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Impact of sleep duration and dietary patterns on risk of metabolic syndrome in middle-aged and elderly adults: a cross-sectional study from a survey in Anhui, Eastern China

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Abstract

The aim of this study was to assess the sleep status of middle-aged and elderly adults in Bengbu City, Anhui Province, China, to identify the major dietary patterns, and to analyze the association of different sleep duration and dietary patterns with metabolic syndrome (MetS) and its related influencing factors, as well as to explore the predictive value of sleep duration and dietary patterns. A cross-sectional analysis was performed utilizing data collected from the Community-based Cardiovascular and Health Promotion Study 2019 (COCHPS 2019) conducted in Bengbu. The definition of MetS adhered to the criteria of Guidelines for the Prevention and Treatment of Dyslipidemia in Chinese Adults (2016 Revision). Dietary information was obtained using the Food Frequency Questionnaire (FFQ) to assess dietary intake over the past year. Principal component analysis (PCA) was performed to identify dominant dietary patterns. A logistic regression model was developed to analyze the associations among sleep duration, dietary patterns, and MetS, and a decision tree (DT) model was developed to compare factors affecting MetS and screen people at high risk for MetS. The prevalence of MetS was 13.4% among the 9132 middle-aged and elderly residents over 45 years of age included in COCHPS 2019. Participants were divided into short (<6 h/d), normal (6–8 h/d), and long (>8 h/d) groups based on their daily sleep duration. Three dietary patterns were identified by PCA, the fruit-milk pattern, the tubers-meat pattern, and the vegetable-cereal pattern. After adjusting for covariables, logistic regression analysis showed that long sleep duration was significantly negatively associated with MetS. The fruit-milk and vegetable-cereal patterns were negatively associated with MetS, whereas the tubers-meat pattern was positively correlated with MetS. The results of the DT model analysis showed that the vegetable-cereal pattern is the most important factor impacting MetS, followed by marital status, the tubers-meat pattern, the fruit-milk pattern, exercise, sleep duration, and gender. The DT model also screened out five types of MetS high-risk groups. The results of our study indicate that normal sleep duration and consumption of either a fruit-milk or vegetable-cereal diet may lower the likelihood of developing MetS in middle-aged and elderly adults.

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Introduction

The clinical condition known as metabolic syndrome (MetS) is characterized by abdominal obesity, dyslipidemia, hypertension, and hyperglycemia [1]. Based on the definition of MetS by the International Diabetes Federation (IDF), approximately 20–25% of people globally suffer from MetS [2], with the prevalence of MetS ranging from 13.6 to 46.3% in China [3, 4]. The research findings have demonstrated a significant association between MetS and an elevated risk of developing diabetes, cardiovascular disease, and various types of cancer, as well as increased mortality [5]. MetS is clearly a significant and expanding global public health issue and clinical challenge [6]. Earlier studies have shown that the prevalence of MetS varies markedly throughout the regions of China due to variations in culture, economics, lifestyle, and degree of aging [7, 8]. For the purpose of implementing public health interventions, it is crucial to assess the distribution of MetS and investigate the variables impacting MetS in detail.

Although the findings have been inconsistent, an unhealthy lifestyle, which includes an unbalanced diet and inadequate sleep, is strongly associated with MetS. Whereas one study found no evidence of a significant correlation between prolonged sleep and MetS [9], a meta-analysis indicated a U-shaped relationship between sleep duration and MetS [10]. Dietary patterns are composed of a group of food elements believed to impact the occurrence and development of MetS [11, 12]. When evaluating the link between diet and illness, dietary patterns consisting of multifaceted, nutrient-rich foods play a more crucial role than singular nutrients or dietary elements. Therefore, it is believed that eating a holistic diet rather than focusing on specific foods will more strongly assist in avoiding the development of disease [13]. Three healthy diets that have been shown to help reduce the overall risk of MetS are the Mediterranean diet, the Dietary Approaches to Stop Hypertension (DASH) diet, and the Mediterranean-DASH Intervention for Neurodegenerative Delay (MIND) diet [7, 14–16]. The varying frequency of MetS and its components in China has been partly explained by variations in dietary practices among Chinese regions.

Data mining is the process of using sophisticated algorithms and data analysis techniques to identify previously unidentified patterns in data to reveal relationships between various factors and analyze the extent of influence of related variables [17]. The use of a decision tree (DT) algorithm, a method of data mining, enables physicians to identify the most beneficial choice for their patients by establishing a set of prioritized categorization criteria [18]. Because of their visual and comprehensible features [19], DT models are a widely used modeling approach in economics and clinical practice. Numerous studies have demonstrated their efficacy as instruments for clinical data interpretation [20–22]. Creating predictive models to pinpoint those most susceptible to MetS could aid in the creation of preventive therapies for the syndrome and its associated cardiovascular conditions.

The objective of this study was to investigate the prevalence of MetS in middle-aged and elderly adults in Bengbu, Anhui Province, China. By so doing, it aimed to assess sleep status and identify the main dietary patterns, as well as to analyze the potential association between different sleep duration, dietary patterns with metabolic syndrome and its associated influencing factors. High-risk groups were identified using a mix of logistic regression and decision tree models, and specific recommendations for minimizing the incidence of metabolic syndrome in terms of sleep and food were presented.

Materials and methods

Data source and survey population

The study data were sourced from the Community-based Cardiovascular and Health Promotion Study 2019 (COCHPS 2019), this cross-sectional study was conducted in Longzihu district, Bengbu city of Anhui province in Southeastern China. The recruitment took place from September 2019 to December 2019 [23]. A multistage stratified cluster sampling method was used to select the middle-aged and elderly residents in our study. The communities in Longzihu district were stratified and randomly selected according to the economic levels proportionally [24, 25]. The overall survey included: face-to-face questionnaire, dietary assessment, anthropometric measurement and laboratory examinations. A total of 10,258 Bengbu community members were enrolled in our study. Potential participants were excluded if they met one or more of the following criteria: age under 45 years (n=274), lack of sufficient demographic data (missing or abnormal information on one or more items such as gender, age, marital status, education level)(n=761), lack of sufficient sleep data (missing or abnormal sleep information)(n=28), or lack of sufficient dietary data (missing or abnormal information on one or more food items)(n=63). Ultimately, 9132 Bengbu residents were included in this research. Figure 1 illustrates the precise screening procedure. Informed consent was provided by all participants. This study accorded with the Helsinki

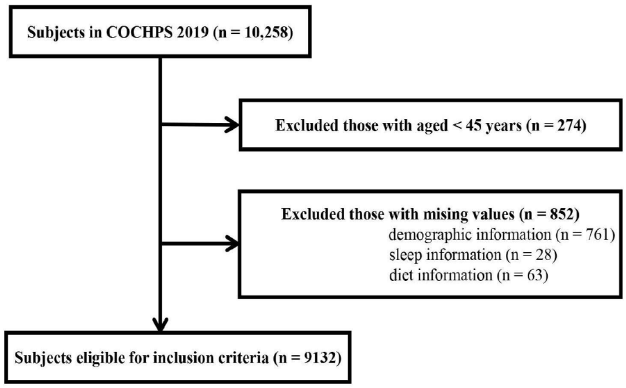

Fig. 1 The flowchart of participants in this study

Declaration and was approved by the Ethics Committee of Bengbu Medical University.

