chronic bronchitis, and respiratory symptoms, including sputum production, wheezing, and exertional dyspnea [33]. Collectively, these findings highlight the broad applicability and potential value of NPS as a predictive tool.

Our research revealed that a higher score of NPS is strongly associated with increased morbidity and all-cause mortality in stroke individuals, which may be closely linked to the systemic inflammatory response and the individual's nutritional condition. Atherosclerosis, a primary cause of stroke, is heavily influenced by inflammation, which acts as a crucial driver in the formation and progression of atherosclerotic plaques. Upon the occurrence of a stroke, blood supply to specific regions of the brain is disrupted, leading to a hypoxic environment. Without adequate blood perfusion, the affected brain tissue undergoes ischemic necrosis. Necrotic and dying cells release damage-associated molecular patterns (DAMPs), which activate immune cells and trigger the release of proinflammatory cytokines and chemokines [34]. Neutrophils are among the earliest immune cells infiltrating the brain during the stroke cascade. The reactive oxygen species (ROS) they generate not only impede the formation of new blood vessels and repair mechanisms but also promote neuronal death, hindering functional recovery [27]. In addition, the acute inflammatory response triggered by stroke leads to the recruitment and activation of monocytes, which secrete inflammatory cytokines and chemokines that contribute to the neural repair process. However, excessive monocyte activation may lead to further damage to neural tissue [35, 36].

Moreover, alterations in the function and number of lymphocyte subpopulations, including T cells and B cells, may significantly influence the degree of neural damage and the subsequent repair processes following a stroke. For example, both CD4+ and CD8+ T cells are involved in the inflammatory response and neural injury, while also playing a role in the repair process. Although an exaggerated inflammatory response can exacerbate neural damage, a balanced immune reaction may facilitate recovery [37, 38].

Malnutrition, such as deficiencies in albumin, fatty acids, and essential vitamins, has a detrimental impact on the cardiovascular system, thereby elevating the risk of stroke. As a result, adequate nutritional intervention plays a critical role in enhancing stroke prognosis by mitigating inflammation and promoting recovery [39, 40].

From the perspective of NPS, NLR and LMR serve as key markers of systemic inflammation and immune imbalance according to multiple studies. A Chinese study based on 408 cases of stroke induced by atrial fibrillation indicated that NLR and LMR are independent prognostic factors for ischemic stroke patients' outcomes [41]. Additionally, a prospective study based on the UK Biobank, which analyzed data from 6020 participants and adjusted for multiple covariates, revealed a linear negative correlation between LMR and stroke participants, while NLR showed a positive correlation. Specifically, when LMR was less than 4 (HR 1.14, 95% CI 1.01–1.29, $P=0.03$), the risk of all-cause mortality increased by 14%, and when NLR was ≥ 2 (HR 1.26, 95% CI 1.11–1.43, $P<0.001$), the risk of all-cause mortality increased by 26% [42]. Furthermore, a retrospective study demonstrated that NLR and LMR are closely associated with early neurological deterioration (END) after thrombolysis in acute stroke patients, suggesting that they can serve as critical prognostic indicators for stroke patients [43]. These findings are closely aligned with the baseline results of our study, further supporting the significant role of systemic inflammation biomarkers in stroke prognosis.

NLR serves as a marker of systemic inflammatory response, and its elevation is closely associated with endothelial cell injury. Studies have shown that inflammatory responses can exacerbate endothelial cell damage, leading to vascular wall instability and subsequently increasing the risk of thrombosis [44, 45]. Moreover, elevated NLR is closely related to atherosclerosis, which predisposes individuals to stroke. LMR, on the other hand, is an important marker of immune system balance. Low levels of LMR may indicate an imbalance between lymphocytes and monocytes, which promotes excessive inflammatory and immune responses, thus exacerbating endothelial cell damage, facilitating thrombosis, and contributing to atherosclerosis, further increasing the risk of stroke [46, 47].

