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A Latent Class Analysis of Planetary Health Diet Index-informed Dietary Patterns Association with Overweight and Obesity Among Middle-Aged and Older Women: A Cross-Sectional Study

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Title page

A Latent Class Analysis of Planetary Health Diet Index-informed Dietary Patterns Association with Overweight and Obesity Among Middle-Aged and Older Women: A Cross-Sectional Study

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Abbreviations: PHDI , Planetary Health Diet Index; LCA, Latent Class Analysis; HCSAQ, Health Checkup Self-Assessment Questionnaire; BMI, Body Mass Index; WC, Waist Circumference; AIC, Akaike Information Criterion; BIC, Bayesian Information Criterion; aBIC Adjusted, Bayesian Information Criterion; LMR, Lo–Mendell–Rubin Adjusted Likelihood Ratio Test; BLRT, Bootstrap Likelihood Ratio Test; AOR, Adjusted Odds Ratio; CI, Confidence Interval; SPSS, Statistical Package for the Social Sciences; CVD, Cardiovascular Disease.

Abstract:

Background: Middle-aged and older women face a heightened risk of overweight and obesity driven by physiological and social transitions. The Planetary Health Diet Index (PHDI) quantifies adherence to sustainable, health-promoting eating guidelines across key plant and animal food groups, yet how specific PHDI dietary behavior combinations cluster and influence weight in this population is poorly understood. This study used latent class analysis (LCA) based on nine PHDI-

informed dietary behavior indicators to identify distinct dietary patterns in this population and examine their associations with overweight and obesity.

Methods: This cross-sectional study included 21,856 middle-aged and older women who underwent health examinations at a tertiary hospital in southern China between 2015 and 2023. Sociodemographic characteristics, anthropometric measurements, medical history, and nine PHDI-informed dietary behavior indicators were extracted. LCA was applied to identify dietary patterns, and multivariable binary logistic regression was used to evaluate their associations with overweight/obesity. Age-stratified subgroup and sensitivity analyses excluding participants with baseline hypertension or diabetes were conducted to evaluate robustness.

Results: The prevalence of combined overweight and obesity was 31.94%. LCA identified four dietary patterns: High PHDI-Adherent (19.07%), Grain-Dominant (21.02%), Protein-Focused (26.93%), and Low PHDI-Adherent (32.98%). Compared with the High PHDI-Adherent pattern, the Protein-Focused pattern (AOR = 1.216, 95% CI: 1.114–1.328) and Low PHDI-Adherent pattern (AOR = 1.236, 95% CI: 1.133–1.349) were statistically significantly associated with higher odds of overweight/obesity, whereas the Grain-Dominant pattern showed no significant association (AOR = 1.046, 95% CI: 0.953-1.149). Older age, lower education, postmenopausal status, cardiovascular family history, smoking, alcohol consumption, and low physical activity were independent risk factors. Further sensitivity analyses confirmed the stability of these associations.

Conclusions: Among the identified dietary patterns, the Protein-Focused and Low PHDI-Adherent patterns were associated with higher odds of overweight and obesity among middle-aged and older women in southern China. These findings highlight the importance of overall dietary balance and provide an empirical basis for developing tailored dietary and weight management strategies for

distinct population subgroups.

Keywords: middle-aged and older women; Planetary Health Diet Index; dietary patterns; overweight and obesity; latent class analysis

1. Background

Overweight and obesity are major global health concerns, affecting an estimated 2.11 billion adults worldwide in 2021, with China accounting for the largest share at nearly 402 million individuals[1]. Middle-aged and older women are particularly vulnerable to excess body weight due to a convergence of physiological shifts during menopause and transitions in social roles such as retirement that alter daily routines[2, 3]. Globally, the prevalence of overweight and obesity among middle-aged and older women was estimated at 46.7% in 2021 and is projected to reach 60.3% by 2050, substantially worsening health-related quality of life and elevating the risk of premature mortality[1]. Therefore, identifying and addressing modifiable lifestyle drivers is essential for mitigating weight-related health risks.

As a foundational modifiable factor in weight management, dietary intake operates holistically through overall dietary patterns rather than isolated nutrients or individual food groups[4-6]. Evaluating overall dietary patterns captures the complex synergetic combinations of long-term eating behaviors and their varied impacts on body weight[7]. To comprehensively assess overall diet quality and sustainability across multiple food dimensions, the EAT–Lancet Commission proposed the Planetary Health Diet Index (PHDI), which evaluates individual intake by prioritizing whole grains, fruits, vegetables, legumes, and unsaturated oils while limiting red meat, dairy, and added sugars[8, 9]. Emerging evidence indicates that greater adherence to the PHDI is associated with favorable adiposity profiles, lower BMI, and reduced risk of obesity among

middle-aged and older women[10-12].

Despite these insights, significant research gaps remain regarding the application of the PHDI framework. Most existing PHDI studies rely on continuous, cumulative adherence scores as their primary metric. While effective for assessing linear diet quality, summary scores obscure person-centered heterogeneity and fail to capture how specific combinations of dietary behaviors co-occur within individuals. Furthermore, evidence on PHDI-informed dietary behavior combinations and their associations with overweight and obesity specifically among middle-aged and older Chinese women remains limited. Uncovering distinct dietary behavior profiles within the PHDI framework is therefore critical for moving beyond generic recommendations toward targeted nutritional guidance.