Data collection

Trained investigators conducted face-to-face interviews with community residents using a modified and standardized questionnaire [26] to collect data on general demographics, lifestyle habits, and chronic disease history. The questionnaire contained items regarding (1) basic personal data, including name, gender, age, education level (none/illiterate, primary school, middle school, high school, or above), and marital status (single, married, divorced, or widowed); (2) lifestyle habits, including smoking status (non-smoker, current smoker, or former smoker), alcohol consumption (non-drinker, occasional drinker, or current drinker), dietary habits (mainly meat-based diet, balanced diet, or vegetarian-oriented diet), and exercise (regular, occasional, or none); and (3) medical history, including history of hypertension, diabetes mellitus, hyperlipidemia, and medication use.

Sleep duration assessment

Information on sleep duration was obtained using a self-reported questionnaire. In order to obtain accurate sleep dutation, we ensure the questions specific and clear, we asked the residents such as " What time do you usually go to bed at night? " and " What time do you usually wake up in the morning? ", in the questionnaire, we asked for specific time periods rather than vague times, " Do you usually go to bed between 10 PM and 11 PM in the past week? " Consider as many people have different schedules for sleep time on weekdays and weekends, the average sleep time =(weekday sleep dutation * 5+weekend sleep dutation * 2). Based on their reported daily sleep length, participants were divided into three groups—a short group (<6 h/d), a normal group (6–8 h/d), and a long group (>8 h/d)—according to studies suggesting that adults over 45 years should get six to eight hours of sleep every day [27].

Dietary assessment

Dietary data were gathered using a semi-quantitative food frequency questionnaire (FFQ) [28] that asked respondents to recollect the intake and frequency of diverse foods during the past year. Based on the similarity of local dietary habits and the nutritional composition of foods consumed in Bengbu, 35 foods in the FFQ were classified into the following eight food groups (Supplemental Table S1): cereals, tubers, vitamin A-rich vegetables and fruits, red meat (i.e., beef and pork) and poultry, fish, eggs, and milk. These foods were categorized into the following eight grades based on the frequency of consumption: 3 times a day, 1–2 times a day, 5–6 times a week, 3–4 times a week, 1–2 times a week, 1–3 times a month, less than 12 times a year, and no consumption. Trained investigators showed the participants photographs and models to help them accurately estimate food portion sizes so that they could report the frequency and portion size of each food group consumed. The average daily consumption (g/day) was then estimated by multiplying the frequency of consumption by the size of the meal portion. Finally, the average daily consumption was divided by body weight to obtain the food intake per kilogram of body weight (g/kg×day).

Anthropometric measurement and blood pressure test

The weight (kg) and height (cm) of all participants were measured by trained examiners using a fully automatic height and weight measuring apparatus (HengDing Technology DMH-301, Zhengzhou, China), and the body mass index (BMI, kg/m^2) was automatically obtained. Waist circumference (WC, cm) was measured using an inelastic flexible ruler in the fasting state. All measurements were taken twice to obtain the average value. Blood pressure (BP) was measured three times continuously using an electronic sphygmomanometer (Omron HBP-1300; Omron Healthcare, Hoffman Estates, IL, USA) with a 1 mmHg accuracy, and then the average for each participant was calculated. To guarantee the accuracy of values, the participants rested for at least 10 min between measurements.

Laboratory examinations

After fasting for at least 8 h, the participants' fasting blood glucose (FBG) and blood lipids were measured using a fully automated biochemistry analyzer (Roche Modular P800; Roche Diagnostics, Basel, Switzerland). For FBG concentration determination, a hexokinase method was used, with an enzymatic colorimetry method used for triglyceride (TG) determination and a direct elimination method for high-density lipoprotein cholesterol (HDL-C) determination. Laboratory quality was strictly controlled for all tests.

Metabolic syndrome definition

The diagnostic criteria of MetS were derived from the Guidelines for the Prevention and Treatment of Dyslipidemia in Chinese Adults (2016 Revision) [29]. It includes the following five components: (1) abdominal obesity: males WC≥90 cm and females WC≥85 cm; (2) hyperglycemia: FPG level≥6.1 mmol/L, or a previous diagnosis of diabetes mellitus for which one is receiving treatment; (3) hypertension: BP≥140/90 mmHg or a diagnosis of hypertension for which one is receiving treatment; (4) low HDL-C: HDL-C level<1.04 mmol/L; and (5) high TG: TG level≥1.70 mmol/L. Participants who met three or more of the five criteria were diagnosed as having MetS.

Statistical analysis

Data were analyzed using Epidata 3.1 (EpiData Association, Odense, Denmark) and SPSS version 25.0 (SPSS Inc., Chicago, IL, USA) software. Principal component analysis (PCA) was performed to determine dietary patterns. The Kaiser–Meyer–Olkin (KMO) and Bartlett's sphericity tests were performed to determine whether factor analysis was appropriate before the analysis. The initial factor loading matrix was then rotated to obtain maximum variance, and eigenvalue>1 and cumulative contribution variance were used as criteria for the inclusion of common factors. Foods with a large factor loading (>0.5) were categorized into dietary patterns, and the factor scores of each dietary pattern were divided into four groups (Q1, Q2, Q3, and Q4) by quartiles. To evaluate the normality of the data, the Kolmogorov–Smirnov test was performed. Quantitative data are presented as mean±standard deviation (SD) and qualitative data as the percentage. MetS and non-MetS groups were compared using t-tests for continuous variables and chi-square tests for categorical variables. Logistic regression analysis was performed to calculate odds ratios (ORs) and 95% confidence intervals (CIs) to determine the relationship among MetS, sleep duration, and dietary patterns.

