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A nomogram for predicting the risk of malnutrition in hospitalized older adults: a retrospective study

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Abstract

Background Malnutrition is highly prevalent but under-recognized in hospitalized older adults, which is closely related to increased risk of adverse clinical outcomes and mortality. It is crucial to identify high-risk individuals at an early stage and manage them promptly. This study aimed to explore the predictive factors and develop a nomogram model for predicting the risk of malnutrition in hospitalized elderly patients.

Methods We conducted a retrospective study of data collected from 456 older individuals admitted to geriatric wards from four hospitals in China between August 2020 and December 2020 (136 in the malnutrition group and 320 in the non-malnutrition group). Least Absolute Selection and Shrinkage Operator (LASSO) regression and stepwise multivariate logistic regression were applied to screen predictors and create a nomogram. The predictive performance of the model was assessed by receiver operating characteristic (ROC) curve, concordance index (C-index) and calibration curve. The clinical utility was estimated by decision curve analysis (DCA). Youden's Index was used to identify the optimal cut-point of the nomogram.

Results Four independent predictive factors were utilized to construct the nomogram model after being selected by LASSO regression and multivariate logistic regression, namely body mass index (BMI), heart failure, frailty and hemoglobin. C-index of the model was 0.906 (95% CI: 0.872–0.939) and the area under the curve (AUC) was 0.906. The optimal cut-point of the nomogram was 82.74 with a sensitivity of 78.7% and specificity of 92.2% (Youden's index: 0.709). The calibration curve demonstrated a high degree of consistency between predicted probability and actual observation. The DCA indicated a favorable clinical benefit for the nomogram.

Conclusions We have established a multi-dimensional nomogram model to predict the risk of malnutrition in Chinese hospitalized older adults. The model yields favorable predictive performance and clinical utility, which provides an effective approach for rapid identification of high-risk malnourished older individuals in clinical practice.

Keywords Malnutrition, Older adults, Predictor, Nomogram, Chinese

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Background

China has entered a rapid stage of aging. It is estimated that the population aged 65 years and older have accounted for 14.2% in 2021, and is expected to reach 395 million by 2050 [1]. The number of oldest old people (aged 80 years and older) is expected to grow to 135 million and China will become the oldest country among the twenty most populous countries by 2065 [2]. Malnutrition, a common geriatric syndrome, is a major risk factor for poor prognosis and increased morbidity and mortality rates in the elderly, leading to impaired function, reduced quality of life and even death [3–5]. A state of malnutrition can lead to increased healthcare costs and pose a huge economic burden to society. As a result of aging, malnutrition has become a critical public health problem in China. An analysis of 2009 wave of China Health and Nutrition Survey (CHNS) reported that 8.5% of participants aged 60 years or older were underweight [6]. A meta-analysis showed that the prevalence of malnutrition in Chinese community-dwelling elderly was 2.4–52.5% [7]. The prevalence of malnutrition and of being at risk of malnutrition in hospitalized elderly was about 8.77% and 30.68% respectively, and even reached up to 36.0% and 50.3% in older people over 80 years of age [8, 9]. However, only 1/3 of the malnourished patients have received nutritional support [9]. As a matter of fact, malnutrition in the elderly population is under-recognized in clinical practice and the rate of missed diagnosis is considerably high, as it is usually only detected when the patient has obvious visual signs [10]. Early detection and appropriate nutrition support may help to reverse and halt the malnutrition trajectory and the negative outcomes associated with poor nutritional status. As a result, rapid identification of high-risk malnourished individuals is of great significance.

Clinical prediction models can provide effective information for clinicians to recognize high-risk individuals and take further assessment and intervention. Although several well known nutritional screening tools have been developed so far, such as Mini Nutrition Assessment Short Form (MNA-SF), Malnutrition Universal Screening Tool (MUST), Nutrition Risk Screening 2002 (NRS 2002), among others [11, 12], there is no international consensus on a single best tool to identify risk of malnutrition, and most of them come from studies based on Western populations and do not aim for Chinese older people. On the other hand, nomogram is widely used to predict the occurrence of diseases in recent years [13] which can quantify the influence of each prediction variable on the results and facilitate more efficient clinical decisions [14]. However, no studies have been conducted using nomogram to predict the occurrence of malnutrition in the elderly yet. Therefore, our study aimed to screen out the predictive factors and develop a practical nomogram model for predicting the risk of malnutrition in hospitalized older adults in China.

Methods

Study design and population

This study was designed as a retrospective investigation of data obtained from National Key Research and Development Program of China (2018YFC2002100, 2018YFC2002101) led by West China Hospital of Sichuan University. Data were collected from patients admitted to geriatric wards from four hospitals in China participating in the program (Ruijin Hospital Shanghai Jiao Tong University School of Medicine, Xuanwu Hospital Capital Medical University, Shanghai General Hospital Shanghai Jiao Tong University School of Medicine and Fuxing Hospital Capital Medical University) between August 2020 and December 2020. Inclusion criteria: (1) aged 60 and older; (2) socio-demographic and relevant clinical data complete; (3) evaluation of nutritional status was performed. Exclusion criteria: (1) socio-demographic or relevant clinical data incomplete; (2) evaluation of nutritional status was not performed; (3) refuse to participate in or fail to complete the investigation. 530 elderly patients were assessed for eligibility for this study, 74 were excluded due to lack of complete socio-demographic and clinical information ($n = 62$) or absence of evaluation of nutritional status ($n = 12$). Finally, a total of 456 older individuals were enrolled in the study (Fig. 1).

The study was approved by the Ethics Committee on Biomedical Research, West China Hospital of Sichuan University (2021 – 965). Informed written consents were obtained from all participants.

Evaluation of nutritional status

The nutritional status of participants was evaluated using the European Society for Clinical Nutrition and Metabolism (ESPEN) standard. The diagnostic criteria for malnutrition were reached according to an ESPEN consensus statement in 2015 [15]. We defined malnutrition as individuals who met one of the two following alternatives: (1) body mass index (BMI) < 18.5 kg/m^2; (2) unintentional weight loss > 10% indefinite of time or > 5% over the last 3 months, combined with either BMI < 20 kg/m^2 if < 70 years of age or < 22 kg/m^2 if ≥ 70 years of age, or fat free mass index (FFMI) < 15 and 17 kg/m^2 in women and men respectively. BMI was calculated by dividing weight (in kilograms) by height (in meters) squared. FFMI was assessed by bio-impedance analysis (BIA).

