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A comparison of principal component analysis, reduced-rank regression, and partial least–squares in the identification of dietary patterns associated with cardiometabolic risk factors in Iranian overweight and obese women

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Abstract

Background According to epidemiological studies, unhealthy dietary patterns and lifestyle lead to rising obesity and cardiometabolic diseases in Iran. Hybrid techniques were used to identify a dietary pattern characterized by fiber, folic acid, and carotenoid intake due to their association with cardiometabolic risk factors such as anthropometric measurements, blood pressure, lipid profile, C-Reactive Protein (CRP), Plasminogen Activator Inhibitor (PAI), Homeostatic Model Assessment Index (HOMA Index), cardiometabolic index (CMI), and monocyte chemoattractant protein (MCP-1). So, the objective of the recent study is to compare the reduced-rank regression (RRR) and partial least–squares (PLS) approaches to principal component analysis (PCA) for estimating diet-cardiometabolic risk factor correlations in Iranian obese women.

Methods Data on dietary intake was gathered from 376 healthy overweight and obese females aged 18 to 65 years using a 147-item food frequency questionnaire (FFQ). In this cross-sectional study, participants were referred to health centers of Tehran. Dietary patterns were developed using PCA, PLS, and RRR, and their outputs were assessed to identify reasonable patterns connected to cardiometabolic risk factors. The response variables for PLS and RRR were fiber, folic acid, and carotenoid intake.

Results In this study, 3 dietary patterns were identified by the PCA method, 2 dietary patterns by the PLS method, and one dietary pattern by the RRR method. High adherence to the plant-based dietary pattern identified by all methods were associated with higher fat free mass index (FFMI) ($P<0.05$). Women in the highest tertile of the plant-

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based dietary pattern identified by PLS had 0.06 mmol/L (95% CI: 0.007,0.66, $P=0.02$), 0.36 mmHg (95% CI: 0.14,0.88, $P=0.02$), and 0.46 mg/l (95% CI: 0.25,0.82, $P<0.001$), lower FBS, DBP, and CRP respectively than women in the first tertile. Also, PLS and RRR-derived patterns explained greater variance in the outcome (PCA: 1.05%; PLS: 11.62%; RRR: 25.28%), while the PCA dietary patterns explained greater variance in the food groups (PCA: 22.81%; PLS: 14.54%; RRR: 1.59%).

Conclusion PLS was found to be more appropriate in determining dietary patterns associated with cardiometabolic-related risk factors. Nevertheless, the advantage of PLS over PCA and RRR must be confirmed in future longitudinal studies with extended follow-up in different settings, population groups, and response variables.

Keywords PCA, RRR, PLS, Dietary patterns, Cardiometabolic risk factors

Introduction

Being overweight or obese is linked to a wide range of non-communicable diseases like cardiometabolic disorders, which cause reduced life quality and increase the risk of morbidity and mortality [1, 2]. Epidemiological studies in Iran discovered an increase in the prevalence of obesity and, as a result, the risk of cardiovascular disease increased [3, 4]. Long-standing research on diet-cardiometabolic relationships has indicated that a poor diet has a greater impact on cardiovascular events and death than other risk factors such as smoking [5]. However, the findings are inconsistent due to using different analysis methods [6]. Instead of focusing on a single nutrient or food group as a new comprehensive insight, the dietary pattern approach has been taken into consideration in recent years [7].Posterior methods, which are based on collected data in a specific population group, can investigate the association between overall dietary intake and disease outcomes [8]. The most common posterior method used for empirical dietary patterns is the principal component analysis (PCA) [9, 10]. PCA generates patterns based on the cross-correlations between the original food intake variables [11]. Dietary patterns derived using PCA tend to explain much of the variability in dietary intake and thus the actual dietary pattern of the population. However, these patterns may have little association with disease risk [12]. The two other methods in dietary data analysis that are considered alternatives for PCA are partial least squares (PLS) and reduced-rank regressions (RRR) [8, 13]. RRR aims to construct a linear function of food that best describes the variability of outcome variables (disease-related nutrients, potential or clinical endpoints, etc.). PLS aims to identify patterns that maximize the inherent variance of both dietary intake and intermediate response variables associated with health or disease outcomes. Such hybrid methods, by including some response variables and combining a statistical approach with theoretical knowledge, are used to drive dietary patterns [13, 14]. Response variables are defined as intermediate factors that have a reasonably strong association with outcomes [15]. In The current study, response variables were defined as fiber, folic acid, and carotenoid intake due to their association with cardiometabolic risk factors [16–18].According to previous studies, dietary fiber intake was related to improving glucose control and decreasing insulin secretion, lower levels of serum cholesterol, and lower blood pressure [19, 20]. One of the vitamin B family members, folic acid is naturally found in a variety of foods, including beans, nuts, fruits, vegetables, and eggs [21].Folic acid has been shown to improve fasting blood glucose, alter the lipid profile, and lower fasting insulin concentrations [22, 23]. Therefore, folic acid deficiency may be related to cardiometabolic disorders [24]. Several reports have suggested that a higher intake of carotenoids commonly found in fruit and vegetables decreases the risk of cardiovascular disease by the capability of eliminating single oxygen and reducing inflammatory.