The DT model was built using IBM SPSS Modeler version 18.0 software (IBM, Armonk, NY, USA). In the DT structure, the main node represents the test condition, the branch node represents the result of the condition test, and the leaf node represents the outcome of the classification. Each node of the DT is a formula that decides whether the incoming data follows a path based on a variable. As a consequence, each node can split the input data into many categories, with the tree's leaf nodes representing the classification results [30, 31]. To analyze relevant influences on MetS, the chi-square automatic interaction detector (CHAID) algorithm was used, and the predictor variable with the largest category difference became the node's separation variable. The chi-square test is used by the CHAID algorithm to determine whether two variables should be merged. The predictor variable that has the largest class difference becomes the separation variable for that node if it can be constructed [32]. The tree growth layer was set at 3, and the stopping rule was α=0.05, with a minimum sample size of 100 at the parent node and 50 at the child node. Whether DT continued to grow in the node was determined by calculating its *P*-value and whether CHAID stopped the propagation of the pivots before application [33]. The area under receiver operating characteristic curve (AUROC) values and 95% CI values for each model were calculated and compared using MedCalc version 18 software (MedCalc Software Ltd., Ostend, Belgium) to assess the predictive effectiveness of the models. Statistics were conducted with two-tailed tests, and a difference of $P<0.05$ was considered statistically significant.

Results

General characteristics

As shown in Tables 1 and 9132 residents were included in the study, 3901 of whom were males and 5231 females, Among the 9132 residents, who had an average age of 62.87±6.11 years, 1220 residents (13.4%) were diagnosed with MetS. Significant differences were observed among the groups in terms of gender, marital status, dietary habits, exercise, sleep duration, and BMI ($P<0.05$). The prevalence of MetS was 10.8%, 13.2%, and 15.9% for participants who were single, married, divorced, and widowed, respectively ($\chi^2=6.443$, $P=0.040$). The majority of MetS participants who had a balanced diet ($\chi^2=12.688$, $P=0.005$) reported that they did not exercise ($\chi^2=17.090$, $P<0.001$). The mean BMI of MetS participants was 26.93 ± 3.12 kg/m^2, whereas that of non-MetS participants was 24.36 ± 3.16 kg/m^2 (t=-26.737, $P<0.001$).

Dietary patterns

Based on the KMO index of 0.677 and Bartlett's test result ($P<0.001$), PCA was able to be conducted. The overall three dietary patterns explained 48.896% of the variance in the study. Dietary pattern 1 (DP1), which had high loadings for fruits, milk, and eggs, was labeled the "fruit-milk pattern" and found to explain 16.960% of the variance in food intake. Dietary pattern 2 (DP2), which had high loadings for tubers, poultry, red meat, and fish, was labeled the "tubers-meat pattern" and found to explain 16.730% of the variance in food intake. Dietary pattern 3 (DP3), which had high loadings for vegetables and cereal, was labeled the "vegetable-cereal pattern" and found to explain 15.206% of the variance in food intake. The factor-loading matrixes for the three dietary patterns are displayed in Table 2.

Table 1 General characteristics of the study population

Characteristics	Total($n = 9132$)	Mets($n = 1220$)	Non-Mets($n = 7912$)	t/χ^2	*P*
Age(years)	62.87 ± 6.111	62.96 ± 5.806	62.86 ± 6.157	-0.526	0.599
Gender				6.235	0.013
Male	3901(42.7)	481(12.3)	3420(87.7)		
Female	5231(57.3)	739(14.1)	4492(85.9)		
Education level				3.000	0.223
Illiteracy or primary school	18(0.2)	0(0.0)	18(100.0)		
Middle school	9103(99.7)	1218(13.4)	7885(86.6)		
High school and above	11(0.1)	2(18.2)	9(81.8)		
Marital status				6.443	0.040
Single	223(2.4)	24(10.8)	199(89.2)		
Married	8062(88.3)	1061(13.2)	7001(86.8)		
Divorced or Widowed	847(9.3)	135(15.9)	712(84.1)		
Smoking Status				0.976	0.614
Non-smoker	8180(89.6)	1086(13.3)	7094(86.7)		
Current smoker	820(9.0)	118(14.4)	702(85.6)		
Former smoker	132(1.4)	16(12.1)	116(87.9)		
Alcohol status				2.397	0.302
Non-drinker	8109(88.8)	1077(13.3)	7032(86.7)		
Occasional drinker	470(5.1)	58(12.3)	412(87.7)		
Current drinker	553(6.1)	85(15.4)	468(84.6)		
Dietary habits				12.196	0.002
Meat oriented	139(1.5)	32(23.0)	107(77.0)		
Balanced diet	7567(82.9)	989(13.1)	6578(86.9)		
Vegetarian oriented	1426(15.6)	199(14.0)	1227(86.0)		
Exercise				17.090	< 0.001
Regularly	3078(33.7)	461(15.0)	2617(85.0)		
Occasionally	966(10.6)	146(15.1)	820(84.9)		
Never	5088(55.7)	613(12.0)	4475(88.0)		
Sleep duration				6.540	0.038
Short	1324(14.5)	186(14.0)	1138(86.0)		
Normal	6981(76.4)	902(12.9)	6079(87.1)		
Long	827(9.1)	132(16.0)	695(84.0)		
Energy Intake(kcal/day)	1774.39 ± 466.40	1794.35 ± 473.61	1771.31 ± 465.23	-1.585	0.113
BMI(kg/m^2)	24.70 ± 3.27	26.93 ± 3.12	24.36 ± 3.16	-26.737	< 0.001
Mets components					
WC(cm)	86.45 ± 9.90	94.51 ± 8.73	85.21 ± 9.48	-32.221	< 0.001
TG(mmol/L)	1.52 ± 1.09	2.30 ± 1.40	1.40 ± 0.98	-28.066	< 0.001
SBP (mmHg)	132.68 ± 15.16	144.90 ± 15.61	130.79 ± 14.18	-31.891	< 0.001
DBP (mmHg)	78.93 ± 8.97	83.70 ± 9.86	78.20 ± 8.59	-20.400	< 0.001
FBG(mmol/L)	5.78 ± 1.86	7.51 ± 2.37	5.52 ± 1.61	-37.447	< 0.001

Quartile characteristics of dietary patterns

Characteristics across the quartiles of dietary patterns are summarized in Table 3. Participants in the higher quartile group of DP1 were more likely to be female, more likely to consume alcohol, more likely to have a higher energy intake, and more likely to have a lower BMI ($P < 0.05$). Participants in the higher quartile of DP2 were more likely to be female, more likely to be older, more likely to be married, less likely to smoke, less likely to consume alcohol, less likely to eat meat, more likely to have a higher energy intake, and more likely have a lower BMI ($P < 0.05$). Participants in the higher quartile of DP3 were more likely to be female, more likely to be older, more likely to be married, less likely to smoke, less likely to consume alcohol, less likely to eat meat, and more likely to have a lower BMI ($P < 0.05$).