Data collection

We collected socio-demographic and clinical data from all participants. To improve the feasibility of the model, we chose variables that were readily available in the clinic, which included: (1) general information (age, sex,

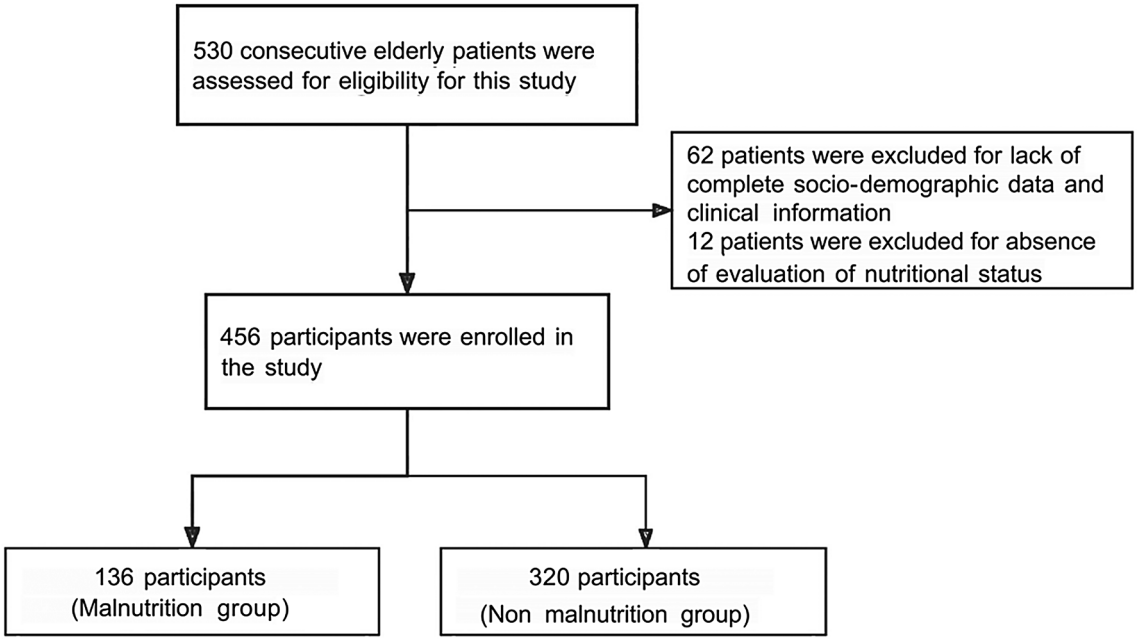

Fig. 1 Flow diagram of the participant selection

marital status, educational level) and lifestyle habits (history of smoking, consumption of alcohol, dietary habit, physical activity, social activity); (2) comorbid medical conditions (cardiovascular disease, endocrinal and metabolic disease, respiratory disease, chronic renal and liver disease, neuropsychological disease, frailty, etc.); (3) laboratory tests of biochemical markers (hemoglobin, alanine aminotransferase (ALT), albumin, creatinine, urea, uric acid, estimated glomerular filtration rate (eGFR), fasting blood glucose (FBG), triglyceride, total cholesterol, high-density lipoprotein of cholesterol (HDL-C), low-density lipoprotein of cholesterol (LDL-C), etc.); (4) anthropometric measurements (height, weight, body mass index (BMI), mid arm circumference (MAC), calf circumference). General information and medical history were obtained through an electronic medical record system. Marital status was dichotomized as "married" and "divorced or widowed". Educational level was categorized according to years of education. Consumption of alcohol was dichotomized as "no" (never drink alcoholic beverage or less than once a week) and as "yes" (drink one day or more than one day a week). To assess cigarette smoking, the following question was used: "Do you currently smoke cigarettes?" and the answer option was dichotomized as "no" and "yes" [16]. Physical activity was defined as exercise of moderate intensity with duration of 30 min per time and was categorized according to the frequency per week (> 3 times per week, 1–3 times per week, and < 1 time per week). Social activity included 6 items (visiting friends or relatives, going to restaurants or sporting events or playing games, group meeting, religious services, trips, and volunteer work) [17] and was also categorized according to the frequency per week. Balanced dietary habit was defined as eating a variety of food that contains multiple nutritional components. The laboratory tests of biochemical markers were obtained at the time of admission. MAC was measured at the midpoint level of the upper arm with a tape with the subject in a standing position upright with the arm hanging loosely. Calf circumference was measured in the most prominent region of the leg with the subject in a sitting position with both legs on the floor and relaxed.

Statistical analysis

All the statistical analyses were performed using IBM SPSS version 26.0 and R 4.2.0. Continuous variables of normal distribution were described as mean ± standard deviation ($\bar{x} \pm s$), and the comparison between groups was conducted by *t*-test. Continuous variables of non-normal distribution were expressed as median (interquartile range, IQR), and the Mann-Whitney *U* test was used for comparison between groups. Count or categorical data were displayed as number (percentage, %), and analyzed with *Chi*-square test or Fisher's exact test for comparison. Univariate logistic regression analysis was performed to preliminary explore the association.

The least absolute shrinkage and selection operator (LASSO) method was applied to screen for predictive factors with the best predictive characteristics and statistically significant variables ($P < 0.05$) were included in the stepwise multivariate logistic regression analysis. Independent predictors identified by the multivariate logistic analysis were selected to construct a prediction nomogram. The discrimination and consistency

of the nomogram were evaluated by concordance index (C-index), the area under the receiver operating characteristic (ROC) curve (AUC), and the calibration curve. Youden's Index was applied to identify the optimal cut-point of the nomogram for maximizing sensitivity and specificity. The decision curve analysis (DCA) was used to estimate the clinical utility of the model. P value < 0.05 was considered to be statistically significant.

Results

Socio-demographic and clinical characteristics

After applying inclusion and exclusion criteria, a total of 456 older individuals were enrolled in the study, including 310 men (68.0%) and 146 women (32.0%). All the participants were divided into a malnutrition group ($n = 136$) and a non-malnutrition group ($n = 320$) according to the ESPEN consensus, of which the median ages were 88 and 80 years respectively ($P < 0.001$). The socio-demographic and clinical characteristics were listed in Table 1. Comparison between the malnutrition group and non-malnutrition group revealed significant differences ($P < 0.05$) in age, marital status, physical activity, social activity, dietary habit, heart failure, diabetes mellitus, dyslipidemia, metabolic syndrome, chronic kidney disease (CKD), depression, cognitive impairment, frailty, BMI, MAC, calf circumference, hemoglobin, ALT, albumin, urea, uric acid, eGFR, FBG, triglycerides, total cholesterol, HDL-C and LDL-C. Univariate logistic regression analysis demonstrated that age, age group (≥ 85 years), divorced or widowed, unbalanced dietary habit, heart failure, CKD, depression, cognitive impairment, frailty, urea and HDL-C were significantly positively associated with malnutrition, while frequency of physical activity and social activity, diabetes mellitus, dyslipidemia, metabolic syndrome, BMI, MAC, calf circumference, hemoglobin, albumin, uric acid, eGFR, triglyceride, total cholesterol and LDL-C were negatively associated with malnutrition, as presented in Table 1.