markers [25–28]. We considered many factors associated with cardiometabolic risk factors such as calorie intake, SFA, MUFA, PUFA, etc. as response factors and put them in the analytical models, but the model obtained was not suitable, therefore the three factors of folic acid, Fiber, and carotenoids, which led to better pattern formation, were selected as response factors.

So far, restricted researches assay the relationship between RRR-derived dietary patterns and cardiometabolic risk factors [29–31] and only a few studies employ the PLS methods in addition to the RRR approach [32, 33]. To the information we have, this is the first study that compares the RRR and PLS strategies with the PCA for identifying diet cardiometabolic risk factor associations in Iranian overweight and obese women. As a result, the primary aims of the recent study are (1) to investigate dietary patterns associated with cardiometabolic-related risk factors, including anthropometric measurements, blood pressure, lipid profile, CRP, PAI, HOMA Index, CMI, and MCP-1, and (2) to use the RRR and PLS methods and compare the performance of the mentioned methods to that of PCA for estimation of diet-cardiometabolic risk factor relationships in Iranian obese women for the first time.

Materials and methods

Research design and participants

In this cross-sectional study, after considering eligibility criteria 376 healthy overweight and obese women by using community-based multi-stage simple random sampling were selected from random 20 health centers located throughout West and Central Tehran, Iran between February 2018 and May 2019. In this study, 402 people were invited, but only 376 of these people answered all the questions and were included in the study. The response rate was 93.53%. Last studies have shown some female reproductive factors, including history of childbearing, age at menarche, and menopause, to be associated with adiposity, so these factors may be responsible for developing of type 2 diabetes and cardiovascular complications {de Jong, 2020 #172}. All study participants' written informed permission was evaluated and approved by the Tehran University of Medical Sciences (TUMS) in Tehran, Iran. Eligible subjects' ages ranged from 18 to 68, their BMI varied from 25 to 40 kg, and consent to participate in the study Blood samples were obtained from women who did not have diagnosed cardiovascular disease (CVD), type I or type II diabetes, malignancies, thyroid disease, liver disease, or kidney disease. Other exclusion criteria included menopause, pregnancy, breastfeeding, taking supplements for weight loss, dieting within the previous year, and taking medications that lower lipids, glucose, and blood pressure [34]. The current study was carried out in accordance with the principles outlined in the Declaration of Helsinki, and all operations involving human subjects were authorised by the Tehran University of Medical Sciences Ethics Committee under the ethical consideration number IR.TUMS.MEDICINE.REC.1400.1515. All subjects provided their written, informed consent.

Dietary assessment

A 147-item semi-quantitative food frequency questionnaire (FFQ) that has been previously validated in terms of reliability and validity was used to assess dietary exposure [35]. Participants reported their intake frequency based on their typical diet in grams and milliliters while a dietitian watched over them. The NUTRITIONIST 4 food analyzer (First Data Bank, San Bruno, CA) was used to analyse dietary consumption [36].

Body composition and anthropometric measurements

Each participant was weighed to the nearest 100 g without shoes and in as little clothing as possible using a calibrated digital scale. Normal, standing volunteers' heights were measured to within 0.5 cm with a non-elastic tap. To calculate BMI, divide the weight by height, which is measured in square meters. We measured the waist circumference at the end of a natural exhale from the narrowest point of the waist using an elastic measuring tape with a precision of 0.5 cm. We estimated the hip circumference by placing a strapless tape on the most observable, marked area. To reduce measurement mistakes, all of the measurements were made by one person. A bioelectrical impedance analyzer (BIA) (Inbody 770 Co., Seoul, Korea) was used to measure body composition following the manufacturer's technique, process, and precautions [37]. Bioelectrical Impedance Analysis calculates body fat percentage, fat mass, fat-free mass, and muscle mass from Dual Energy X-ray Absorptiometry (DXA) data. Participants remove their shoes, extra clothing, and metal objects. Checking weight, BMI, and body composition, including skeletal muscle mass, fat-free mass, and fat, takes 15 to 20 s.