On the other side of NPS, serum albumin and total cholesterol levels are widely recognized as key indicators reflecting the nutritional status of the organism. Stroke can lead to acute cerebral dysfunction, presenting with symptoms such as hemiplegia, aphasia, and dysphagia. These clinical manifestations can significantly impair the patient's appetite and food intake, ultimately leading to malnutrition [48–50]. For instance, dysphagia hinders normal eating, preventing adequate nutrition intake. Hemiplegia, by causing limb dysfunction, affects the patient's ability to feed themselves and perform daily activities, thereby resulting in insufficient caloric and nutritional intake [51, 52]. Malnutrition, particularly hypoalbuminemia, leads to a marked decline in immune function, thereby increasing the susceptibility to post-stroke infections [53, 54]. Furthermore, hypoalbuminemia may compromise vascular elasticity, disrupting cerebral blood flow stability, elevating the risk of cerebrovascular events. During the post-stroke recovery period,

the overall nutritional status is vital for brain repair, as nutritional levels are closely associated with the recovery of brain function [55].

Low serum albumin levels are typically associated with malnutrition, inflammatory responses, and impaired liver function. A decrease in serum albumin reduces vascular wall elasticity and increased vascular permeability and promotes edema and tissue damage [56, 57]. Prolonged low albumin levels may also impair immune function, increasing the vulnerability of cerebral blood vessels and the risk of stroke. Low cholesterol levels are linked to metabolic disorders, hormonal imbalances, and malnutrition, which may weaken the stability of cerebral blood vessels. Additionally, low cholesterol may affect the integrity and repair capacity of cell membranes, resulting in damage to the structure and function of cerebral blood vessels, thereby increasing the risk of stroke [20, 58].

Therefore, formulating targeted therapeutic interventions based on stroke risk factors and individual patient conditions could significantly improve outcomes. Early rehabilitation and physical therapy interventions can enhance motor function, reduce disability, and improve the quality of life for stroke patients [59]. Initiating early physical rehabilitation programs, including task-oriented training and mobilization exercises, can reduce the degree of hemiplegia and improve overall motor recovery [60, 61]. Moreover, a comprehensive stroke management plan, which includes mental health support and stroke education, can address cognitive impairments and psychological challenges faced by patients, contributing positively to long-term recovery and well-being [62].

Moreover, in this study, we analyzed the relationship between NPS and stroke prevalence across different subgroups. Particularly in the TYG subgroup, a significant interaction between NPS and stroke prevalence was observed. TYG is an index derived from triglyceride and fasting glucose levels, widely used to assess insulin resistance and metabolic syndrome [63]. Insulin resistance is a major risk factor for stroke, cardiovascular diseases, and other chronic conditions [64–66]. It contributes to inflammation, endothelial dysfunction, and disturbed lipid metabolism, which increases the risk of atherosclerosis and stroke [67]. On the other hand, NPS integrates markers of inflammation and nutritional status, providing a comprehensive reflection of systemic inflammation and nutritional status. Previous studies have indicated a close link between systemic inflammation and insulin resistance, and both contribute to the progression of atherosclerosis [68, 69].

In our analysis, we found that TYG levels significantly modified the relationship between NPS and stroke prevalence, especially in the lower to moderate TYG quartiles (Q1–Q3). We hypothesize that as insulin resistance worsens, it may enhance the inflammatory response, thus exacerbating the effects of NPS and further increasing stroke risk. This mechanism could be mediated through the upregulation of inflammatory markers (such as NLR and LMR) and the reduction of beneficial nutritional factors (like albumin). In contrast, at higher TYG levels (Q4), the impact of this interaction diminishes, possibly due to a saturation effect of both metabolic and inflammatory processes.