Screening for predictive factors and construction of the nomogram for malnutrition

The feature selection was conducted by using LASSO regression and stepwise multivariate logistic regression. Eight variables had nonzero coefficients in the LASSO regression model, including age group, BMI, physical activity, heart failure, frailty, hemoglobin, MAC and calf circumference (Fig. 2). The stepwise multivariate regression analysis showed that BMI (OR: 0.698, 95% CI: 0.621–0.784), heart failure (OR: 16.492, 95% CI: 3.932–69.169), frailty (OR: 2.932, 95% CI: 1.519–5.660), hemoglobin (OR: 0.979, 95% CI: 0.963–0.996) and MAC (OR: 0.674, 95% CI: 0.597–0.762) were identified as independent predictors of malnutrition (Table 2).

A nomogram model was constructed based on the above significant predictors by cumulatively calculating all the scores corresponding to the factors. Higher total points indicated a higher risk of malnutrition. As the influence of the variable of MAC to the model was too intense due to its corresponding points width occupying the entire total points width of the model and resulting in considerable uncertainty of model prediction, it was removed and finally we established an optimized prediction model including four variables, namely BMI (OR: 0.608, 95% CI: 0.546–0.677), heart failure (OR: 13.599, 95% CI: 3.462–53.414), frailty (OR: 2.958, 95% CI: 1.647–5.310) and hemoglobin (OR: 0.973, 95% CI: 0.959–0.987) (Fig. 3).

Predictive performance and clinical utility of the nomogram

The diagnostic performance of the nomogram for malnutrition was presented in Fig. 4. The AUC of the nomogram was 0.906 and the C-index was 0.906 (95% CI: 0.872–0.939), reflecting a favorable predictive power and good discrimination ability of the model. The optimal cut-point of the nomogram was 82.74 with a sensitivity of 78.7% and specificity of 92.2% (Youden's index: 0.709). The calibration curve showed a good consistency between predicted probability and actual incidence probability across the cohort (Fig. 5), indicating a high predictive accuracy of the nomogram. Meanwhile, the clinical applicability of the model was evaluated by the DCA, as demonstrated in Fig. 6. The DCA curve revealed a net benefit of the nomogram in predicting malnutrition across a wide range of threshold probability.

Discussion

The prevalence of malnutrition is considerably high in the elderly population especially in hospitalized older adults, which increases the risk of adverse clinical outcomes and long-term mortality [4–5, 10]. However, only a minority of malnourished elderly were diagnosed and received nutritional support [9]. It is crucial to establish a feasible prediction model which can be directly and conveniently applied in routine clinical practice to identify high-risk individuals. Given the multifactorial nature of malnutrition in the elderly, there is no consensus on a single objective measure or gold standard yet. Although several well known nutrition screen tools have been developed, most of them come from studies based on Western populations. Although some prediction models have been developed for malnutrition [18–21], they were not specifically designed for the geriatric population. As far as we know, our study is the first to establish a multidimensional nomogram model for predicting the risk of malnutrition in hospitalized older adults based on Chinese elderly population.

Table 1 Demographic and clinical characteristics between the malnutrition group and non-malnutrition group

	Comparison between malnutrition group and non malnutrition group				Univariate logistic regression analysis		
Characteristics	**Malnutrition group (*n* = 136)**	**Non-malnutrition group (*n* = 320)**	***Z/t/X²***	***P* value**	**OR**	**OR 95%CI**	***P* value**
Age, years[&]	88.00 (9.00)	80.00 (18.00)	-7.109	< 0.001	1.081	1.056–1.107	< 0.001
Age group, n (%)[Δ]							
60–64 years	4 (2.9%)	26 (8.1%)	47.463	< 0.001	Reference		
65–69 years	6 (4.4%)	53 (16.6%)			0.736	0.191–2.837	0.656
70–74 years	7 (5.2%)	43 (13.4%)			1.058	0.282–3.967	0.933
75–79 years	7 (5.2%)	36 (11.2%)			1.264	0.335–4.769	0.730
80–84 years	17 (12.5%)	45 (14.1%)			2.456	0.746–8.083	0.139
≥ 85 years	95 (69.8%)	117 (36.6%)			5.278	1.780-15.649	0.003
Sex, n (%) [Δ]							
Male	92 (67.6%)	218 (68.1%)	0.010	0.920	0.978	0.637–1.503	0.920
Female	44 (32.4%)	102 (31.9%)			Reference		
Marital status, n (%)[Δ]							
Married	97 (71.3%)	260 (81.3%)	5.533	0.019	Reference		
Divorced or widowed	39 (28.7%)	60 (18.7%)			1.742	1.094–2.776	0.019
Educational level, n (%)*							
< 1 year	3 (2.2%)	6 (1.9%)	3.545	0.469	Reference		
1-5years	15 (11.0%)	20 (6.3%)			1.500	0.322–6.991	0.606
6–9 years	36 (26.5%)	98 (30.6%)			0.735	0.174–3.093	0.674
10–12 years	75 (55.1%)	179 (55.9%)			0.838	0.204–3.439	0.806
≥ 13 years	7 (5.1%)	17 (5.3%)			0.824	0.159–4.253	0.817
Physical activity, n (%)[Δ]							
> 3 times per week	14 (10.3%)	57 (17.8%)	53.049	< 0.001	Reference		
1–3 times per week	32 (23.5%)	168 (52.5%)			0.776	0.387–1.556	0.474
< 1 time per week	90 (66.2%)	95 (29.7%)			3.857	2.010–7.402	< 0.001
Social activity, n (%)[Δ]							
> 3 times per week	29 (21.3%)	163 (50.9%)	52.598	< 0.001	Reference		
1–3 times per week	24 (17.7%)	73 (22.8%)			1.848	1.007–3.391	0.047
< 1 time per week	83 (61.0%)	84 (26.3%)			5.554	3.375–9.139	< 0.001
History of smoking, n (%)[Δ]							
Yes	9 (6.6%)	29 (9.1%)	0.747	0.387	0.711	0.327–1.546	0.389
No	127 (93.4%)	291 (90.9%)			Reference		
Consumption of alcohol, n (%)[Δ]							
Yes	7 (5.1%)	30 (9.4%)	2.288	0.130	0.525	0.225–1.225	0.136
No	129 (94.9%)	290 (90.6%)			Reference		
Dietary habit, n (%)[Δ]							
Balanced	95 (69.9%)	294 (91.9%)	36.927	< 0.001	Reference		
Unbalanced	41 (30.1%)	26 (8.1%)			4.880	2.835-8.400	< 0.001
Hypertension, n (%)[Δ]							
Yes	100 (73.5%)	245 (76.6%)	0.477	0.490	0.850	0.537–1.348	0.490
No	36 (26.5%)	75 (23.4%)			Reference		
CHD, n (%)[Δ]							
Yes	58 (42.6%)	128 (40.0%)	0.277	0.599	1.115	0.743–1.675	0.599
No	78 (57.4%)	192 (60.0%)			Reference		
Atherosclerosis, n (%)[Δ]							
Yes	87 (64.0%)	189 (59.1%)	0.962	0.327	1.231	0.813–1.864	0.327
No	49 (36.0%)	131 (40.9%)			Reference		
Atrial fibrillation, n (%)[Δ]							
Yes	18 (13.2%)	34 (10.6%)	0.644	0.422	1.283	0.697–2.362	0.423
No	118 (86.8%)	286 (89.4%)			Reference		
Heart failure, n (%)[Δ]							