To address these gaps, a person-centered approach is needed to identify naturally occurring population subgroups with shared dietary behavioral profiles. Latent class analysis (LCA) provides a robust probabilistic framework for grouping individuals based on categorical indicators, resolving heterogeneity into discrete latent classes evaluated via model fit indices[13, 14]. Utilizing LCA across nine PHDI-informed dietary behavior indicators, this study aims to identify distinct dietary patterns among middle-aged and older Chinese women and examine their specific associations with overweight and obesity, laying the foundation for tailored weight management and dietary interventions.

2. Methods

2.1 Study design

This cross-sectional study analyzed health check-up records collected between January 2015 and December 2023 at the Health Management Center of a tertiary general hospital in Southern

China. For each participant, cross-sectional data were extracted from their most recent annual health examination. Study design and reporting adhered to the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) guidelines[15] (Supplementary File 1).

2.2 Participants

Eligible participants were females aged ≥ 45 years with normal communication abilities who underwent routine health screening during the study window. As illustrated in Figure 1, 32,083 women aged ≥ 45 years were initially screened. Sequential exclusions were applied for incomplete PHDI dietary data (n=2,957), missing covariate information (n=7,134, predominantly educational attainment), exogenous hormone use (n=114), and a history of mental illness (n=22). This selection procedure yielded a final analytical cohort of 21,856 middle-aged and older women.

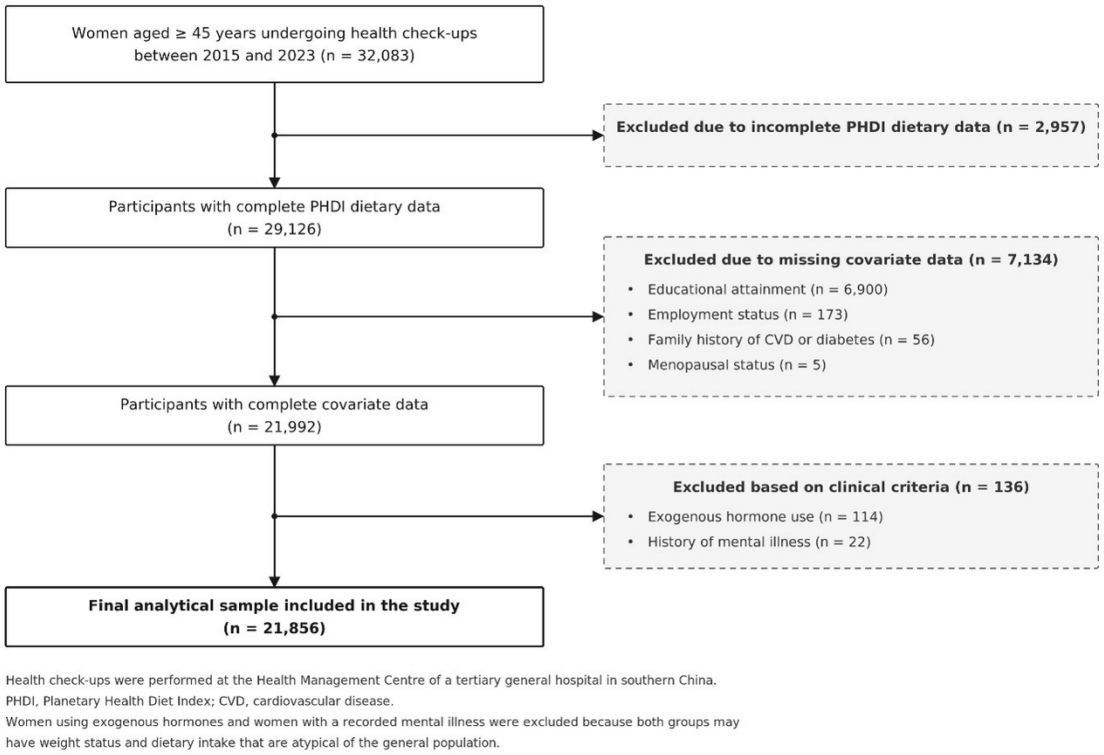


Fig. 1 The flow chart of the participant selection procedure (women aged ≥45 years who underwent health check-

ups at a tertiary general hospital in southern China, 2015–2023).

2.3 Sample size consideration

Because this study used retrospective health check-up database records, we enrolled all eligible participants during the study period without a formal a priori sample size calculation (n=21,856). This large sample provided robust data for estimating latent class models across nine categorical dietary indicators. Notably, even the smallest latent class comprised 4,168 individuals, and the study achieved >99% power (two-sided α=0.05) to detect an odds ratio of 1.20 for overweight and obesity relative to the reference class.

2.4 Data collection and measurements

Data were extracted from the electronic health check-up database using unique file identification numbers, including demographic characteristics, physical examination results, and laboratory test results. Self-reported information was captured using the Health Checkup Self-Assessment Questionnaire (HCSAQ)[16]. The HCSAQ is a validated tool encompassing six health domains—medical history, physical symptoms, lifestyle habits, psychological stress, sleep quality, and health literacy—and has been widely implemented in epidemiological studies[17-20]. To ensure participant confidentiality, all direct personal identifiers were de-identified by database administrators prior to data extraction.