We suggest that TYG, as a marker of insulin resistance, interacts with NPS, which reflects inflammation and nutritional status, to better explain stroke risk. Clinically, measuring both TYG and NPS could provide a multifaceted risk assessment tool to identify individuals at high risk for stroke and guide personalized treatment strategies.

Our study demonstrated that the NPS is significantly associated with both the prevalence and severity of stroke, as well as all-cause mortality among stroke individuals. The NPS is a comprehensive tool that effectively reflects the complex association between inflammation, immune response, and malnutrition, particularly in stroke individuals. Our findings are consistent with previous research, further highlighting the critical role of systemic inflammation and nutritional status in stroke prognosis.

The NPS can serve as an effective tool for risk stratification and prognosis assessment, helping to identify high-risk stroke populations early and enabling personalized management of stroke patients. Comprehensive interventions targeting inflammation levels and nutritional status in stroke patients can significantly improve their prognosis. Additionally, community-based screening programs can utilize NPS for initial risk stratification, providing a scientific foundation for resource allocation and the prioritization of health interventions.

For stroke prevalence, the AUC value was 0.622, and for all-cause mortality, the AUC value was 0.610, indicating that the NPS model has moderate predictive ability. While this result is promising, it also reflects that the model still has limitations in accurately distinguishing between individuals at risk and those not at risk. Although the model can provide an initial reference for risk assessment, its clinical application requires further validation and optimization to improve its predictive accuracy and broader applicability. In clinical terms, this moderate AUC value underscores the necessity of complementing the NPS with additional biomarkers or clinical assessments to improve its predictive accuracy. However, despite its moderate AUC, the NPS can still serve a role in early risk stratification, especially when combined with other screening tools. The clinical utility of the NPS

in primary prevention strategies lies in its potential to prioritize further diagnostic testing for high-risk individuals, thereby optimizing resource allocation. The model's performance could also be enhanced through future validation studies, which could explore the incorporation of more diverse datasets and consider longitudinal outcomes to refine the model's clinical applicability.

Although this study has certain strengths, it also has some limitations that need further discussion and acknowledgment. Firstly, NHANES data primarily hinges upon self-reports from participants, which may result in recall bias and affect the accuracy of the data. To better address this limitation in future research, we recommend the inclusion of objective measures, such as imaging-confirmed stroke diagnoses. While we employed robust statistical techniques to address missingness, we acknowledge that some degree of bias may still exist, particularly if certain variables were missing not at random. To further strengthen the validity of our findings, future studies should consider enhanced study designs or incorporate external validation datasets. Secondly, although the study has controlled for known potential confounders such as age, gender, and smoking status, there may still be unmeasured or unknown confounding factors such as dietary habits [70], physical activity [71], and medication adherence [72]. Furthermore, the study data is primarily based on the U.S. population, which may limit its external validity, particularly in economically underdeveloped countries or other cultural contexts. Future studies could aim to replicate our findings in more diverse populations to assess the robustness and applicability of the NPS across different demographic groups and healthcare systems. Last but not the least, the cross-sectional design of NHANES limits the ability to establish causality between NPS and stroke outcomes. Cross-sectional studies capture data at a single point in time, which means they cannot reveal the temporal causality between variables. Therefore, although our study shows significant associations between NPS and stroke prevalence and mortality, we cannot establish whether these associations are causal. To better understand the role of NPS in predicting stroke risk, future prospective or longitudinal studies should be conducted. In conclusion, the limitations of this study suggest that future research should focus on incorporating diverse data sources, better controlling for potential confounders, and using longitudinal designs or randomized controlled trials to verify both correlations and causations. These steps will help improve the scientific validity and applicability of research conclusions.

Conclusion

Our findings support the clinical utility of NPS as a predictor for both stroke prevalence and all-cause mortality, and suggest that it may serve as a valuable tool for risk stratification in stroke prevention and long-term prognosis. For primary prevention, an NPS ≥ 2 may help identify high-risk individuals, whereas for post-stroke mortality risk, an NPS ≥ 3 serves as an effective prognostic threshold. Future studies should validate these findings in prospective cohorts and explore how the NPS can be integrated with existing clinical risk models to increase predictive accuracy and guide personalized treatment strategies.