Table 1 (continued)

	Comparison between malnutrition group and non malnutrition group				Univariate logistic regression analysis		
Characteristics	**Malnutrition group (*n* = 136)**	**Non-malnutrition group (*n* = 320)**	***Z/t/X²***	***P* value**	**OR**	**OR 95%CI**	***P* value**
Yes	22 (16.2%)	6 (1.9%)	33.870	< 0.001	10.099	3.994–25.540	< 0.001
No	114 (83.8%)	314 (98.1%)			Reference		
Stroke, n (%)[Δ]							
Yes	46 (33.8%)	111 (34.7%)	0.032	0.859	0.962	0.630–1.470	0.859
No	90 (66.2%)	209 (65.3%)			Reference		
Parkinson's disease, n (%)[Δ]							
Yes	1 (0.7%)	7 (2.2%)	0.477	0.490	0.331	0.040–2.718	0.304
No	135 (99.3%)	313 (97.8%)			Reference		
Diabetes mellitus, n (%)[Δ]							
Yes	39 (28.7%)	132 (41.2%)	6.438	0.011	0.573	0.371–0.883	0.012
No	97 (71.3%)	188 (58.8%)			Reference		
Dyslipidemia, n (%)[Δ]							
Yes	30 (22.1%)	137 (42.8%)	17.710	< 0.001	0.378	0.238-0.600	< 0.001
No	106 (77.9%)	183 (57.2%)			Reference		
Metabolic syndrome, n (%)[Δ]							
Yes	5 (3.7%)	39 (12.2%)	7.930	0.005	0.275	0.106–0.714	0.008
No	131 (96.3%)	281 (87.8%)			Reference		
OSAHS, n (%)[Δ]							
Yes	20 (14.7%)	29 (9.1%)	3.169	0.075	1.730	0.941–3.181	0.078
No	116 (85.3%)	291 (90.9%)			Reference		
Liver disease, n (%)[Δ]							
Yes	6 (4.4%)	15 (4.7%)	0.017	0.898	0.938	0.356–2.473	0.898
No	130 (95.6%)	305 (95.3%)			Reference		
CKD, n (%)[Δ]							
Yes	37 (27.2%)	49 (15.3%)	8.822	0.003	2.067	1.273–3.357	0.003
No	99 (72.8%)	271 (84.7%)			Reference		
Depression, n (%)[Δ]							
Yes	13 (9.6%)	11 (3.4%)	7.172	0.007	2.969	1.295–6.807	0.010
No	123 (90.4%)	309 (96.6%)			Reference		
Anxiety, n (%)[Δ]							
Yes	15 (11.0%)	21 (6.6%)	2.619	0.106	1.765	0.881–3.538	0.109
No	121 (89.0%)	299 (93.4%)			Reference		
Cognitive impairment, n (%)[Δ]							
Yes	45 (33.1%)	58 (18.1%)	12.221	< 0.001	2.234	1.415–3.526	0.001
No	91 (66.9%)	262 (81.9%)			Reference		
Frailty, n (%)[Δ]							
Yes	89 (65.4%)	99 (30.9%)	46.891	< 0.001	4.227	2.762–6.469	< 0.001
No	47 (34.6%)	221 (69.1%)			Reference		
Constipation, n (%)[Δ]							
Yes	31 (22.8%)	51 (15.9%)	3.042	0.081	1.557	0.944–2.568	0.083
No	105 (77.2%)	269 (84.1%)			Reference		
BMI, kg/m^{2} [&]	18.88 (3.80)	24.44 (3.80)	-12.558	< 0.001	0.584	0.527–0.646	< 0.001
MAC, cm[&]	21.50 (3.00)	27.00 (4.00)	-13.358	< 0.001	0.579	0.522–0.641	< 0.001
Calf circumference, cm[&]	29.00 (4.78)	34.00 (4.08)	-12.192	< 0.001	0.674	0.623–0.729	< 0.001
Hemoglobin, g/L[&]	114.00 (25.50)	132.00 (23.00)	-8.183	< 0.001	0.961	0.951–0.972	< 0.001
ALT, IU/ml[&]	14.00 (10.75)	17.10 (11.10)	-3.463	0.001	0.993	0.978–1.008	0.366
Albumin, g/L[&]	35.75 (6.77)	37.80 (4.90)	-5.027	< 0.001	0.880	0.837–0.924	< 0.001
Creatinine, μmol/L[&]	74.50 (35.05)	73.05 (30.85)	-0.532	0.595	1.001	0.998–1.004	0.370
Urea, mmol/L[&]	6.68 (4.67)	5.87 (2.47)	-2.155	0.031	1.052	1.003–1.104	0.036
Uric acid, μmol/L[#]	301.16 ± 106.35	344.82 ± 94.11	-4.356	< 0.001	0.995	0.993–0.998	< 0.001

Table 1 (continued)