2.4.1 Construction of PHDI-informed dietary behavior indicators

Our dietary pattern analysis was conceptually informed by the PHDI, which evaluates 15 distinct food groups spanning plant-based foods, animal proteins, added fats, and sugars[9]. Because retrospective HCSAQ data did not map directly onto all 15 discrete PHDI components, we adapted a person-centered methodology previously used in LCA[21]. Specifically, we

constructed nine PHDI-informed dietary behavior indicators from logically corresponding HCSAQ items and dichotomized them into binary variables (0 = risky behavior, 1 = healthy behavior) based on the Chinese Dietary Guidelines and relevant literature[22]. The nine binary indicators were operationalized as follows:

Vegetable consumption was classified as healthy (≥200 g/day) or risky (<200 g/day) [19], while fruit consumption was categorized as healthy (>5 times per week) or risky (≤5 times per week)[19]. Grain management differentiated staple intake consisting mainly of whole grains (healthy) versus refined grains (risky)[23]. Seafood and aquatic product intake was considered healthy with regular or daily consumption and risky with occasional or no consumption[24]. Animal protein intake was defined as healthy when daily meat consumption fell within 50–100 g and risky if daily intake was <50 g or >100 g[22]. Sugar and seasoning restriction was defined as healthy for participants who rarely or never consumed sugary-sweetened beverages and preferred mild flavors, and risky for those who frequently consumed sugary beverages or had a diet high in salt and spices[5, 25]. Milk intake was categorized as healthy (≥3 times per week) or risky (<3 times per week)[26]. Egg intake was classified as healthy (≥3 eggs per week) or risky (<3 eggs per week)[27]. Soy protein alternative was defined as healthy (regular or daily soy product intake) or risky (rare or no intake)[28]. Table S1 summarizes item assignments and coding schemes for the nine PHDI-informed dietary behavior indicators and their correspondence to the 15 PHDI components.

2.4.2 Sociodemographic information

Sociodemographic variables included age, educational attainment, and occupation status. Age was categorized into two groups: 45–59 years (reference category) and ≥ 60 years. Educational attainment was classified into three levels: senior high school or below, junior college/undergraduate degree, and master's degree or above (reference category). Occupational

166 status was categorized as unemployed (including retirees, reference category) or employed
167 (encompassing manual and nonmanual labor).

168 2.4.3 Anthropometric measurements and outcome definition

169 Anthropometric measurements included body weight, height, and waist circumference (WC).
170 Body mass index (BMI) was calculated as weight in kilograms divided by height in meters squared
171 (kg/m²). BMI was categorized according to Chinese adult criteria[29]: underweight (<18.5 kg/m²),
172 normal weight (18.5–24 kg/m²), overweight (24–28 kg/m²), and obesity (≥28 kg/m²).

173 2.4.4 Medical history

174 Medical history was exported from the hospital electronic health systems. Family history of
175 cardiovascular disease (encompassing hypertension, coronary heart disease, and stroke) and
176 diabetes, menopausal status, and personal medical history (specifically personal diagnoses of
177 hypertension and diabetes) were obtained via self-reported data.

178 2.4.5 Non-dietary lifestyle behaviors

179 Non-dietary lifestyle behaviors were assessed using self- reported modules embedded within
180 the HCSAQ. Smoking status was classified as non-smoking (including former smokers) or current
181 smoking (including daily active and passive smoking)[30], while alcohol consumption was
182 classified as non-drinking (including former drinkers) or current drinking[31]. Aligned with World
183 Health Organization criteria[32], physical activity was classified into three levels based on weekly
184 frequency and duration: inactive (no regular exercise), low physical activity (< 150 minutes/week,
185 such as < 30 minutes/day on < 5 days/week), and regular exercise (≥ 150 minutes/week, such as ≥
186 30 minutes/day on ≥ 5 days/week). Finally, sleep duration was assessed using the sleep-related
187 items embedded in the HCSAQ and classified into three categories: short (< 6 hours/day), normal

(6 – 8 hours/day), and long (> 8 hours/day)[33].

2.5 Ethical consideration

Ethical approval for this study was granted by the Ethics Committee of Xiangya Hospital, Central South University (Approval No. 2025020295). The requirement for written informed consent was waived by the Ethics Committee because the analysis used pre-existing, de-identified health check-up records. The study was conducted in accordance with the Declaration of Helsinki.

2.6 Data analysis

2.6.1 LCA of dietary patterns

We performed LCA using nine PHDI-informed dietary behavior indicators to categorize participants into distinct, mutually exclusive dietary pattern subgroups by maximizing between-class heterogeneity and within-class homogeneity[14]. Models ranging from 1 to 6 classes were systematically evaluated using statistical fit indices: Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), adjusted BIC (aBIC), Lo-Mendell-Rubin adjusted likelihood ratio (LMR), and bootstrap likelihood ratio test (BLRT)[34]. Lower AIC, BIC, and aBIC values indicated superior fit, whereas significant BLRT and LMR p-values ($p < 0.05$) supported the k-class model over the (k−1)-class model[13]. Given our large sample size (n >3,000), entropy was excluded as a formal selection criterion due to its documented sensitivity to sample size inflation[18, 35]. The final model solution was selected by jointly evaluating fit statistics, class proportions, substantive interpretability, and clinical relevance[13]. Participants were assigned to specific latent classes based on their highest posterior class membership probabilities.