Analysis of the prevalence of metabolic syndrome according to dietary patterns and sleep duration

Figure 2 shows the prevalence of MetS and its components according to dietary patterns and sleep duration. Compared with those with a normal sleep duration, participants with short and long sleep durations had a significantly higher prevalence of MetS. Among participants

Table 2 Factor-loading matrix for the three dietary patterns among middle-aged and elderly adults in Bengbu city

Food groups	DP1 (Tubers-meat pattern)	DP2 (Fruit-milk pattern)	DP3 (Vegetable-cereal pattern)
Fruits	-0.017	**0.736***	0.231
Milk	0.137	**0.636***	-0.026
Eggs	0.429	0.380	0.024
Vegetables	-0.037	0.146	**0.717***
Tubers	**0.600***	0.085	0.024
Cereal	0.145	0.021	**0.742***
Fish	**0.690***	-0.224	-0.110
Livestock and poultry meat	**0.543***	0.305	0.117
Percentage of variance (%)	16.730	16.960	15.206

* Food groups with factor loadings ≥ 0.50 are highlighted in bold

following the fruit-milk and vegetable-cereal dietary patterns, those with higher pattern scores had a lower prevalence of MetS. However, participants with higher scores in the tubers-meat pattern had a higher prevalence of MetS except for those at the Q4 level. Participants with higher scores in the fruit-milk pattern had a lower prevalence of abdominal obesity, hyperglycemia, and hypertension. Participants with higher scores in the vegetable-cereal pattern had a lower prevalence of abdominal obesity, hyperglycemia, and hyperlipidemia. Participants with higher scores in the tubers-meat pattern had a lower prevalence of abdominal obesity and a higher prevalence of hyperlipidemia.

Multivariable logistic regression analysis of sleep duration, dietary patterns, and MetS

The results of the analysis of the association among sleep duration, dietary pattern, and MetS are shown in Table 4. Participants with long sleep duration were more likely to develop MetS than those with normal sleep duration, both in Model 2 (OR = 1.288, 95% CI: 1.055–1.572) and Model 3 (OR = 1.284, 95% CI: 1.052–1.568). Participants with Q4 factor scores were less likely to have MetS in Model 2 (OR = 0.586, 95% CI: 0.489–0.702) and Model 3 (OR = 0.591, 95% CI: 0.493–0.709) if they followed the fruit-milk dietary pattern. In both models, participants with dietary scores at the Q3 (OR = 0.647, 95% CI: 0.547–0.765; OR = 0.651, 95% CI: 0.550–0.770) and Q4 (OR = 0.443, 95% CI: 0.369–0.533; OR = 0.444, 95% CI: 0.369–0.534) levels had a significantly decreased risk of MetS if they followed the vegetable-cereal pattern. By contrast, the risk of developing MetS was increased for participants who scored at the Q2 (OR = 1.212, 95% CI: 1.019–1.441; OR = 1.213, 95% CI: 1.020–1.443) and Q3 (OR = 1.323, 95% CI: 1.116–1.570; OR = 1.323, 95% CI: 1.115–1.570) levels if they followed the tubers-meat pattern.

Analysis of factors impacting MetS based on the DT model

According to the parameter settings in the research method, the variables with statistical significance in single-factor analysis were incorporated into the DT model. The results generated are shown in Fig. 3. A total of 3 layers, 22 nodes, and 12 terminal nodes were generated in the DT model. The accuracy rate of the model was 86.6%, which demonstrated good predictive and classification ability. The root node of the model was DP3, indicating that DP3 had the strongest correlation with MetS. The other variables listed in descending order of importance were marital status, DP2, DP1, exercise, sleep duration, and gender. Dietary habits were not included in the model. The model screened out five high-risk categories for MetS, which are shown in Table 5.

Assessment of model prediction effect

Significant factors screened out by both the logistic regression and DT models were gender, marital status, exercise, sleep duration, DP1, DP3, and DP2. Significant factors also screened out by the logistic regression model were dietary habits. The AUC values of sleep duration, DP1, DP2, and DP3 predicted by the logistic regression model were 0.561, 0.564, 0.578, and 0.599, respectively. However, the AUC value of the DT model was 0.608, indicating that the DT model is a slightly better predictor than the logistic regression model, as shown in Fig. 4.

Discussion

This population-based, cross-sectional study explored the effects of sleep duration and dietary patterns on the risk of MetS in middle-aged and elderly adults in Bengbu, China. Regarding sleep, the results revealed a notable increase in the risk of MetS with long sleep duration in contrast with normal sleep duration. Regarding dietary pattern, a positive association was identified between the tubers-meat dietary pattern and MetS, whereas a negative association was associated with the vegetable-cereal and fruit-milk dietary patterns and MetS. The DT and logistic regression models were compared regarding their ability to determine whether dietary patterns or sleep duration more significantly affects the likelihood of developing MetS. From the predictive perspective, the DT model marginally outperforms the logistic regression model in predictive accuracy.

In general, the prevalence of MetS is slightly higher in males than females under 50 years. However, over 50 years of age, alterations in genetic and biological routes post-menopause lead to females having a higher likelihood of developing MetS compared with males, with socioeconomic status being an additional influence [34]. Previous studies are consistent with the findings of this study, which found that the prevalence of MetS is higher in females (14.1%) than males (12.3%). The prevalence of