	Comparison between malnutrition group and non malnutrition group				Univariate logistic regression analysis		
Characteristics	**Malnutrition group (*n* = 136)**	**Non-malnutrition group (*n* = 320)**	***Z/t/X*²**	***P* value**	**OR**	**OR 95%CI**	***P* value**
eGFR, ml/min/1.73m² [#]	72.88 ± 25.41	80.42 ± 27.58	-2.735	0.006	0.989	0.982–0.997	0.007
FBG, mmol/L [&]	5.11 (1.45)	5.41 (1.53)	-2.767	0.006	0.958	0.866–1.059	0.402
Triglyceride, mmol/L [&]	0.91 (0.54)	1.17 (0.83)	-5.333	< 0.001	0.500	0.349–0.715	< 0.001
Total cholesterol, mmol/L [&]	3.91 (1.61)	4.06 (1.46)	-2.207	0.027	0.808	0.662–0.985	0.035
HDL-C, mmol/L [&]	1.23 (0.51)	1.09 (0.40)	-4.312	< 0.001	3.968	2.142–7.352	< 0.001
LDL-C, mmol/L [&]	2.08 (1.16)	2.41 (1.26)	-3.412	0.001	0.627	0.484–0.812	< 0.001

[Δ]Chi-square test. *Fisher's exact test. [&]Mann-Whitney *U* test and variables were described in median (IQR). [#]*t*-test and variables were described in mean ± SD. CHD, coronary heart disease; OSASH, obstructive sleep apnea hypopnea syndrome; COPD, chronic obstructive pulmonary disease; CKD, chronic kidney disease; BMI, body mass index; MAC, mid arm circumference; ALT, alanine aminotransferase; eGFR, estimated glomerular filtration rate; FBG, fasting blood glucose; HDL-C, high-density lipoprotein of cholesterol; LDL-C, low-density lipoprotein of cholesterol

We conducted LASSO regression, an extension of generalized linear regression that decreases the variance of regression coeffients and the prediction error by adding a term to the log-likelihood to penalize model complexity [22], and stepwise multivariate logistic regression to screen and identify independent predictive factors. Finally, four significant variables (BMI, frailty, heart failure and hemoglobin) were utilized to construct the nomogram by combining statistical and clinical significance. The predictors selected are relatively available in clinical practice and integrated information related with anthropometric measurement, geriatric syndrome, comorbidity and laboratory test, taking a full consideration of the multifactorial nature of malnutrition in the elderly. The nomogram demonstrated favorable predictive performance with an AUC greater than 0.9 and good clinical utility, rendering it suitable for application in Chinese older population.

BMI, an index calculated from height and weight strongly associated with nutritional status, is often included in nutritional screening and assessment tools and also in prediction models for risk of malnutrition as an essential component [20, 23–25]. Quite a few studies in different populations have demonstrated that low BMI value is an independent risk factor for malnutrition while high BMI value is a protective factor [20, 23, 26]. Underweight by BMI (< 18.5 kg/m^2) was more prevalent in the malnourished group [27]. BMI of older subjects at high risk of malnutrition evaluated by various tools was significantly lower than those without a risk [28], and very low BMI was associated with adverse clinical outcomes [29]. These results indicated that BMI contributed significantly to the malnutrition effect, which was accordant with our findings. However, it is worth noting that BMI is insufficient as measure of body composition and may not fully capture nutritional status in older adults. As increasing prevalence of overweight and obesity would impact on the sensitivity of BMI as a screening component [30, 31], BMI alone was not valid for identifying the risk of malnutrition [28]. The present commonly applied BMI cut-off value might be misleading and fail to predict malnutrition accurately and needs to be adapted [30, 32, 33]. Thus, other metrics such as anthropometric measurements and body composition parameters should be complemented. From this point of view, the variables in our prediction model met the multi-dimensional requirements and the predictive value of BMI was set as a wide range.

In the present study, low hemoglobin level was also found to be an independent predictor for malnutrition in the elderly, consistent with previous findings [34, 35]. Anemia was closely related and frequently concomitant with malnutrition in the older population. A case-control study of very old hospitalized patients showed that anemic patients were more frequently malnourished or at risk of malnutrition [36]. Another research of elderly nursing home residents revealed that anemia risk was 2.12-fold higher in individuals at risk of malnutrition and 5.05-fold higher in those with malnutrition [37]. Hemoglobin levels were significantly lower in malnourished patients and individuals at high risk of malnutrition than in those with normal nutritional status and without a risk [28, 38, 39]. As hemoglobin level increased by 1gm/dl, the risk of malnutrition decreased by 15% [40]. These results indicated that hemoglobin level was an essential indicator reflecting nutritional status. In our study, the similar result was obtained so that it is important to include it in the model for predicting the risk of malnutrition.

One of the prominent characteristics of the geriatric population is the multimorbidity of chronic diseases. Our study revealed that the comorbidity of heart failure was a significant predictive factor for malnutrition. Malnutrition is highly prevalent in patients with heart failure and is associated with a worse clinical outcome