2.6.2 Association between dietary patterns and overweight/obesity

Categorical variables are presented as frequencies and percentages and compared across latent classes using Pearson's chi-square test. Missing values (height: 4.70%, weight: 4.67%, waist circumference [WC]: 0.97%) were handled via multiple imputation using linear regression models for continuous variables, after which BMI was recalculated. Multivariable binary logistic regression was performed to examine associations between dietary pattern classes (with the "High PHDI-Adherent" pattern as the reference group) and overweight/obesity (coded as 1 = overweight/obesity, 0 = normal weight or underweight). Models were adjusted for potential confounders identified *a priori*: age, educational attainment, occupational status, family history of cardiovascular disease, family history of diabetes, menopausal status, smoking status, alcohol consumption, physical activity, and sleep duration.

2.6.3 Sensitivity analyses

Two sensitivity analyses were conducted to verify result robustness: (1) subgroup analyses stratified by age group (45–59 vs. ≥ 60 years), and (2) re-estimation of multivariable models after excluding participants with self-reported baseline hypertension or diabetes to minimize the potential reverse causation driven by disease-induced dietary changes. All statistical tests were two-tailed with significance set at $p < 0.05$. All analyses were performed using SPSS 28.0 and Mplus 8.3.

3. Results

3.1. Baseline characteristics of study participants

Among 21,856 participants, 6,980 (31.94%) were classified as overweight or obese. Overall, most women were aged 45–59 years (82.45%), held a junior college or undergraduate degree (63.47%), and were employed (74.96%). Compared to normal-weight participants, women with

231 overweight or obesity were significantly older (≥ 60 years: 21.76% vs. 15.58%), had lower
232 educational attainment (senior high school or below: 34.83% vs. 27.52%), and were more likely
233 to be unemployed (27.75% vs. 23.76%) and postmenopausal (62.69% vs. 57.41%; all $p < 0.001$).
234 They also reported higher rates of smoking (4.56% vs. 3.65%), alcohol intake (7.89% vs. 7.09%),
235 family history of cardiovascular disease (23.31% vs. 21.36%) and diabetes (8.95% vs. 8.01%), and
236 short sleep duration (13.40% vs. 12.17%; all $p < 0.05$). See more details in Table 1.

237 **Table 1** Baseline Characteristics of middle-aged and older women by overweight/obesity status and latent dietary pattern class (N = 21,856)

Variables	ALL	Overweight/obesity status			Dietary patterns				
	(N=21,856)	No(N=14,876)	Yes (N=6,980),	*P*	Class 1: High PHDI-Adherent (N=4,168)	Class 2: Grain-Dominant (N=4,593)	Class 3: Protein-Focused (N=5,886)	Class 4: Low PHDI-Adherent (N=7,209)	*P*
Age									
45-59	18,020(82.45)	12,559(84.42)	5,461(78.24)	＜0.001	3,159(75.79)	3,669(79.88)	4,903(83.30)	6,289(87.24)	＜0.001
⩾60	3,836(17.55)	2,317(15.58)	1,519(21.76)		1,009(24.21)	924(20.12)	983(16.70)	920(12.76)	
Educational Attainment									
Senior high school and below	6,524(29.85)	4,093(27.52)	2,431(34.83)	＜0.001	960(23.03)	1,518(33.05)	1,532(26.03)	2,514(34.87)	＜0.001
Junior college or undergraduate	13,873(63.47)	9,686(65.11)	4,187(59.99)		2,847(68.31)	2,809(61.16)	3,894(66.16)	4,323(59.97)	
Master’s degree and above	1,459(6.68)	1,097(7.37)	362(5.18)		361(8.66)	266(5.79)	460(7.81)	372(5.16)	
Occupational Status									
Unemployed/Retired	5,472(25.04)	3,535(23.76)	1,937(27.75)	＜0.001	1,133(27.18)	1,224(26.65)	1,417(24.07)	1,698(23.55)	＜0.001
Employed	16,384(74.96)	11,341(76.24)	5,043(72.25)		3,035(72.82)	3,369(73.35)	4,469(75.93)	5,511(76.45)	
Cardiovascular Family History									

No	17,052(78.02)	11,699(78.64)	5,353(76.69)	0.01	3,203(76.85)	3,636(79.16)	4,528(76.93)	5,685(78.86)	0.003
Yes	4,804(21.98)	3,177(21.36)	1,627(23.31)		965(23.15)	957(20.84)	1,358(23.07)	1,524(21.14)	
Diabetes Family History									
No	20,039(91.69)	13,684(91.99)	6,355(91.05)	0.02	3,815(91.53)	4,281(93.21)	5,350(90.89)	6,593(91.46)	＜0.001
Yes	1,817(8.31)	1,192(8.01)	625(8.95)		353(8.47)	312(6.79)	536(9.11)	616(8.54)	
Menopausal Status									
Premenopausal	8,939(40.90)	6,335(42.59)	2,604(37.31)	＜0.001	1,400(33.59)	1,786(38.89)	2,421(41.13)	3,332(46.22)	＜0.001
Postmenopausal	12,917(59.10)	8,541(57.41)	4,376(62.69)		2,768(66.41)	2807(61.11)	3,465(58.87)	3,877(53.78)	
Smoking status									
Non-smoker	20,995(96.06)	14,333(96.35)	6,662(95.44)	0.01	4,062(97.46)	4,472(97.37)	5,608(95.28)	6,853(95.06)	＜0.001
Current smoker	861(3.94)	543(3.65)	318(4.56)		106(2.54)	121(2.63)	278(4.72)	356(4.94)	
Alcohol consumption									
Non-drinker	20,250(92.65)	13,821(92.91)	6,429(92.11)	0.03	3,836(92.03)	4,360(94.93)	5,380(91.40)	6,674(92.58)	＜0.001
Current drinker	1,606(7.35)	1,055(7.09)	551(7.89)		332(7.97)	233(5.07)	506(8.60)	535(7.42)	
Physical activity									
Inactive	13,067(59.79)	9,022(60.65)	4,045(57.95)	＜0.001	2,450(58.78)	2,921(63.60)	3,676(62.45)	4,020(55.76)	＜0.001
Low physical activity	4,998(22.87)	3,290(22.12)	1,708(24.47)		402(9.64)	867(18.88)	1,265(21.49)	2,464(34.18)	