Table 3 Characteristics across quartiles of dietary patterns

Characteristics	Tubers-meat pattern				*P*	Fruit-milk pattern				*P*	Vegetable-cereal pattern				*P*
	Q1	Q2	Q3	Q4		Q1	Q2	Q3	Q4		Q1	Q2	Q3	Q4	
Age(years)	62.77±6.094	62.77±5.950	62.77±6.107	63.17±6.283	0.062	62.56±5.834	62.73±6.050	62.90±6.091	63.30±6.433	0.000	62.56±5.875	62.70±5.977	62.73±6.050	63.50±6.483	0.000
Gender					0.000					0.000					0.000
Male	1076(47.1)	1063(46.6)	1002(43.9)	760(33.3)		1206(52.8)	1104(48.4)	893(39.1)	698(30.6)		1184(51.9)	1052(46.1)	985(43.1)	680(29.8)	
Female	1207(52.9)	1220(53.4)	1280(56.1)	1524(66.7)		1077(47.2)	1179(51.6)	1390(60.9)	1585(69.4)		1099(48.1)	1231(53.9)	1298(56.9)	1603(70.2)	
Education level					0.206					0.284					0.909
Illiteracy or primary school	2(0.1)	2(0.1)	8(0.4)	6(0.3)		4(0.2)	2(0.1)	4(0.2)	8(0.4)		6(0.3)	4(0.2)	3(0.1)	5(0.2)	
Middle school	2279(99.8)	2277(99.7)	2273(99.6)	2274(99.6)		2274(99.6)	2279(99.8)	2278(99.8)	2272(99.5)		2275(99.6)	2275(99.6)	2277(99.7)	2276(99.7)	
High school and above	2(0.1)	4(0.2)	1(0.0)	4(0.2)		5(0.2)	2(0.1)	1(0.0)	3(0.1)		2(0.1)	4(0.2)	3(0.1)	2(0.1)	
Marital status					0.449					0.005					0.000
Single	55(2.4)	60(2.6)	52(2.3)	56(2.5)		62(2.7)	57(2.5)	58(2.5)	46(2.0)		48(2.1)	58(2.5)	57(2.5)	60(2.6)	
Married	2026(88.7)	2026(88.7)	2020(88.5)	1990(87.1)		2046(89.6)	2019(88.4)	2014(88.2)	1983(86.9)		2059(90.2)	2024(88.7)	2034(89.1)	1945(85.2)	
Divorced or Widowed	202(8.8)	197(8.6)	210(9.2)	238(10.4)		175(7.7)	207(9.1)	211(9.2)	254(11.1)		176(7.7)	201(8.8)	192(8.4)	278(12.2)	
Smoking Status					0.484					0.000					0.000
Non-smoker	2024(88.7)	2052(89.9)	2036(89.2)	2068(90.5)		1995(87.4)	2022(88.6)	2077(91.0)	2086(91.4)		1991(87.2)	2052(89.9)	2049(89.8)	2088(91.5)	
Current smoker	221(9.7)	197(8.6)	214(9.4)	188(8.2)		243(10.6)	229(10.0)	176(7.7)	172(7.5)		262(11.5)	187(8.2)	202(8.8)	169(7.4)	
Former smoker	38(1.7)	34(1.5)	32(1.4)	28(1.2)		45(2.0)	32(1.4)	30(1.3)	25(1.1)		30(1.3)	44(1.9)	32(1.4)	26(1.1)	
Alcohol status					0.026					0.000					0.000
Non-drinker	1997(87.5)	2025(88.7)	2019(88.5)	2068(90.5)		1961(85.9)	2017(88.3)	2050(89.8)	2081(91.2)		1978(86.6)	2021(88.5)	2024(88.7)	2086(91.4)	
Occasional drinker	138(6.0)	125(5.5)	111(4.9)	96(4.2)		131(5.7)	133(5.8)	109(4.8)	97(4.2)		131(5.7)	124(5.4)	123(5.4)	92(4.0)	
Current drinker	148(6.5)	133(5.8)	152(6.7)	120(5.3)		191(8.4)	133(5.8)	124(5.4)	105(4.6)		174(7.6)	138(6.0)	136(6.0)	105(4.6)	
Dietary habits					0.551					0.045					0.029
Meat oriented	29(1.3)	40(1.8)	38(1.7)	32(1.4)		49(2.1)	33(1.4)	33(1.4)	24(1.1)		40(1.8)	46(2.0)	28(1.2)	25(1.1)	
Balanced diet	1877(82.2)	1905(83.4)	1896(83.1)	1889(82.7)		1906(83.5)	1892(82.9)	1883(82.5)	1886(82.6)		1916(83.9)	1863(81.6)	1907(83.5)	1881(82.4)	
Vegetarian oriented	377(16.5)	338(14.8)	348(15.2)	363(15.9)		328(14.4)	358(15.7)	367(16.1)	373(16.3)		327(14.3)	374(16.4)	348(15.2)	377(16.5)	
Exercise					0.365					0.353					0.963
Regularly	802(35.1)	769(33.7)	759(33.3)	748(32.7)		786(34.4)	804(35.2)	742(32.5)	746(32.7)		776(34.0)	785(34.4)	757(33.2)	760(33.3)	
Occasionally	245(10.7)	257(11.3)	237(10.4)	227(9.9)		252(11.0)	231(10.1)	245(10.7)	238(10.4)		245(10.7)	232(10.2)	247(10.8)	242(10.6)	
Never	1236(54.1)	1257(55.1)	1286(56.4)	1309(57.3)		1245(54.5)	1248(54.7)	1296(56.8)	1299(56.9)		1262(55.3)	1266(55.5)	1279(56.0)	1281(56.1)	
Energy Intake(kcal/day)	1733.34±462.26	1729.37±450.49	1782.41±156.65	1852.39±466.40	0.000	1754.60±458.63	1758.00±462.84	1757.12±450.57	1827.83±488.87	0.000	1794.90±469.20	1770.53±487.19	1759.62±460.81	1772.50±447.09	0.075
BMI(kg/m2)	25.11±3.33	25.18±3.31	24.75±3.15	23.75±3.09	0.000	25.75±3.33	25.20±3.18	24.46±3.04	23.39±3.04	0.000	25.70±3.31	25.27±3.23	24.62±2.99	23.21±2.99	0.000
Mets components															
WC(cm)	87.48±9.83	87.65±10.00	86.64±10.02	84.05±9.33	0.000	88.96±9.90	87.81±9.87	85.66±9.56	83.37±9.35	0.000	88.90±10.46	87.76±9.82	86.16±9.43	83.00±8.82	0.000
TG(mmol/L)	1.37±0.84	1.51±1.10	1.58±1.15	1.62±1.23	0.000	1.50±1.05	1.49±0.98	1.55±1.15	1.52±1.19	0.267	1.61±1.25	1.54±1.06	1.51±1.07	1.41±0.97	0.000
SBP (mmHg)	132.53±15.28	133.14±14.99	132.88±14.90	132.15±15.44	0.140	133.57±14.77	133.16±15.46	132.58±15.24	131.39±15.09	0.000	133.22±14.67	133.11±15.47	132.14±15.01	132.23±15.45	0.022
DBP (mmHg)	78.82±9.02	79.09±8.89	79.32±9.01	78.50±8.94	0.015	79.78±8.73	79.12±8.93	78.70±9.04	78.12±9.09	0.000	79.74±8.80	79.33±9.01	78.61±8.95	78.05±9.02	0.000
FBG(mmol/L)	5.74±1.77	5.88±1.91	5.81±1.89	5.70±1.85	0.008	5.88±1.93	5.84±1.92	5.74±1.78	5.67±1.80	0.000	5.87±1.88	5.79±1.78	5.79±1.91	5.67±1.86	0.010