Physical activity assessment

By using the International Physical Activity Questionnaire's short form (IPAQ), we were able to evaluate people's levels of physical activity. In 12 different countries, the validity and reliability of IPAQ questionnaires were assessed. The validated self-report IPAQ measured recent physical activity [38].

Biochemical and laboratory assessment

We collected venous blood after fasting overnight. We centrifuged all of the serum, aliquoted it, kept it at -80 °C, and analyzed it all using a single test procedure. Fasting blood glucose (FBS), triglyceride (TG), and total cholesterol (TC) were assessed using glucose oxidase-phenol 4-amino antipyrine peroxidase (GOD-PAP) and glycerol-3-phosphate oxidase–phenol 4-amino antipyrine peroxidase (GPO-PAP). Low-density-lipoprotein (LDL), and high-density lipoprotein (HDL) cholesterol were tested using direct enzymatic clearance. Based on the ratio of triglycerides (TG) to high-density lipoprotein cholesterol (HDL-C) and the waist-to-height ratio (WHtR), the cardiometabolic index (CMI) describes adiposity. It was computed using the following equation: $CMI = TG/HDL\text{-}C \times WHtR$. Also, fasting insulin (microU/L) x fasting glucose (nmol/L)/22.5 was used to calculate HOMA-IR. Galectin, MCP-1, and hs-CRP were measured via standard protocols.

In triplicate, plasminogen activator inhibitor-1 (PAI-1) was evaluated using a Human PAI-1*96 T ELISA kit from Crystal Company. The intra CV was 2.19%, and the inter CV was 4.4%, with a minimum detectable insulin concentration of 1.76 mIU/mL. Immunoturbidimetric tests evaluated inflammatory markers (high sensitivity assay, Hitachi 902). For all measures, we used the Randox Laboratories (Hitachi 902) kit at TUMS's Nutrition and Biochemistry Laboratory.

Statistical analysis Dietary analysis

Utilizing data reduction techniques such as PCA, PLS, and RRR, dietary patterns were identified for a total of 28 food groups. These methods are similar according to their mathematical foundation and their technique of deriving factors. Computing pattern scores using the three statistical methods relies on computing the eigenvalues and corresponding eigenvectors of the covariance matrices of both the predictors and the response. Only the first sample evaluation with the largest eigenvalue is of interest, since the eigenvalues represent the proportion of variation attributable to the corresponding evaluations.

Based on their nutrient profiles and taxonomy, we categorized various food items. The food groups used in the analysis are shown in Table 1. All techniques used an energy-adjusted food group. To assure unrelated conditions and enhance interpretability, variables were extracted using varimax rotation in PCA, and the Kaiser-Mayer-Olkin (KMO) test was used to determine whether the sample size was sufficient. In the end, factors were discovered by taking into account an eigenvalue greater than 1.5 and a scree plot. The reference daily intake of each food was correlated to the DPs, and the factor scores were calculated as the sum of each factor loading≥0.2. Based on the scree plot, the first three dietary patterns were selected. The amount of variation in a dietary pattern that can be attributed to the food groups or response variables is measured by an explained variance. We used RRR and PLS to extract the major dietary patterns. To perform both models, we first normalized the response and predictor variables. Then, because of the non-normal distribution of response variables, we applied power transformation before the main analysis.

Two first factors were retained for PLS, and the first factor was retained for RRR as they explained more variation in the intermediate response variables than the food groups. The scores in each of the three techniques are constructed using various algorithms. The PCA factors try to take into consideration as much variety among the food group as they can [39]. Instead of using PCA, RRR derives the scores using a covariance matrix of the answers and predictors (food groups). PLS integrates the two methods to produce scores that simultaneously consider the predictor (food group) and response matrices [12]. The explained variance of the response variables and food groups in this case is predicted to fall between the two prior methods. Tertiles were created out of the factor scores (T1 for lowest intake, T2 for middle intake, and T3 for greatest intake). The factor loadings on the factors for each food group were also calculated.