Abbreviations

NPS	Naples prognostic score
NLR	Neutrophil-to-lymphocyte ratio
LMR	Lymphocyte-to-monocyte ratio
NANES	National Health and Nutrition Examination Survey
NCHS	National Center for Health Statistics
CDC	Centers for Disease Control and Prevention
MEC	Mobile Examination Centers
NDI	National death index
BMI	Body mass index
PIR	Poverty income ratio
TYG	Triglyceride-glucose index
GBM	Glioblastoma
TNBC	Triple-negative breast cancer
STEMI	ST-segment elevation myocardial infarction
DAMPs	Damage-associated molecular patterns
ROS	Reactive oxygen species

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s41043-025-00819-0.

Additional file 1.
Additional file 2.
Additional file 3.
Additional file 4.
Additional file 5.
Additional file 6.
Additional file 7.
Additional file 8.

Acknowledgements

We would like to thank all participants in this study.

Author contributions

Jin Zhao and Shiping Liu designed the experiments. Jin Zhao, Xingfu Fan, Yang Luo, and Xiaofang Li collected and analyzed the data. Jin Zhao drafted the manuscript. Jin Zhao and Shiping Liu revised the manuscript. All authors contributed to the article and approved the submitted version.

Funding

This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Availability of data and materials
Publicly available datasets were analyzed in this study. These data can be found on the NHANES website (https://www.cdc.gov/nchs/nhanes/index.htm).

Declarations

Human ethics and consent to participate
All participants provided written informed consent and study procedures were approved by the National Center for Health Statistics Research Ethics Review Board.

Competing interests
The authors declare no competing interests.