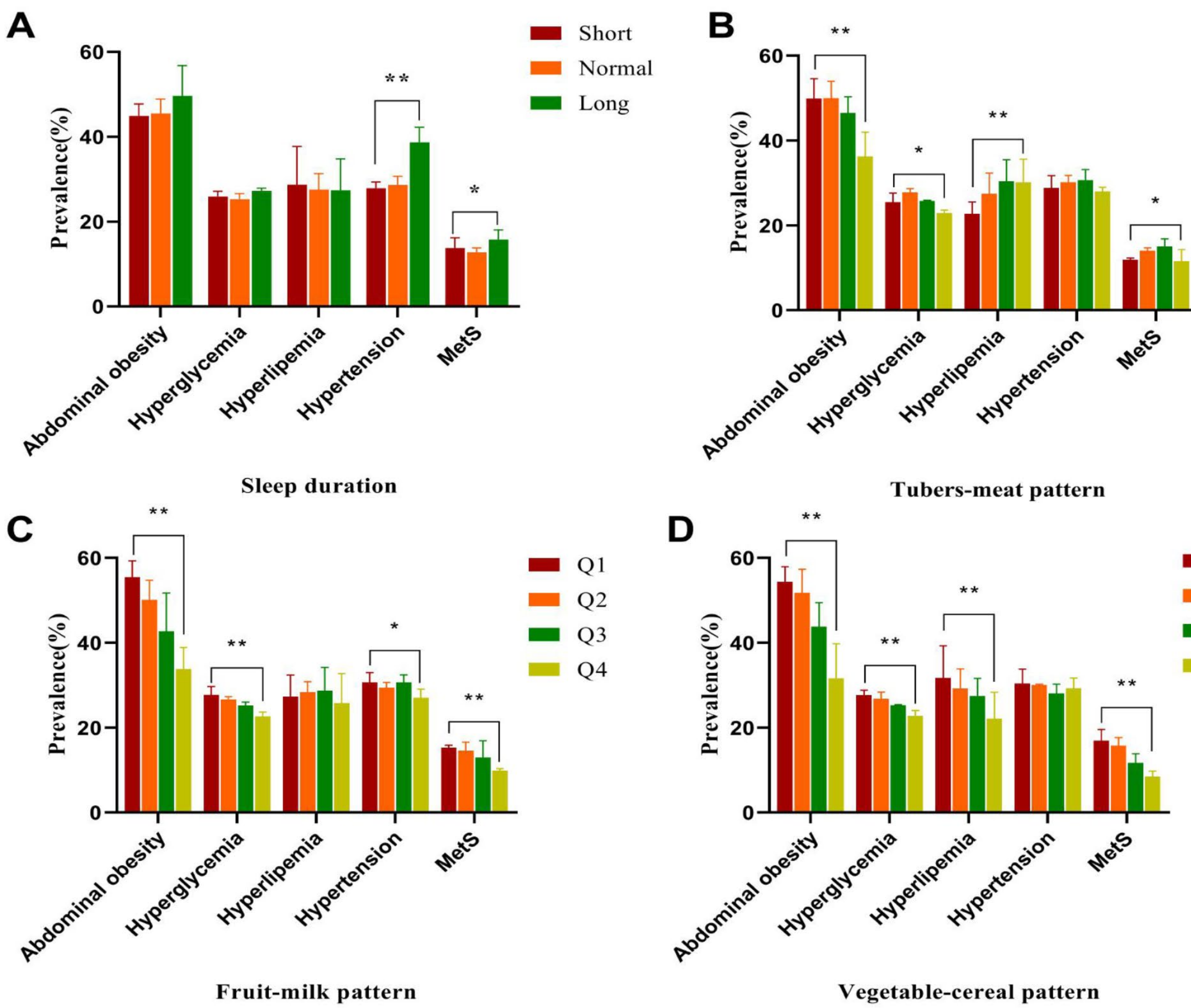

Fig. 2 Comparison of MetS prevalence among different sleep duration and dietary patterns. * $P<0.05$, ** $P<0.001$

MetS in middle-aged and elderly adults in Bengbu was 13.4%, lower than that reported by Tao Xu et al. in the 2009 China Health and Nutrition Survey (21.3%) [35] and higher than that reported in a cross-sectional study covering six provinces from 2007 to 2011 (10.47%) [36]. The IDF reported that the prevalence of MetS globally varies between 6% and 50% [37, 38], and differences in prevalence may be attributed to variations in sampling procedures, data collection methods, and age.

Sleep represents a dynamic physiological condition marked by active variations in the central nervous system, breathing, blood flow dynamics, and metabolic aspects. The impact of sleep on pathology and heart health can manifest in multiple forms [39]. Numerous research works have established a link between the length of sleep and MetS, although the definition of MetS varies [40]. The inconsistent outcomes in four research projects employing the National Cholesterol Education Program (NCEP) Adult Treatment Panel III (ATP III) criteria [41–44] could stem from limited sample sizes in certain studies [41, 42] and scarce data on confounding variables in others [43]. Research in Europe involving 1332 women revealed a correlation between extended sleep periods (≥9 h) and a higher incidence of MetS [44]. An extensive cross-sectional analysis of Chinese individuals aged over 50 years employing a narrow definition of MetS also identified a positive correlation between prolonged sleep (≥9 h) and MetS [45]. Prolonged bed rest (≥9.5 h) appears to be associated with increased somnolence and decreased physical activity [46]. In middle-aged and elderly individuals, extended sleep duration (>9 h) is associated with diminished muscle mass [47] and a decline in glucose metabolism [48]. The causal connection between these elements remains ambiguous, suggesting a probable bidirectional correlation.

This study revealed a positive correlation between the tubers-meat dietary pattern (excluding at the Q4 level) and MetS in contrast to the fruit-milk and vegetable-cereal dietary patterns, which had a negative association with MetS. The tubers-meat dietary pattern is

Table 4 The odds ratio (95% CI) of MetS prevalence in different sleep duration and dietary pattern groups

	MetS(%)	Model 1* (OR, 95% CI)	*P*	Model 2[&] (OR, 95% CI)	*P*	Model 3[#] (OR, 95% CI)	*P*
Sleep duration							
Normal	902(12.9)	1.000	0.038	1.000	0.034	1.000	0.037
Short	186(14.0)	1.102(0.929 ~ 1.306)	0.265	1.102(0.929 ~ 1.306)	0.265	1.102(0.929 ~ 1.307)	0.267
Long	132(16.0)	1.280(1.049 ~ 1.562)	0.013	1.288(1.055 ~ 1.572)	0.013	1.284(1.052 ~ 1.568)	0.014
Tubers-meat pattern							
Q1	272(11.9)	1.000	0.002	1.000	0.001	1.000	0.001
Q2	322(14.1)	1.214(1.021 ~ 1.433)	0.028	1.212(1.019 ~ 1.441)	0.030	1.213(1.020 ~ 1.443)	0.029
Q3	347(15.2)	1.326(1.118 ~ 1.572)	0.001	1.323(1.116 ~ 1.570)	0.001	1.323(1.115 ~ 1.570)	0.001
Q4	279(12.2)	1.029(0.861 ~ 1.229)	0.755	1.003(0.839 ~ 1.200)	0.974	1.004(0.839 ~ 1.202)	0.962
Fruit-milk pattern							
Q1	347(15.2)	1.000	< 0.001	1.000	< 0.001	1.000	< 0.001
Q2	334(14.6)	0.956(0.812 ~ 1.125)	0.589	0.945(0.802 ~ 1.112)	0.494	0.952(0.808 ~ 1.121)	0.554
Q3	311(13.6)	0.880(0.746 ~ 1.038)	0.129	0.852(0.721 ~ 1.007)	0.060	0.861(0.729 ~ 1.017)	0.079
Q4	228(10.0)	0.619(0.518 ~ 0.740)	< 0.001	0.586(0.489 ~ 0.702)	< 0.001	0.591(0.493 ~ 0.709)	< 0.001
Vegetable-cereal pattern							
Q1	386(16.9)	1.000	< 0.001	1.000	< 0.001	1.000	< 0.001
Q2	362(15.9)	0.926(0.792 ~ 1.083)	0.337	0.910(0.777 ~ 1.065)	0.238	0.911(0.778 ~ 1.067)	0.249
Q3	271(11.9)	0.662(0.560 ~ 0.783)	< 0.001	0.647(0.547 ~ 0.765)	< 0.001	0.651(0.550 ~ 0.770)	< 0.001
Q4	201(8.8)	0.474(0.396 ~ 0.569)	< 0.001	0.443(0.369 ~ 0.533)	< 0.001	0.444(0.369 ~ 0.534)	< 0.001