Table 1 Food group components

Food Group	Food group components
Dark green vegetables	Spinach, leafy greens, and lettuce
Legumes	Beans, peas, lentils, mung beans, chickpeas, beans
Spices	All kinds of spices
Olive oil	Olive oil, olives
Other vegetables	Cucumbers, tomatoes, celery, green beans, green peppers, bell peppers, turnips, zucchini, pumpkin, mushrooms, onion, garlic, and any kind of cabbage
Red and orange vegetables	Carrots, tomatoes, pumpkin
Low-fat dairy	Low-fat milk, cheeses, low-fat yogurt
Potatoes	Potatoes
Fruits	Apples, cherries, apricots, plums, figs (dried or fresh), kiwi, strawberries, grapes or raisins, dates, bananas, pomegranates, melons, oranges, tangerines, grapefruits, pears, persimmons, cantaloupe, melons, watermelons, nectarines, peaches, greengage, lemons, berries (dried or fresh), and other dried fruits, orange juice, apple juice, cantaloupe juice
Fish	Fish and canned tuna fish
Egg	Egg
Mayonnaise	Mayonnaise
Red meat	Beef, lamb
Poultry	Poultry
Salty food	Salt, pickles
Organ meat	Internal organs of lamb such as the liver, heart, kidney
Nuts & soy	Almonds, peanuts, walnuts, pistachios, hazelnuts, seeds, and soy
Vegetable oil	Vegetable oil
High-fat dairy	High-fat milk, cream, high fat yogurt, high-fat cheeses, strained yogurt
Simple sugar	Biscuits, crackers, cakes, sugar, candy, chocolate, honey, commercially produced fruit juices, jam, fruit compote, and all kinds of sweets
Snacks	Chips and corn puffs
Sweetened beverages (SSB)	Commercially produced fruit juices, soft drinks, and chocolate milk
Unhealthy oil	Hydrogenated oil, animal oil
Fast food	Pizza and sausages
Butter and margarine	Butter and margarine
Tea and coffee	Tea and coffee
Grain	All kinds of bread, rice, pasta, noodles, vermicelli, wheat flour, bulgur, and corn
Ice cream	Ice cream

Descriptive analysis and modeling

For continuously distributed normally distributed variables, the mean, standard deviation, and proportions were computed. The tertiles of factor scores produced by PCA, PLS, and RRR analyses were used to analyse the connection between dietary patterns and cardiometabolic risk factors. The following criteria were used to categorize cardiometabolic risk factors: LDL, CRP, HOMA, and HDL according to Karelis's criteria [40], FBG above and below 100 mg/dl, BMI between 25 and 29.99 kg/m2, and 30 to 40 kg/m2 [41], blood pressure over 130/85 mm

Hg or lower than 130/85 mm Hg [41], and total cholesterol levels below 200 mg/dl and above 200 mg/dl. Other variables were classified as being lower or higher than the median. Indicators such as age, energy intake, physical activity, and BMI were considered as confounding factors. We applied binary logistic models to evaluate the associations between tertiles of each factor score and cardiometabolic risk factors. Model 1 was adjusted for age, energy intake, physical activity, and BMI. SPSS software was used to perform the binary logistic analysis and PCA (version 21.0; SPSS Inc, Chicago, IL). Statistical significance was accepted at $p<0.05$. PLS and RRR analyses were obtained using the rrr (version 1.0.0) package and pls (version 2.8-1) from R software (R-4.1.2).

Comparison of methods

In this study, we compared PCA, PLS, and RRR methods mainly based on the relative loading of food groups within each dietary pattern and their association with cardiometabolic risk factors [42]. Additionally, we assessed the techniques based on how much each one differed from the others in terms of how well they explained the response variables and food groups.

Results

Study population characteristics

This research was completed by 376 individuals in total. Participants in the study were 106 (28.2%) single and 270 (71.8%) married, with an average age of 36.71±9.19 years. 182 respondents (48.4%) had bachelor's degrees or more, whereas 117 (31.1%) of the respondents had just completed high school. The average body weight (kg), BMI (kg/m2), fat mass index (FMI), fat-free mass index (FFMI), waist circumference (cm), systolic blood pressure (mmHg), and diastolic blood pressure (mmHg) of the study subjects were 80.65±11.34, 31.02±3.86, 13.26±3.11, 18.16±6.88, 99.20±9.60, 11.27±13.58, 77.59±9.58 respectively.