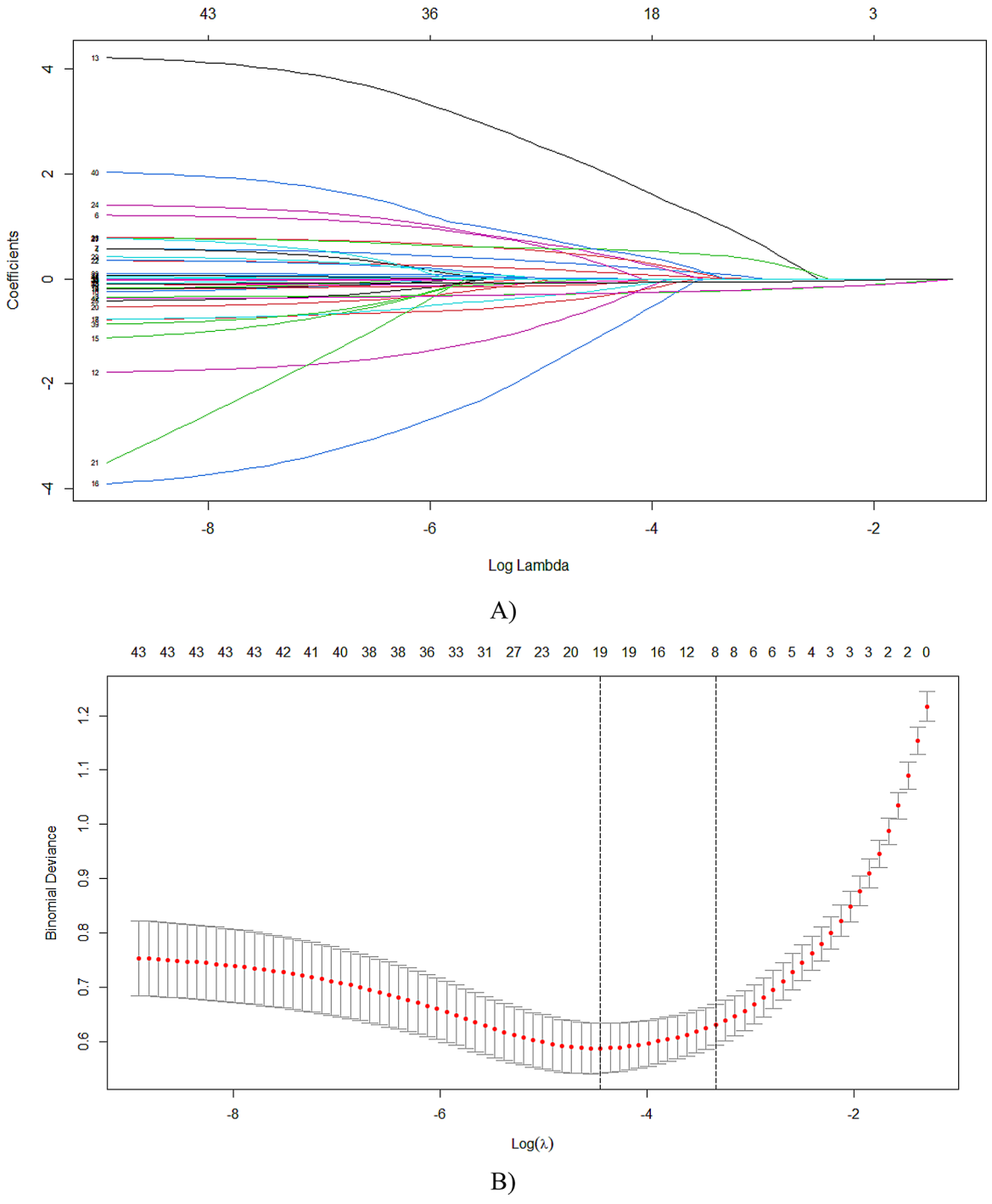

Fig. 2 Demographic and clinical features of malnutrition selection using the LASSO regression model. (**A**) Profiles of the LASSO coefficients for the features. (**B**) Lambda (λ) selection utilized fivefold cross-validation with minimal criteria. LASSO: least absolute contraction and selection operator

and increased mortality rate [27, 41–43]. The prevalence of malnutrition in patients with chronic heart failure is as high as 69% [44], and even reached up to 75–90% in advanced and acute decompensated heart failure [45]. The incidence of malnutrition in heart failure ranged from 15 to 90% depending on various assessment methods [41, 46]. Sze et al. reported that 57% of outpatients with heart failure were at least mildly malnourished by at least 1 nutritional scoring system [47]. Previous evidence also suggested that the presence of heart failure was a significant influencing factor to malnutrition which may alter the nutritional status. The reason may be attributed to venous congestion, sustained neurohormonal activation and insidious inflammation caused by heart failure,

Table 2 Multivariate logistic regression analysis of predictive factors for malnutrition

Variables	β	SE	Wald	OR	95% CI	*P* value
BMI (kg/m^2)	-0.360	0.060	36.452	0.698	0.621–0.784	< 0.001
Heart failure	2.803	0.731	14.683	16.492	3.932–69.169	< 0.001
Frailty	1.076	0.336	10.274	2.932	1.519–5.660	0.001
Hemoglobin (g/L)	-0.021	0.009	5.653	0.979	0.963–0.996	0.017
MAC (cm)	-0.394	0.062	40.359	0.674	0.597–0.762	< 0.001

BMI, body mass index; MAC, mid arm circumference; OR: odds ratio; CI: confidence interval; β: regression coefficient

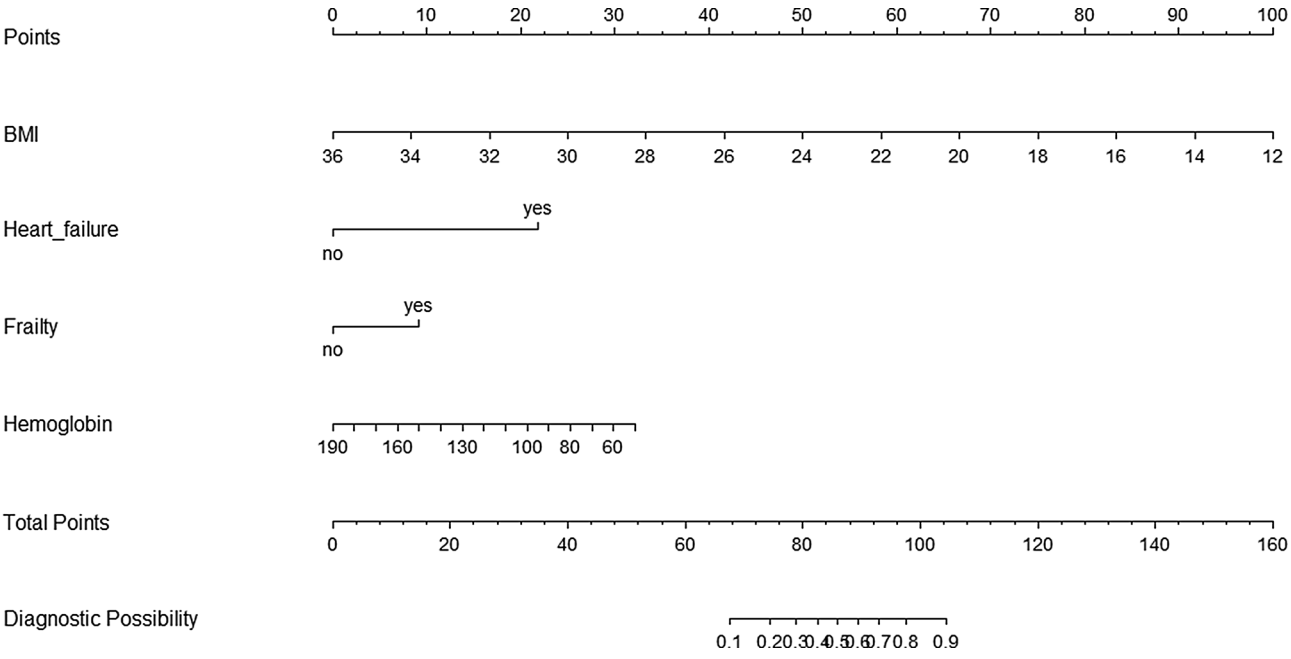

Fig. 3 A nomogram for predicting the risk of malnutrition in hospitalized older adults. BMI, body mass index

which predispose to bowel oedema, defective intestinal absorption and low body stores of nutrients and energy, sequentially leading to malnutrition [48, 49]. In accordance with previous findings, our study revealed that heart failure had statistical significance in the multivariate analysis screen, suggesting that heart failure was a non-negligible component in identifying the risk of malnutrition.