Regular exercise	3,791(17.34)	2,564(17.23)	1,227(17.58)		1,316(31.58)	805(17.52)	945(16.06)	725(10.06)	
Sleep duration									＜0.001
Short (<6 h/d)	2,745(12.56)	1,810(12.17)	935(13.40)	0.03	430(10.32)	576(12.54)	714(12.13)	1,025(14.22)	
Normal (6-8 h/d)	14,535(66.50)	9,958(66.94)	4,577(65.57)		2,772(66.51)	2,995(65.21)	3,976(67.55)	4,792(66.47)	
Long (>8 h/d)	4,576(20.94)	3,108(20.89)	1,468(21.03)		966(23.18)	1,022(22.25)	1,196(20.32)	1,392(19.31)	

Note: Data are presented as n (%). *P*-values were calculated using Pearson's chi-square test across groups. Class 1, High PHDI-Adherent; Class 2, Grain-Dominant; Class 3, Protein-Focused; Class 4, Low PHDI-Adherent

3.2. Identification and characterization of latent dietary patterns

Latent class models ranging from 1 to 6 classes were evaluated using the nine binary PHDI-informed dietary behavior indicators (Table 2). Although information criteria (AIC, BIC, and aBIC) decreased progressively with higher class numbers, the Lo-Mendell-Rubin (LMR) adjusted likelihood ratio test became non-significant at 6 classes ($p = 0.0578$). Integrating statistical fit statistics, model parsimony, class proportions, and conceptual interpretability, the 4-class model was selected as the optimal solution, yielding well-distributed subgroups comprising 19.07% (n=4,168), 21.02% (n=4,593), 26.93% (n=5,886), and 32.98% (n=7,209) of the study population, respectively.

Table 2 Fitting indices for the latent class analysis of dietary patterns among middle-aged and older women

Category	Loglikelihood	AIC	BIC	aBIC	LMR	BLRT	Category probability (%)
1	-123072.631	246163.263	246235.193	246206.591	—	—	—
2	-118818.023	237674.045	237825.897	237765.516	0.0000	0.0000	41.28/58.72
3	-118506.915	237071.830	237303.604	237211.444	0.0000	0.0000	14.84/33.16/52.00
4	-118268.449	236614.898	236926.595	236802.655	0.0000	0.0000	19.07/21.02/26.93/32.98
5	-118154.773	236407.546	236799.165	236643.445	0.0000	0.0000	17.34/36.68/17.23/11.66/17.09
6	-118084.821	236287.642	236759.183	236571.683	0.0578	0.0000	14.45/35.28/16.28/12.32/12.12/9.56

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion; aBIC, Adjusted Bayesian Information Criterion; LMR, Lo-Mendell-Rubin Likelihood Ratio; BLRT, Bootstrapped Likelihood Ratio Test.

The class-specific conditional probabilities of meeting healthy dietary criteria across the nine indicators are illustrated in Figure 2 and Supplementary Figure S1. Based on these item-response probability profiles, the four latent classes were characterized using index-adherent terminology as follows:

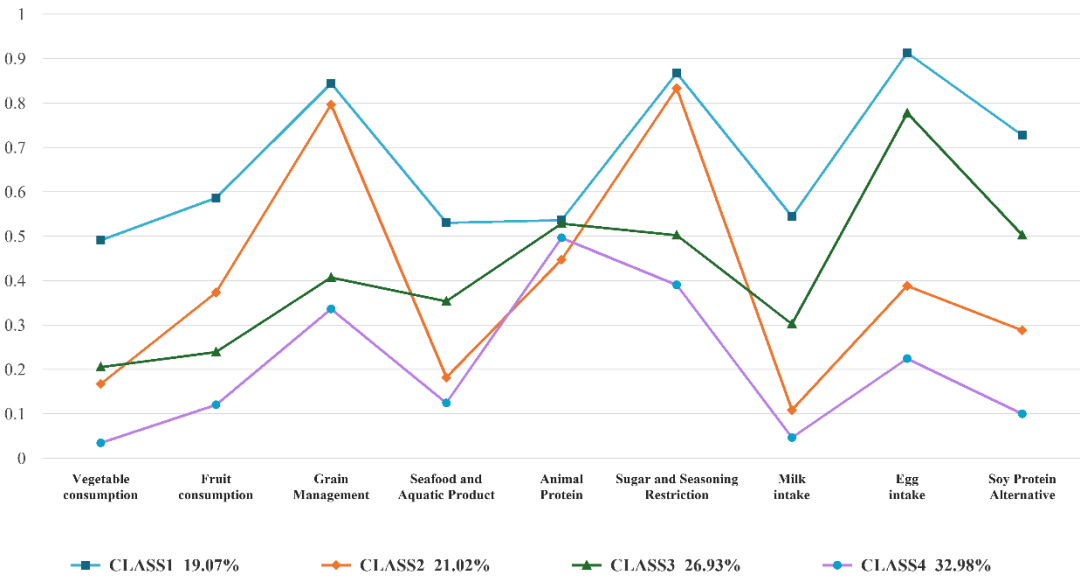


Fig. 2 Class probability based on PHDI informed dietary behavior indicators

Class 1 was named the High PHDI-Adherent Pattern (19.07%), exhibiting consistently high conditional probabilities of meeting healthy criteria across most dietary indicators, particularly egg intake (91.30%), sugar and seasoning restriction (86.70%), whole grain management (84.40%), soy protein intake (72.70%), and fruit consumption (58.60%). This subgroup represented individuals with the highest overall compliance with planetary health dietary guidelines.

Class 2 was named the Grain-Dominant Pattern (21.02%), characterized by high adherence to whole grain management (79.60%) and sugar and seasoning restriction

(83.30%), along with moderate fruit intake (37.30%). However, participants in this class displayed low conditional probabilities for milk (10.80%), vegetables (16.70%), and seafood consumption (18.10%).

Class 3 was named the Protein-Focused Pattern (26.93%), characterized by relatively greater adherence to egg intake (77.70%), animal protein (52.80%), soy protein alternatives (50.20%), and sugar and seasoning restriction (50.20%), but lower compliance for fruit (23.90%) and vegetable consumption (20.50%).

Class 4 was named the Low PHDI-Adherent Pattern (32.98%), exhibiting generally low adherence across almost all dietary indicators—including vegetables (3.40%), milk (4.60%), soy protein alternatives (10.00%), fruit (12.00%), seafood (12.40%), and eggs (22.40%)—despite moderate compliance for animal protein (49.60%).

Across the four latent dietary pattern classes, baseline characteristics varied significantly (all $p < 0.005$). Class 1 showed the highest prevalence of post-graduate education (8.66%) and postmenopausal status (66.41%), whereas Class 4 comprised a younger cohort (87.24% aged 45–59 years) with lower regular exercise rates (10.06%) and higher short sleep prevalence (14.22%) (Table 1).

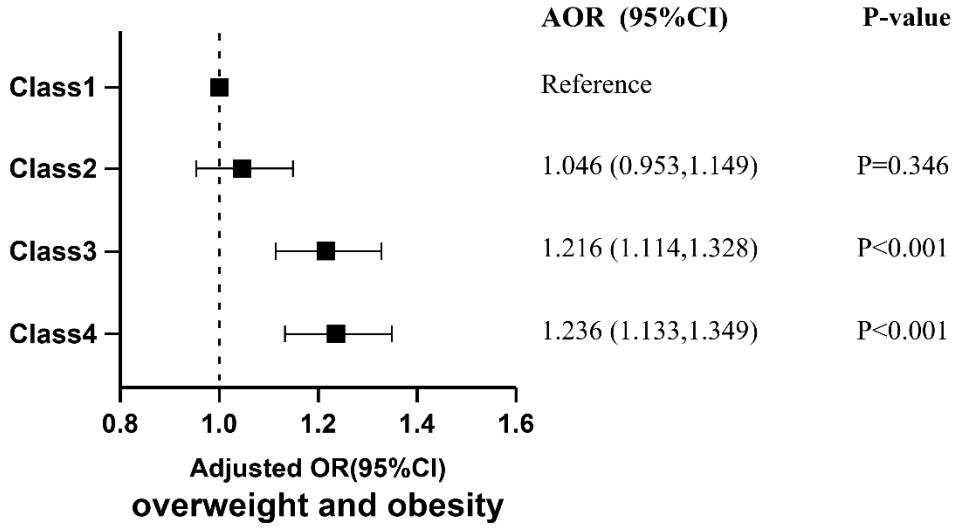
3.3. Association between latent dietary patterns and overweight/obesity

A multivariable binary logistic regression analysis was conducted to evaluate the associations between dietary latent class membership and the risk of overweight/obesity,

controlling for sociodemographic, clinical, and lifestyle covariates (Figure 3, Table S2).

Compared with participants in the High PHDI-Adherent Pattern (Class 1, reference), participants in the Protein-Focused Pattern (Class 3) (AOR = 1.216, $p < 0.001$) and Low PHDI-Adherent Pattern (Class 4) (AOR = 1.236, $p < 0.001$) exhibited significantly higher odds of overweight or obesity. In contrast, odds of overweight/obesity among participants in the Grain-Dominant Pattern (Class 2) did not differ significantly from the reference group (AOR=1.046, 95% CI:0.953-1.149, p=0.346).

Several covariates were also independently associated with overweight/obesity in the adjusted model. Older age (≥60 vs. 45–59 years: AOR=1.369, 95% CI:1.259-1.488, p<0.001) and lower educational attainment (senior high school or below vs. graduate degree or above: AOR=1.549, 95% CI:1.355-1.771, p<0.001) were strongly associated with higher odds of overweight/obesity. Additional significant risk factors included a family history of cardiovascular disease (AOR=1.120, 95% CI:1.041-1.204, p=0.002), postmenopausal status (AOR=1.117, 95% CI:1.047-1.191, p=0.001), current smoking (AOR=1.233, 95% CI:1.068-1.424, p=0.004), current alcohol consumption (AOR=1.121, 95% CI:1.006-1.250, p=0.039), and low physical activity (AOR=1.107, 95% CI:1.007-1.217, p=0.034).