Received: 30 January 2025 Accepted: 7 March 2025
Published online: 25 March 2025

References

1. Ingall T. Stroke—incidence, mortality, morbidity and risk. J Insur Med. 2004;36:143–52.
2. Feigin VL, Brainin M, Norrving B, Martins S, Sacco RL, Hacke W, et al. World Stroke Organization (WSO): global stroke fact sheet 2022. Int J Stroke. 2022;17:18–29.
3. Feigin VL, Stark BA, Johnson CO, Roth GA, Bisignano C, Abady GG, et al. Global, regional, and national burden of stroke and its risk factors, 1990–2019: a systematic analysis for the global burden of disease study 2019. Lancet Neurol. 2021;20:795–820.
4. Feigin VL, Owolabi MO, Feigin VL, Abd-Allah F, Akinyemi RO, Bhattacharjee NV, et al. Pragmatic solutions to reduce the global burden of stroke: a World Stroke Organization-Lancet Neurology Commission. Lancet Neurol. 2023;22:1160–206.
5. Ekker MS, Boot EM, Singhal AB, Tan KS, Debette S, Tuladhar AM, et al. Epidemiology, aetiology, and management of ischaemic stroke in young adults. Lancet Neurol. 2018;17:790–801.
6. Feigin VL, Norrving B, Mensah GA. Global burden of stroke. Circ Res. 2017;120:439–48.
7. Pandian JD, Gall SL, Kate MP, Silva GS, Akinyemi RO, Ovbiagele BI, et al. Prevention of stroke: a global perspective. Lancet. 2018;392:1269–78.
8. Berkovitch A, Mazin I, Younis A, Shlomo N, Nof E, Goldenberg I, et al. CHA2DS2-VASc score performance to predict stroke after acute decompensated heart failure with and without reduced ejection fraction. EP Eur. 2019;21:1639–45.
9. Ayash B, Malaeb D, Hallit S, Hosseini H. Assessing adherence to treatment guidelines and complications among atrial fibrillation patients in the United Arab Emirates. Front Cardiovasc Med. 2024;11:1359922. https://doi.org/10.3389/fcvm.2024.1359922/full.
10. Lin Y-S, Huang Y-C, Lin C-P, Wu VC-C, Kao Y-W, Chiang H-Y, et al. Atrial fibrillation in adult congenital heart increase ischemic stroke risk even at low CHA2DS2-VASc score. Rev Cardiovasc Med. 2023;24:225.
11. Padwale V, Chivate C, Kirnake V, Patil H, Kumar S, Pantbalekundri N. Comparative prognostic value of the National Institutes of Health Stroke Scale (NIHSS) and the Glasgow Coma Scale (GCS) in supratentorial and infratentorial stroke patients in Western India. Cureus. 2024. https://doi.org/10.7759/cureus.65778.
12. Strambo D, Michel P, Nguyen TN, Abdalkader M, Qureshi MM, Strbian D, et al. Endovascular versus medical therapy in posterior cerebral artery stroke: role of baseline NIHSS score and occlusion site. Stroke. 2024;55:1787–97.
13. Wei W, Xiang J, Li A, Chen B. NIHSS score prognostic effect of mechanical thrombectomy in patients with acute mild ischemic stroke complicated with large vessel occlusion. Int J Clin Exp Med Res. 2024;8:522–7.
14. Galizia G, Cardella F, Castellano P. Naples prognostic score, based on nutritional and inflammatory status, is an independent predictor of long-term outcome in patients undergoing surgery for colorectal. Cancer. 2017;60:1273–84.
15. Hosoda K, Shimizu A, Kubota K, Notake T, Kitagawa N, Yoshizawa T, et al. Clinical significance of the Naples prognostic score in predicting short- and long-term postoperative outcomes of patients with hepatocellular carcinoma. World J Surg. 2024;49:502–11.
16. Xiong J, Hu H, Kang W, Liu H, Ma F, Ma S, et al. Prognostic impact of preoperative Naples prognostic score in gastric cancer patients undergoing surgery. Front Surg. 2021;8: 617744.
17. Chen F, Xie C, Ren K, Xu X. Prognostic value of the Naples prognostic score in patients with gastrointestinal cancers: a meta-analysis. Nutr Cancer. 2023;75:1520–30.
18. Qiu Y, Chen Y, Shen H, Yan S, Li J, Wu W. Naples prognostic score: a novel predictor of survival in patients with triple-negative breast cancer. J Inflamm Res. 2024;17:5253–69.