The results of feature selection showed that frailty, another highly prevalent geriatric syndrome characterized by increased vulnerability to poor resolution of homeostasis after a stress event and confers to an increased risk of adverse outcomes, including falls, disability and death [50], was also an important predictor for malnutrition in hospitalized older adults. Frailty and malnutrition are two closely related and frequently concomitant geriatric syndromes that may share similar determinants [51–53]. A meta-analysis revealed a high association and considerable overlap between physical frailty and malnutrition in older hospitalized adults [54]. The co-ocurrence of frailty and malnutrition reached up to 40.5% among institutionalized older adults in a multicenter study [55]. Besides, there was significant associations between variables of malnutrition and frailty [56]. Notably, frailty was identified as a major risk factor for malnutrition in older people [57], while no frailty was inversely related with malnutrition [58]. As living with frailty may lead to changes in eating behavior and deterioration of nutritional status [59], assessment of frailty could enhance nutritional interventions. We included frailty in the prediction model so that this highly prevalent geriatric syndrome was fully taken into account.

As gender differences are observed in deficiency of energy and nutrient among Chinese adults [60], there might be some disparities in gender distribution of malnutrition. Interestingly, although WHO estimates indicated that the prevalence of underweight was slightly higher among women (17.1%) than men (16.6%) in 2017, and that prevalence rates of malnutrition tend to be higher in women [61], limited information is available to confirm sex differences on prevalence of malnutrition in older population. Similarly, gender was not found to be an independent factor for malnutrition in our study either.

In the present study, we identified the predictive factors of malnutrition in hospitalized older adults and

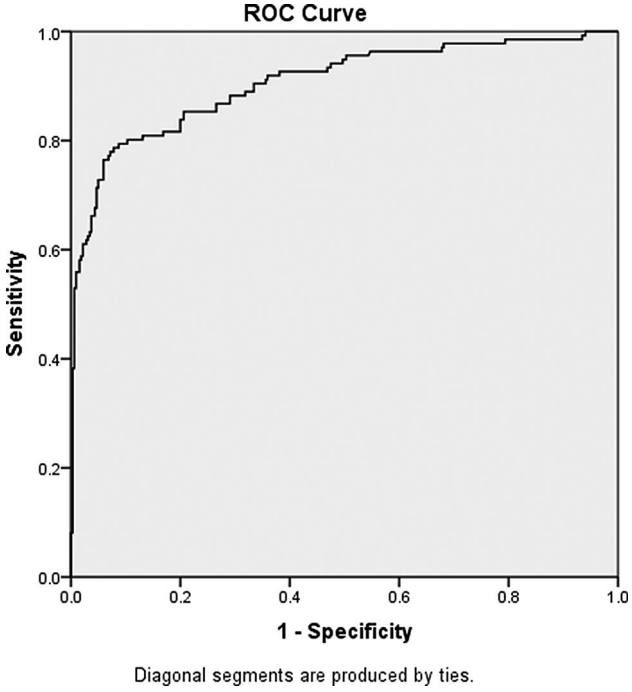

Fig. 4 ROC curve of the nomogram model. ROC: receiver operating characteristic

established a prediction nomogram model for rapid identification of high-risk malnourished individuals. Nevertheless, there are several limitations in our study. First of all, the study was a retrospective analysis in nature and the effects of missing data and case selection bias were inevitable. As this was a multi-center study, there might be some disparities in reporting practice and laboratory test among the hospitals involved. Secondly, the sample size of our study was relatively small. There are several factors (such as age, albumin, calf circumference) which are believed to have theoretical connections with malnutrition and show a certain trend of difference in descriptive statistics, but no statistical significance in multivariate analysis. Therefore, we will expand the sample size and further researches with a larger scale are expected to be conducted. Thirdly, our study may have not explored all possible reasons for malnutrition and prospective data are not included in this study, other meaningful indicators (such as lack of teeth, poor mobility, alteration of appetite, etc.) may also be potential predictors of malnutrition. Finally, the model was based on data from hospital settings which may limit its generalizability in other settings. Although the model was well validated in the internal validation cohort, further external validation is warranted in the future.

Conclusions

In conclusion, in this study we developed a multi-dimensional nomogram model based on BMI, hemoglobin, heart failure and frailty for early warning of malnutrition in hospitalized older adults. This model is specially designed for the Chinese elderly population compared with present western tools. Higher total points reflect a greater risk of malnutrition. The nomogram showed good predictive accuracy, discrimination and clinical utility.