* Model 1: Unadjusted.[&] Model 2: Adjusted for gender, age, education level and marital status.[#] Model 3: Adjusted for gender, age, education level, marital status, smoking status, alcohol status, dietary habits and exercise

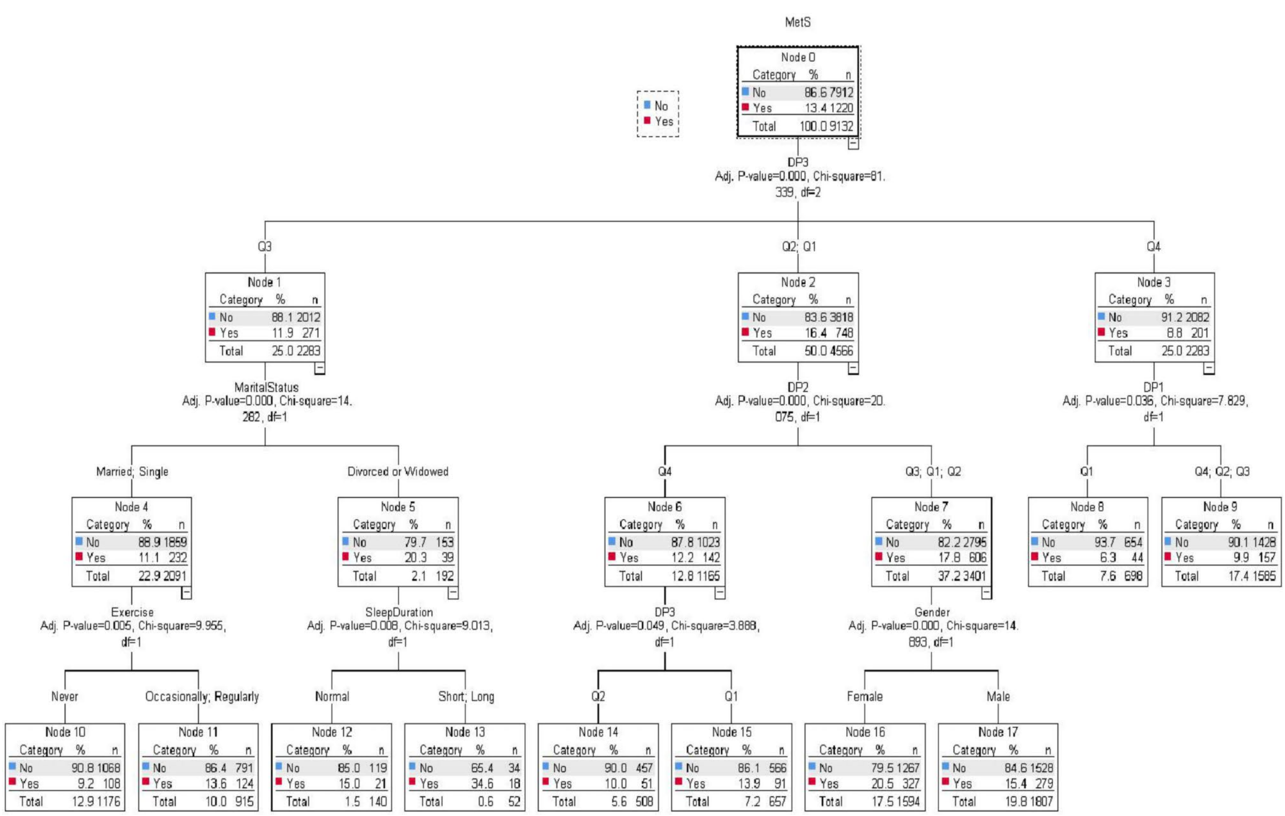

Fig. 3 Decision tree model of influencing factors of MetS

Table 5 Five categories of people at high risk for MetS screened by the model

Group	People at high risk of MetS
1	The Q4 level of DP3 factor scores; The Q2, Q3 and Q4 levels of DP1 factor scores
2	Female; The Q1 and Q2 levels of DP3 factor scores; The Q1, Q2 and Q3 levels of DP2 factor scores
3	The Q1 level of DP3 factor scores; The Q4 level of DP2 factor scores
4	The Q3 levelof DP3 factor scores; Divorced or widowed; Short and Long Sleep Duration
5	The Q3 levelof DP3 factor scores; Married and Single; Exercise occasionally and regularly

Q1: The first quartile of dietary pattern scores; Q2: The second quartile of dietary pattern scores; Q3: The third quartile of dietary pattern scores; Q4: The fourth quartile of dietary pattern scores; DP1: Tubers-meat pattern; DP2: Fruit-milk pattern; DP3: Vegetable-cereal pattern

characterized by a high consumption of poultry, red meat, fish, eggs, and tubers. Earlier research indicates a potential rise in MetS risk with excessive red meat intake [49]. Overconsumption of red meat is linked to elevated levels of saturated fats and cholesterol [50], which are linked to a heightened risk of MetS. Combining the results shown in Fig. 2; Table 4 shows that at the Q1 to Q3 levels, the tubers-meat dietary pattern was positively correlated with MetS, whereas at the Q4 level, no notable link was found between MetS and the tubers-meat dietary pattern. This could be linked to the fact that tubers have high levels of dietary fiber and low levels of fat and protein [51], offering a potent defense against the onset of MetS and type 2 diabetes [52], thus reducing the risk of MetS.