19. Zhu N, Lin S, Cao C. A novel prognostic prediction indicator in patients with acute pulmonary embolism: Naples prognostic score. Thromb J. 2023;21:114.
20. Feng Y, Xu W, Tang S, Ye Z, Fang P, Abdullah G, et al. Inflammation, nutrition, and biological aging: the prognostic role of Naples prognostic score in nonalcoholic fatty liver disease outcomes. Diabetes Res Clin Pract. 2024;213: 111749.
21. Guo Z, Zhang F, Chai S. The naples prognostic score as a new predictor for heart failure: a cross-sectional study. Heart Lung. 2025;70:360–7.
22. Tian A, Zheng Y, Jin J, Huang C. Association of systemic inflammatory response index and stroke: a cross-sectional study of NHANES, 2005–2018. Front Neurol. 2025;16:1538352.
23. Pan L, Peng Y, Jiang L. Association between prognostic nutritional index and stroke: a nationally representative cross-sectional study from NHANES. J Stroke Cerebrovasc Dis. 2025;34: 108165.
24. Lai G, Zhao Y, Yang C, Zheng Y, Sun J, Zhao Y, et al. Association of Naples prognostic score with cardiovascular disease risk and its longitudinal prognostic impact on mortality in cardiovascular disease patients: evidence from NHANES. Nutr Metab Cardiovasc Dis. 2024;35: 103840.
25. Shi R, Tian Y, Tian J, Liu Q, Zhang J, Zhang Z, et al. Association between the systemic immunity-inflammation index and stroke: a population-based study from NHANES (2015–2020). Sci Rep. 2025;15:381.
26. Zhu N, Lin S, Yu H, Liu F, Huang W, Cao C. Naples prognostic score as a novel prognostic prediction indicator in adult asthma patients: a population-based study. World Allergy Organ J. 2023;16: 100825.
27. Kang Y, Tan Y, Tie Y, Zhang Y, Cui C, Zhao Y. Prognostic value of the Naples prognostic score in adult chronic obstructive pulmonary disease: NHANES 2005–2018. Front Nutr. 2024;11:1502266.
28. Elia S, Patirelis A, Hardavella G, Santone A, Carlea F, Pompeo E. The Naples prognostic score is a useful tool to assess surgical treatment in non-small cell lung cancer. Diagn Basel Switz. 2023;13:3641.
29. Liang C, Zhang C, Song J, Yan L, Xiao Y, Cheng N, et al. The Naples prognostic score serves as a predictor and prognostic indicator for cancer survivors in the community. BMC Cancer. 2024;24:696.
30. Li J, Yang W, Yuan Y, Zuo M, Li T, Wang Z, et al. Preoperative Naples prognostic score is a reliable prognostic indicator for newly diagnosed glioblastoma patients. Front Oncol. 2022;12: 775430.
31. Килич О, Суйгюн Х, Мушту М, Карадениз ФО, Озер СФ, Сенол Х, et al. Использование прогностической шкалы Неаполя (Naples Prognostic Score) для прогнозирования смертности от сердечной недостаточности. Кардиология. 2023;63:61–5.
32. Erdogan A, Genc O, Ozkan E, Goksu MM, Ibisoglu E, Bilen MN, et al. Impact of Naples prognostic score at admission on in-hospital and follow-up outcomes among patients with ST-segment elevation myocardial infarction. Angiology. 2023;74:970–80.
33. Wu WW. Association of Naples prognostic score and lung health: a population-based study. Respir Med. 2024;232: 107751.
34. Gimbrone MA, García-Cardeña G. Vascular endothelium, hemodynamics, and the pathobiology of atherosclerosis. Cardiovasc Pathol. 2013;22:9–15.
35. Alsbrook DL, Di Napoli M, Bhatia K, Biller J, Andalib S, Hinduja A, et al. Neuroinflammation in acute ischemic and hemorrhagic stroke. Curr Neurol Neurosci Rep. 2023;23:407–31.
36. Kumari S, Dhapola R, Sharma P, Nagar P, Medhi B, HariKrishnaReddy D. The impact of cytokines in neuroinflammation-mediated stroke. Cytokine Growth Factor Rev. 2024;78:105–19.
37. Tian D, Pan Y, Zhao Y, Wang H, Tian Y, Yang L, et al. TCRαβ+NK1.1-CD4-CD8- double-negative T cells inhibit central and peripheral