307

308 **Fig. 3** Adjusted odds ratios (AOR) for the associations between latent dietary patterns and

309 overweight/obesity among middle-aged and older women.

310 Error bars represent 95 % confidence intervals (CIs). Adjusted odds ratios (AOR), 95 % CIs, and p-

311 values were estimated using binomial logistic regression models adjusting for unchangeable

312 variables (Age, Education, Occupation, Cardiovascular family history, Diabetes family history,

313 Menopausal status) and changeable variables (dietary patterns, Smoking status, Alcohol

314 consumption, Exercise activity, Sleep Patterns). Class 1 served as the reference group. The four

315 latent classes were: Class 1: High PHDI-Adherent Pattern; Class 2: Grain-Dominant Pattern; Class

316 3: Protein-Focused Pattern; Class 4: Low PHDI-Adherent Pattern.

317 **3.4. Sensitivity analyses**

318 Sensitivity analyses confirmed the robustness of the primary findings (Table S3,

319 Table S4). In age-stratified subgroup analyses (n=18, 020 aged 45–59 years; n=3,836

320 aged ≥60 years; Table S3), membership in the Protein-Focused Pattern (Class 3) and

321 Low PHDI-Adherent Pattern (Class 4) remained consistently associated with

significantly higher odds of overweight/obesity across both age brackets compared to the High PHDI-Adherent Pattern (Class 1; Class 3: AOR=1.183 and 1.328; Class 4: AOR=1.168 and 1.599, all $p \leq 0.003$). Similarly, after excluding participants with baseline hypertension or diabetes (N=19,566; Table S4), elevated risks persisted for Class 3 (AOR=1.218, 95% CI:1.107-1.339, $p<0.001$) and Class 4 (AOR=1.247, 95% CI:1.136-1.370, $p<0.001$). Across all sensitivity models, the Grain-Dominant Pattern (Class 2) showed no significant association with overweight/obesity relative to Class 1.

4. Discussion

4.1 Summary and interpretation of the main findings

This study utilized LCA to identify distinct dietary patterns based on PHDI indicators among middle-aged and older women, and evaluated their associations with overweight and obesity. Four distinct latent classes were identified: High PHDI-Adherent, Grain-Dominant, Protein-Focused, and Low PHDI-Adherent. Multivariable logistic regression showed that participants in the Protein-Focused and Low PHDI-Adherent patterns had significantly higher odds of overweight and obesity than the High PHDI-Adherent reference group, whereas the Grain-Dominant pattern showed no statistically significant association. Older age, lower education, postmenopausal status, cardiovascular family history, smoking, alcohol consumption, and low physical activity were independent risk factors. Sensitivity analyses confirmed the robustness of these findings across age strata and after excluding participants with baseline hypertension or diabetes.

Consistent with previous studies on the association between dietary patterns and overweight and obesity[36], participants in the Protein-Focused Pattern (Class 3) had higher odds of overweight and obesity (AOR = 1.216). While this pattern demonstrated favorable adherence to eggs, animal protein, and soy alternatives, it was compounded by lower intake of protective plant-based foods (fruit and vegetables) and less favorable sugar and seasoning restrictions. This underscores that excess adiposity is tied to overall dietary configuration rather than isolated protein intake. A systematic review showed that traditional dietary patterns combining diverse plant foods with balanced proteins protect against excess weight, whereas diets dominated by isolated protein sources without adequate vegetable fiber showed adverse associations[7]. Therefore, dietary interventions for individuals with this pattern should focus on rebalancing food groups, maintaining appropriate protein intake, and increasing consumption of vegetables, fruits, and whole grains while restricting sugar and seasonings.

Notably, participants in the Low PHDI-Adherent Pattern (Class 4) demonstrated the highest risk of overweight and obesity (AOR = 1.236), driven by pervasive non-adherence across multiple PHDI indicators rather than isolated deficiencies[8]. This aligns with the PHDI framework's emphasis on evaluating diet quality from the perspective of overall dietary structure. Previous studies show that greater adherence to the PHDI is associated with lower BMI, reduced waist circumference, and decreased odds of overweight and obesity, particularly among women transitioning through menopause[10, 12]. Consequently, public health interventions for this group should target

holistic dietary restructuring rather than single-nutrient modifications, fostering a stable, diverse, and relatively balanced dietary structure.

Interestingly, the Grain-Dominant pattern (Class 2) did not exhibit a statistically significant association with overweight and obesity relative to the reference group (AOR=1.046, p=0.346). This pattern was characterized by favorable adherence to grain management and sugar and seasoning restriction, but lower adherence to several other recommended food groups (such as vegetables, dairy, and seafood). Previous longitudinal findings from the China Health and Nutrition Survey (CHNS) similarly indicate that starchy or grain-centric patterns can display neutral associations with obesity depending on accompanying food choices[7, 37]. The absence of a statistically significant association in the present study may reflect the coexistence of favorable dietary behaviors in some dimensions and lower adherence in others. For this subgroup, dietary management should focus on maintaining existing strengths—such as whole grain and seasoning management—while addressing nutritional gaps in vegetables and dairy products to support a transition toward a more balanced dietary pattern.