Dietary patterns derived by PCA, RRR, and PLS

The food groups and food items that make up each food group were listed in Table 1. Three different forms of methods (PCA=3, RRR=1, and PLS=2 patterns) were used to find dietary patterns. Among all three analyses, there was one common pattern. Table 2 lists component factor loadings (standardized correlations of the food categories with the dietary patterns) for each of the 28 food groups for the dietary patterns (i.e., factors) derived by PCA, as well as factor loadings for patterns obtained by RRR and PLS. While a large negative loading suggests a significant inverse link, a high positive loading reveals a strong direct association between the food group and the pattern. The first factor from PCA (plant-based dietary pattern) was positively associated with the intake of dark green vegetables, red and orange vegetables, other vegetables, legumes, spices, olive oil, potatoes, low-fat dairy, and grains, and inversely associated with the intake of high-fat dairy, sweetened beverages, ice cream, butter and margarine, and unhealthy oils. The majority of the aforementioned food groups such as red and orange vegetables, dark green vegetables, and legumes loaded positively on the first factor of the RRR and PLS methods. The second factor from PCA (high protein and high fiber dietary pattern), was characterized by high positive loadings of dark green vegetables, other vegetables, red and orange vegetables, fruits, fish, red meat, poultry, and salty foods. The third factor of the PCA (western dietary pattern) was characterized by high positive loadings of fish, mayonnaise, salty food, snacks, sweetened beverages, and fast food. The second factor from the PLS seemed to be close to the third factor of the PCA and was characterized by high positive loading of fast food, sweetened beverages, red meat and salty food.

Explained variations in response variables and food groups

Table 3 provides an overview of the variations in responses and food groups by dietary patterns discovered using the three statistical techniques (PCA, PLS, and RRR). Three dietary patterns that together accounted for 22.81% of the total variation in food groups were retained from PCA. whereas one dietary pattern was retained from RRR and two dietary patterns were retained from PLS, which explained 1.59 and 14.54% of the total variation in food groups, respectively. As expected, PCA explained the least amount of variation in response variables (carotenoids, folic acid, and fiber intake) (1.05%), followed by PLS (11.62%) and RRR (25.28%). The first ("plant-based" dietary pattern), second ("high protein and high fiber" dietary pattern), and third ("western" dietary pattern) factor of PCA explained 7.94%, 7.89%, 6.98 of the variation in food groups respectively (Table 3). As a result, while the PCA-derived patterns only partially account for variation in the response variables, they account for a significant proportion of variation in the food groups. The RRR-derived pattern explains low variation in the food group but a larger variation in the intermediate response variables. When compared to the RRR-derived pattern, the PLS-derived pattern considerably better explains variation in food groups while explaining almost identical amounts of variation in intermediate response variables.

Dietary patterns and cardiometabolic risk factors

The relationships between the factors discovered by PCA, RRR, and PLS and cardiometabolic risk factors are shown in Table 4. The highest adherence (T3) to a plant-based dietary pattern was associated with a higher FFMI compared to the lowest adherence (T1) in the crude

Table 2 Factor loadings of food groups in dietary patterns were identified using principal component analysis, reduced-rank regression, and partial least-squares ($n=376$)

Food groups	Vegetable and fruit dietary pattern			High protein and high fiber dietary pattern	Western dietary pattern	
	PCA	RRR	PLS	PCA	PCA	PLS
Dark green vegetables	0.51	0.20	0.43	0.44		
Legumes	0.51	0.12	0.26		-0.10	-0.32
Spices	0.47			-0.13	0.18	
Olive oil	0.46				0.12	
Other vegetables	0.45		0.47	0.53	-0.20	
Red and orange vegetables	0.44	0.33	0.49	0.45	-0.24	
Low-fat dairy	0.41	-0.14	0.14	0.20	0.10	0.19
Potatoes	0.36		0.13		-0.21	
Fruits	0.17	0.10	0.25	0.32	-0.19	0.23
Fish	0.17		0.12	0.39	0.29	0.25
Egg	0.14					-0.11
Mayonnaise	0.10				0.32	0.11
Red meat			0.12	0.47		0.36
Poultry				0.39	0.16	0.24
Salty food			0.13	0.41	0.25	0.22
Organ meat				0.27		0.19
Nuts & soy					-0.17	
Vegetable oil		-0.16	-0.18	-0.45	0.23	
High-fat dairy	-0.27				-0.18	0.11
Simple sugar				-0.12	-0.12	
Snacks			-0.16	− 0.15	0.52	0.19
Sweetened beverages (SSB)	-0.25		-0.15	0.12	0.56	0.31
Unhealthy oil	-0.26	-0.17			-0.36	
Fast food			-0.11		0.67	0.30
Butter and margarine	-0.22		-0.10			
Tea and coffee					-0.28	-0.10
Grain	0.25		-0.11			-0.48
Ice cream	-0.26					0.12