In a similar manner, the vegetable-cereal dietary pattern is enriched with green vegetables and refined grains, and the fruit-milk pattern is enriched with fruit and dairy products, which are protective against MetS. Both dietary patterns are abundant in dietary fiber, vitamins, minerals, antioxidants, complex carbohydrates, prebiotics, and probiotics. Research indicates that a diet rich in whole grains, including whole wheat, known as a whole-grain diet, offers a wealth of dietary fiber and antioxidants, which are advantageous for maintaining health [53]. Earlier research indicates that a diet from southern China, marked by abundant rice, vegetables, fruits, and water-based items, correlates with a reduced MetS risk. This diet, which is rich in dietary fiber, polyunsaturated fatty acids, vitamins, and minerals and low in saturated fats and sodium, aids in the regulation of blood pressure and lipids [54, 55]. It has also been shown that prebiotics can regulate body weight and insulin action, thereby reducing the risk of abdominal obesity and hyperglycemia [56, 57].

To more deeply visualize the influence of dietary patterns and sleep duration on MetS and to screen the characteristic high-risk population, DT modeling was performed. The findings indicated a more robust link between dietary patterns and MetS compared with sleep duration. The DT stands out as an interpretable machine learning model known for its straightforward, lucid, and instinctive tree structures that effectively categorize predictive variables [58]. DT modeling removes covariance among variables, reflects the interactions among variables, and specifically analyzes the significance of variables in subgroups. In addition, tree models offer the possibility of generating easy-to-understand MetS prevention and control rules. DT modeling is mainly used in clinics in diagnosis, risk, degeneration, prognosis

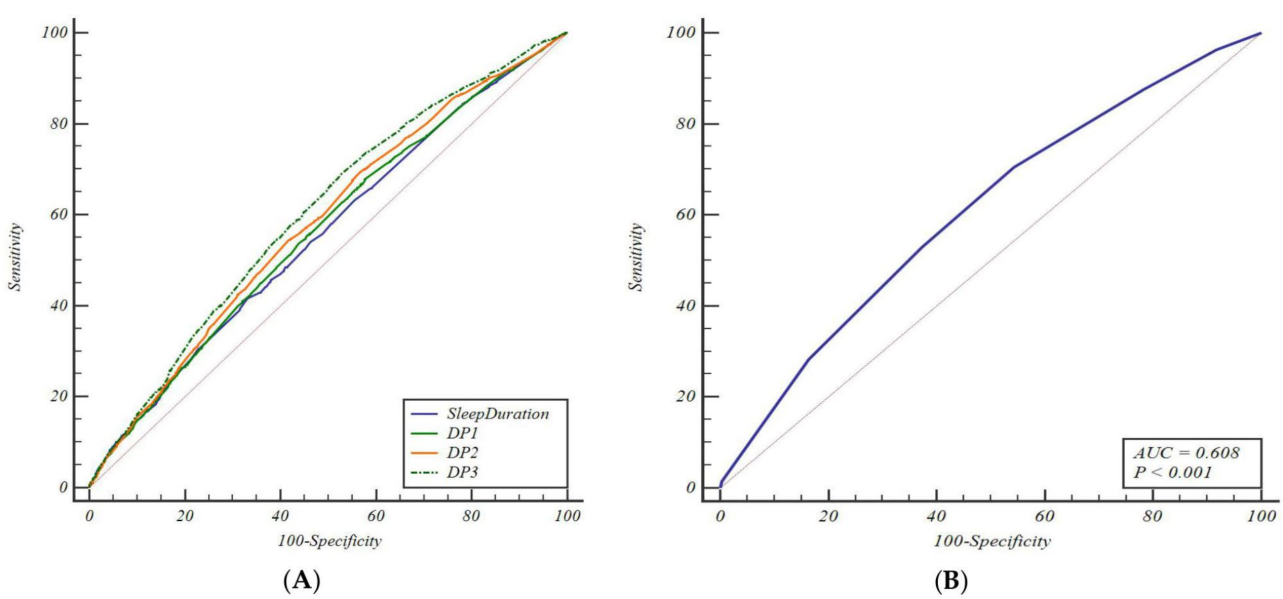

Fig. 4 ROC curves of LR model and DT model. (**A**): Logistic regression model; (**B**): Decision tree model

[59–61], and clinical decision support systems (CDSS) [62], where they have demonstrated powerful performance and high accuracy. This has made DT modeling a useful scoring tool for predicting MetS risk in several clinical applications.

This study is innovative in its use of both logistic regression and DT models to investigate the factors impacting MetS in the population of the Bengbu region and present the model findings using the DT model's dendrogram visualization. Nevertheless, this study has several limitations that should be considered when reviewing the findings. First, Bengbu is only one city and, as such, is not entirely representative of the entire population of the province. Second, the food frequency questionnaire was used to investigate the residents' diet. The classification of food items was too general, and the food items could be further refined to obtain more accurate and more dietary patterns. Third, the sleep duration of residents were mostly obtained through questionnaire surveys, if objective methods such as actigraphy were used for assessment, the accuracy will be improved. Fourth, although the questionnaire was administered by skilled interviewers using a standardized technique, it was self-reported, which may have led to biased reporting. It is impossible to completely rule out the probability that residual confounders came from unmeasured variables or other possible influences. Fifth, because this study was cross-sectional, causation could not be determined. Longitudinal and prospective investigations are therefore required to confirm the aforementioned influences and to provide the Bengbu government departments a theoretical foundation upon which to develop reasonable preventive measures for high-risk populations. Finally, the MetS risk prediction model was not externally validated; instead, it was created and internally verified using a community of medical examiners. Future studies should therefore endeavor to externally validate the model and findings.

Conclusions

According to our research, sleep and diet are significant factors in managing MetS. Regarding sleep, individuals with a longer-than-average sleep duration have a higher risk of developing MetS than participants with an average sleep duration. Regarding diet, individuals who follow the tubers-meat dietary pattern have a higher risk of developing MetS compared with those who follow the fruit-milk and vegetable-cereal patterns. The findings of this study provide a reference regarding the dietary habits of middle-aged and elderly adults of northern Anhui Province, China. These findings should be considered together with previous findings to enhance the sleep and nutrition of residents to help stop the onset and progression of MetS.

Supplementary Information

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Supplementary Material 1

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Author contributions

Conceptualization, H.Z. and L.S.; Investigation, H.Z., T.Z., L.Z., J.Z. and L.J.; Methodology, H.Z. and T.Z.; Supervision, L.S.; Writing—Original Draft, H.Z.; Writing—Review and Editing, H.Z. and L.S.; All authors have read and approved the final manuscript.

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Data availability

No datasets were generated or analysed during the current study.

Declarations

Informed consent

Informed consent was obtained from all subjects involved in the study.

Competing interests

The authors declare no competing interests.

Institutional review board statement

In accordance with the requirements of Helsinki Declaration and with the approval of the Ethics Committee of Bengbu Medical University, the subject was studied.

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