In addition to dietary patterns, several sociodemographic and lifestyle factors were independently associated with overweight and obesity. Older age and postmenopausal status may increase biological susceptibility to weight gain through hormonal shifts and metabolic deceleration[2]. Furthermore, lower educational attainment may reflect disparities in health literacy and lifestyle resources, while concurrent risk factors—such as smoking, alcohol consumption, and lower physical activity—underscore the

multifactorial etiology of obesity in midlife women[5, 38]. Taken together, these findings emphasize that weight management strategies for middle-aged and older women should integrate dietary pattern optimization with broader lifestyle and physiological considerations.

4.2 Implications for future practice

Our findings highlight the heterogeneity of dietary behaviors among middle-aged and older Chinese women, supporting subgroup-oriented dietary management for obesity prevention. In routine health examination settings, brief dietary assessments enable healthcare professionals to identify individuals with specific dietary needs and provide targeted guidance. For instance, individuals with the Grain-Dominant Pattern may benefit from targeted counseling to address specific dietary gaps, those with the Protein-Focused Pattern may need guidance on rebalancing food groups, and those with the Low PHDI-Adherent Pattern may require comprehensive dietary restructuring. Nurses and health management teams can implement these strategies through individualized dietary education, achievable goal-setting, and regular follow-up to support sustainable dietary change[39]. This tailored approach aligns with broader evidence suggesting that obesity prevention in China should account for population-risk profiles and that enhanced adherence to the PHDI can contribute to better weight management[38, 40]. To implement these strategies, health management institutions should integrate structured dietary counseling into routine care and strengthen multidisciplinary collaboration among nurses, dietitians, and physicians.

4.3 Limitations

This study has several limitations. First, the cross-sectional design precludes causal inference and dynamic tracking of dietary shifts over time, highlighting the need for longitudinal studies with repeated dietary and anthropometric measurements. Second, reliance on a single-center health examination cohort limits generalizability, warranting multicenter and community-based validation across diverse populations. Third, self-reported dietary and lifestyle information is subject to recall bias, and the exclusion of participants with incomplete covariate data, particularly missing educational information, may have introduced selection bias. Future studies should incorporate validated dietary assessment tools and objective physical activity measures to improve accuracy. Fourth, because the HCSAQ was not specifically designed to assess the PHDI, omitting components such as nuts, seeds, and unsaturated oils, the nine PHDI-informed dietary behavior indicators cannot be considered fully equivalent to a standard PHDI score. Future studies using dedicated PHDI assessment tools are needed to validate these dietary patterns. Finally, potential residual confounding remains due to unmeasured factors in the database, including total energy intake, income, cooking methods, food portion sizes, and broader sociocultural or familial influences. Future studies incorporating objective measures and comprehensive lifestyle data will be essential to substantiate these findings.

5. Conclusion

This study identified four distinct dietary patterns among middle aged and older

women in southern China, highlighting notable dietary heterogeneity within this population. Specifically, the Protein-Focused and Low PHDI-Adherent patterns were significantly associated with higher odds of overweight and obesity, whereas the Grain-Dominant pattern showed no statistically significant association. These findings highlight the importance of overall dietary configuration and balance, supporting tailored, subgroup-oriented nutritional and weight management strategies for middle-aged and older women. Future longitudinal and interventional studies are warranted to determine whether dietary transitions yield causal and sustained changes in body weight.

Declarations

Authors' contributions

LWJ and **HHW** contributed to the study concept and design. **LWJ** and **LYJ** contributed to data collection and organization. **LWJ** drafted the manuscript and prepared the visualizations. **HHW** and **ZJ** supervised the study and contributed to project administration. **HHW** contributed to funding acquisition. **LWJ, LYJ, LKN, LZX, ZHX, HHW,** and **ZJ** critically revised the manuscript. All authors critically revised the manuscript and approved the final version.

Competing interests The authors declare no competing interests.

Consent for Publication Not applicable

Ethics approval and consent to participate

Ethical approval for this study was granted by the Ethics Committee of Xiangya Hospital, Central South University (Approval No. 2025020295, Approval date: 21 February 2025). The requirement for written informed consent was waived by the Ethics Committee because the analysis used pre-existing, de-identified health check-up records. The study was conducted in accordance with the Declaration of Helsinki.

Clinical trial number not applicable.

Availability of data and materials

Due to ethical restrictions, the raw data has not yet been made public. Upon reasonable request, de-identified data may be obtained from the corresponding author.

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Additional files

Additional file 1: Supplementary material (.docx).

This file contains Figure S1, Tables S1–S4, and the STROBE reporting checklist.

Fig. S1 Heatmap of latent dietary pattern classes among middle-aged and older women (N = 21,856)

Table S1 Assignment of the nine PHDI-informed dietary-behaviour indicators to the healthy and risky categories, and their correspondence with the 15 Planetary Health Diet Index components

Table S2 Multivariable binary logistic regression analysis of the associations between latent dietary patterns and overweight/obesity among middle-aged and older women (N = 21,856)

Table S3 Subgroup analysis of the association between dietary patterns, covariates, and overweight /obesity, stratified by age group (N = 21,856)

Table S4 Sensitivity analysis of the association between latent dietary patterns and overweight/obesity after excluding participants with baseline hypertension or diabetes (N = 19,566)

File 1 The STROBE reporting checklist

Supplementary Files

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- Supplementarymaterial.docx