inflammation and ameliorate ischemic stroke in mice. Theranostics. 2023;13:896–909.
38. Wang Y-R, Cui W-Q, Wu H-Y, Xu X-D, Xu X-Q. The role of T cells in acute ischemic stroke. Brain Res Bull. 2023;196:20–33.
39. Arques S. Human serum albumin in cardiovascular diseases. Eur J Intern Med. 2018;52:8–12.
40. Mirali Z, Majdizadeh G, Baghbani M, Ossareh S, Dalili N, Movahedi A. Relationship between malnutrition inflammation score and dietary fat quality indices with cardiovascular diseases in hemodialysis patients. Iran J Kidney Dis. 2023;17:156–67.
41. Guo J, Wang D, Jia J, Zhang J, Liu Y, Lu J, et al. Neutrophil-to-lymphocyte ratio, lymphocyte-to-monocyte ratio and platelet-to-lymphocyte ratio as predictors of short- and long-term outcomes in ischemic stroke patients with atrial fibrillation. J Inflamm Res. 2024;17:6661–72.
42. Wang A, Wang F, Huang Y, Cui Q, Xu Y, Zhang W, et al. Association between systemic inflammatory markers and all-cause mortality in patients with stroke: a prospective study using data from the UK Biobank. J Stroke Cerebrovasc Dis. 2024;33: 108076.
43. Gong P, Liu Y, Gong Y, Chen G, Zhang X, Wang S, et al. The association of neutrophil to lymphocyte ratio, platelet to lymphocyte ratio, and lymphocyte to monocyte ratio with post-thrombolysis early neurological outcomes in patients with acute ischemic stroke. J Neuroinflamm. 2021;18:51.
44. Liuizė A, Mongirdienė A, Laukaitienė J. Relationship between inflammatory readings and the degree of coronary atherosclerosis (pilot study). J Clin Med. 2025;14:122.
45. García-Escobar A, Vera-Vera S, Tébar-Márquez D, Rivero-Santana B, Jurado-Román A, Jiménez-Valero S, et al. Neutrophil-to-lymphocyte ratio an inflammatory biomarker, and prognostic marker in heart failure, cardiovascular disease and chronic inflammatory diseases: new insights for a potential predictor of anti-cytokine therapy responsiveness. Microvasc Res. 2023;150: 104598.
46. Cao W, Song Y, Bai X, Yang B, Li L, Wang X, et al. Systemic-inflammatory indices and clinical outcomes in patients with anterior circulation acute ischemic stroke undergoing successful endovascular thrombectomy. Heliyon. 2024. https://doi.org/10.1155/2021/6894623.
47. Li X, Li J, Wu G. Relationship of neutrophil-to-lymphocyte ratio with carotid plaque vulnerability and occurrence of vulnerable carotid plaque in patients with acute ischemic stroke. BioMed Res Int. 2021;2021:6894623.
48. Wong HJ, Harith S, Lua PL, Ibrahim KA. Possible sarcopenia and its association with nutritional status, dietary intakes, physical activity and health-related quality of life among older stroke survivors. Ann Geriatr Med Res. 2022;26:162–74.
49. Shestopalov AE, Yakovleva AV, Yadgarov MY, Sergeev IV, Kuzovlev AN. Prevalence and impact of malnutrition risk on outcomes in critically ill patients with traumatic brain injury and stroke: a retrospective cohort study using electronic health records. Nutrients. 2024;16:2396.
50. Starace E, De Pasquale G, Morenghi E, Crippa C, Matteucci S, Pieri G, et al. Hospital malnutrition in the Medicine and Neurology Departments: a complex challenge. Nutrients. 2023;15:5061.
51. Abstracts of scientific papers and posters presented at physiatry'23: February 21–24, 2023. Am J Phys Med Rehabil. 2023;102:A1.
52. Yoon J, Baek S, Jang Y, Lee CH, Lee ES, Byun H, et al. Malnutrition and associated factors in acute and subacute stroke patients with dysphagia. Nutrients. 2023;15:3739.
53. Kusumawati N, Arisanti NLPE, Purnami NKR, Kusumawardani IAJD, Candrawati NW, Andrika P, et al. The relationship between platelet to lymphocyte ratio (PLR), monocyte to lymphocyte ratio (MLR), neutrophil to lymphocyte ratio (NLR), and albumin levels with the severity of community-acquired pneumonia (CAP) in hospitalized elderly patients. Int J Sci Adv. 2024;5:1–8.