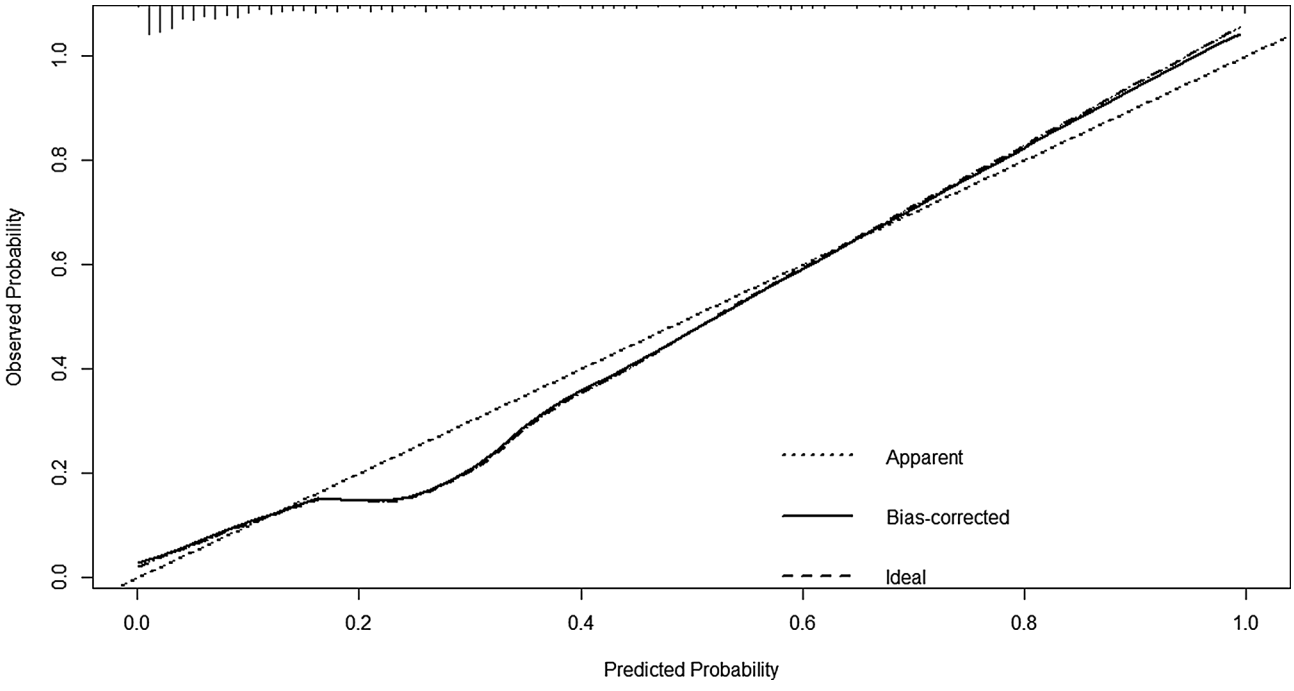

Fig. 5 Calibration curve of the nomogram for predicted probability of malnutrition

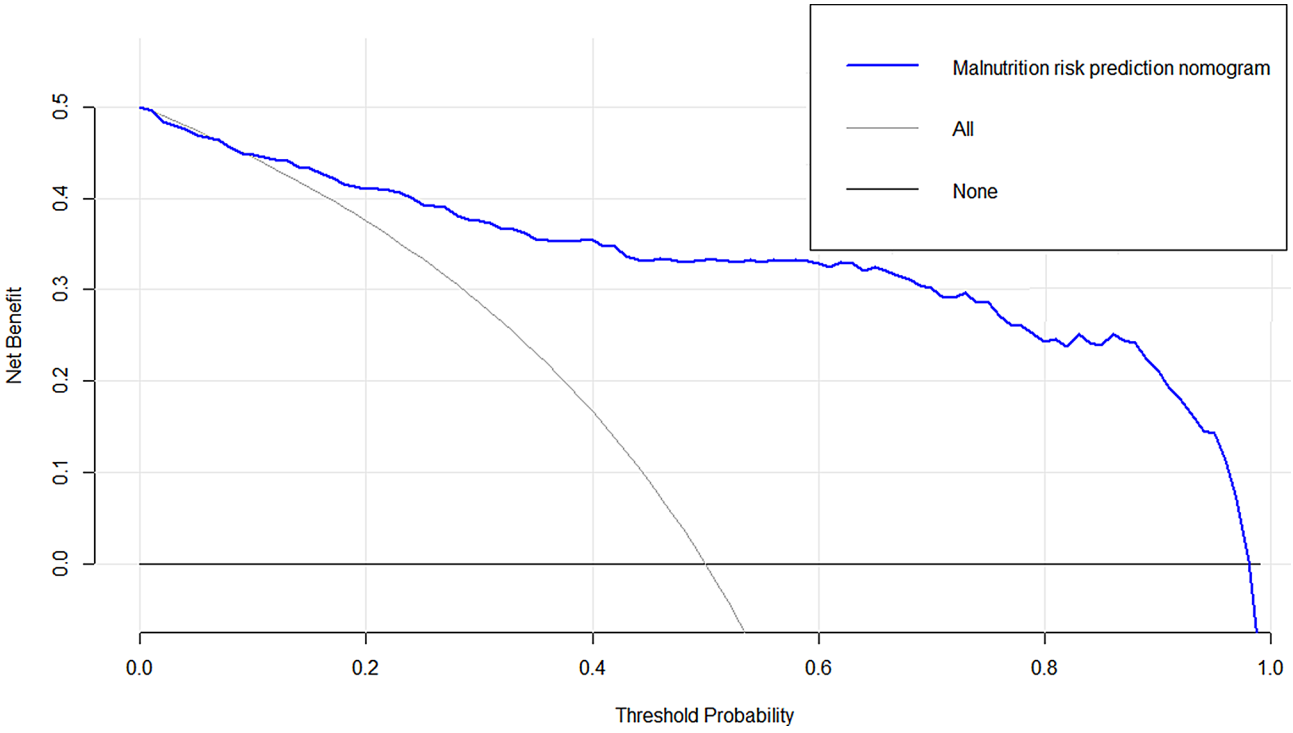

Fig. 6 Decision curve analysis (DCA) of the nomogram

The visualized and practical prediction model provides clinicians with a simple and intuitive tool for rapid detection of high-risk malnourished older individuals in clinical practice, which may be helpful in the fight to reduce relevant adverse clinical outcomes. The use of the nomogram could promote interprofessional collaboration in healthcare settings, such as improved communication between clinicians and dietitians regarding nutritional support for patients.

Abbreviations

ALT	Alanine aminotransferase
AUC	Area under the curve
BMI	Body mass index
CHD	Coronary heart disease
CI	Confidence interval
CKD	Chronic kidney disease
COPD	Chronic obstructive pulmonary disease
DCA	Decision curve analysis
FBG	Fasting blood glucose
FFMI	Fat free mass index
eGFR	Estimated glomerular filtration rate
HDL-C	High-density lipoprotein of cholesterol
IQR	Interquartile range
LASSO	Least absolute contraction and selection operator
LDL-C	Low-density lipoprotein of cholesterol
MAC	Mid arm circumference
OR	Odds ratio
OSASH	Obstructive sleep apnea hypopnea syndrome
ROC	Receiver operating characteristic

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Author contributions
All authors listed have made a substantial, direct, and intellectual contribution to the work. QJ, JW and FW designed the study; FL, LM, XN and QW collected the data; GX analyzed and interpreted the data; QJ was a major contributor in writing the manuscript. All authors read and approved the final manuscript.

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Data availability
Th datasets used and/or analyzed in the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participant
This study was approved by the Ethics Committee on Biomedical Research, West China Hospital of Sichuan University (2021 – 965). Informed written consents were obtained from all participants.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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