54. Ozturk U, Nergiz S, Ozturk O. The association between HALP score and infection in acute ischemic stroke patients. J Stroke Cerebrovasc Dis. 2024;33: 107929.
55. Bao Y, Zhang Y, Du C, Ji Y, Dai Y, Jiang W. Malnutrition and the risk of early neurological deterioration in elderly patients with acute ischemic stroke. Neuropsychiatr Dis Treat. 2022;18:1779–87.
56. Wiedermann CJ. Albumin in normovolemic fluid management for severe traumatic brain injury: controversies and research gaps. J Clin Med. 2024;13:5452.
57. Belinskaia DA, Jenkins RO, Goncharov NV. Albumin Is an integrative protein of blood plasma and beyond. Int J Mol Sci. 2024;25:12627.
58. Upadhyay RK. High cholesterol disorders, myocardial infarction and its therapeutics. World J Cardiovasc Dis. 2023;13:433–69.
59. Li F, Wu Q, Fan Z, Yang N, Liu J, Wang Z. Meta analysis of electric stimulation rehabilitation treatment for dysphagia after stroke. J Radiat Res Appl Sci. 2024;17: 100860.
60. Schaechter JD. Motor rehabilitation and brain plasticity after hemiparetic stroke. Prog Neurobiol. 2004;73:1–61.
61. Lee C-Y, Howe T-H. Effectiveness of activity-based task-oriented training on upper extremity recovery for adults with stroke: a systematic review. Am J Occup Ther. 2024;78:7802180070.
62. Zeng H, Zeng X, Xiong N, Wang L, Yang Y, Wang L, et al. How stroke-related dysphagia relates to quality of life: the mediating role of nutritional status and psychological disorders, and the moderating effect of enteral nutrition mode. Front Nutr. 2024. https://doi.org/10.3389/fnut.2024.1339694/full.
63. Alizargar J, Bai C-H, Hsieh N-C, Wu S-FV. Use of the triglyceride-glucose index (TyG) in cardiovascular disease patients. Cardiovasc Diabetol. 2020;19:8.
64. Dang K, Wang X, Hu J, Zhang Y, Cheng L, Qi X, et al. The association between triglyceride-glucose index and its combination with obesity indicators and cardiovascular disease: NHANES 2003–2018. Cardiovasc Diabetol. 2024;23:8.
65. Huo R-R, Liao Q, Zhai L, You X-M, Zuo Y-L. Interacting and joint effects of triglyceride-glucose index (TyG) and body mass index on stroke risk and the mediating role of TyG in middle-aged and older Chinese adults: a nationwide prospective cohort study. Cardiovasc Diabetol. 2024;23:30.
66. Yang Z, Gong H, Kan F, Ji N. Association between the triglyceride glucose (TyG) index and the risk of acute kidney injury in critically ill patients with heart failure: analysis of the MIMIC-IV database. Cardiovasc Diabetol. 2023;22:232.
67. Anlar GG. Investigating the molecular mechanisms of shear stress induced endothelial dysfunction and progression of atherosclerosis. 2024. Available from: http://qspace.qu.edu.qa/handle/10576/56296.
68. Benjamin M. The relationship between metabolic syndrome, NF-κB signaling, and cardiovascular disease. 2025.
69. Hu Y, Kong Y, Tian X, Zhang X, Zuo Y. Association between heavy metals and triglyceride-glucose-related index: a mediation analysis of inflammation indicators. Lipids Health Dis. 2025;24:46.
70. Micha R, Peñalvo JL, Cudhea F, Imamura F, Rehm CD, Mozaffarian D. Association between dietary factors and mortality from heart disease, stroke, and type 2 diabetes in the United States. JAMA. 2017;317:912–24.
71. Hung SH, Ebaid D, Kramer S, Werden E, Baxter H, Campbell BC, et al. Pre-stroke physical activity and admission stroke severity: a systematic review. Int J Stroke Off J Int Stroke Soc. 2021;16:1009–18.
72. Mafruhah OR, Huang Y-M, Lin H-W. Impacts of medication non-adherence to major modifiable stroke-related diseases on stroke prevention and mortality: a meta-analysis. J Neurol. 2023;270:2504–16.

Publisher's Note