Loadings lower than │0.1│ were deleted for simplicity

and adjusted model (model 1 adjusted for age, physical activity, and energy intake), using PCA ($OR_{model\ 1}=3.50$; 95% CI: 2.00,6.12, $P<0.001$), RRR ($OR_{model\ 1}=1.96$; 95% CI: 1.13,3.42, $P=0.01$), and PLS ($OR_{model\ 1}=1.91$; 95% CI: 1.10,3.32, $P=0.02$) methods. A significant inverse association was observed between "plant-based dietary pattern" and DBP ($OR_{model\ 1}=0.36$; 95% CI: 0.14,0.88, $P=0.02$) identified by PLS in the adjusted model. Additionally, the "plant-based dietary pattern", identified by PLS showed a significant negative association with FBS ($OR_{model\ 1}=0.06$; 95% CI: 0.007,0.66, $P=0.02$). RRR found adverse connections as well, but they weren't statistically significant ($OR_{model\ 1}=0.12$; 95% CI: 0.01,1.10, $P=0.06$). In both the crude and adjusted models, employing the PLS approach, higher scores for the plant-based dietary pattern were linked to a lower risk of elevated CRP ($OR_{model\ 1}=0.46$; 95% CI: 0.25,0.82, $P<0.001$).

The "high protein and high fiber" dietary pattern found by PCA also showed this adverse correlation, although it was not statistically significant after controlling for covariates (age, energy intake, BMI, and physical activity) ($OR_{model\ 1}=0.56$; 95% CI: 0.31,1.00, $P=0.05$).

The western dietary pattern identified by PCA and PLS was not significantly associated with any variables. Likewise, the "high protein and high fiber" dietary pattern, identified by PCA, was not significantly associated with cardiometabolic risk factor variables in the adjusted model (model1) ($P>0.05$).

Discussion

This study provides evidence of the association between dietary patterns and cardiometabolic-related risk factors using PCA, RRR, and PLS methods in Iranian overweight and obese women. To the best of our knowledge, this is the first study comparing the RRR and PLS methods with the PCA for the estimation of diet-cardiometabolic risk factor relationships in overweight and obese women. Out of the dietary patterns identified by three methods, the higher adherence to the "plant-based dietary patterns" identified by PCA, RRR, and PLS were all associated with

Table 3 Explained variation (%) in response and food groups by dietary patterns identified using principal component analysis, reduced-rank regression, and partial least-squares ($n = 376$)

Factors	Proportion (%) of explained variation in responses				Proportion (%) of explained variation in food groups
	Carotenoids	Fiber	Folic acid	total	
PCA- Plant-based dietary pattern	0.00	22.68	0.00	0.35	7.94
PCA-High protein and high fiber dietary pattern	0.00	22.54	0.00	0.35	7.89
PCA-Western dietary pattern	0.00	19.94	0.00	0.35	6.98
Total PCA patterns	1.05				22.81
RRR- Plant-based dietary pattern	72.24	88.35	69.48	25.28	1.59
Total RRR patterns	25.28				1.59
PLS- Plant-based dietary pattern	48.38	8.22	6.80	3.45	9.20
PLS-Western dietary pattern	50.18	21.40	17.94	8.17	5.34
Total PLS patterns	11.62				14.54

Abbreviations: PCA: principle component analysis; RRR: reduced-rank regression; PLS: partial least-squares

The dietary patterns were derived using the energy-adjusted food groups

higher FFMI in the adjusted and crude models. After adjusting for multiple variables, the "plant-based dietary pattern" identified with PLS was inversely associated with DBP and FBS in adjusted and CRP in the crude and adjusted models. Moreover, the "plant-based dietary pattern" identified by RRR tended to have an inverse association with FBS. Furthermore, an inverse association was seen between the "high protein and high fiber" dietary pattern and CRP in the PCA method in the crude model but not in the adjusted model. No significant associations were seen between the identified dietary patterns and the other cardiometabolic-related risk factors evaluated in this study.

Comparison with other studies and potential mechanism between dietary patterns and cardiometabolic-related risk factors

Previous studies have shown that body composition indices predict the risk of cardiovascular disease or mortality [43–45]. In overweight or obese individuals, relative fat-free mass (FFM) deficiency was associated with a greater probability of hypertension, abnormalities of glucose tolerance, and proteinuria [46]. Moreover, in a cross-sectional study on Iranian adults, higher adherence to the plant-based dietary index was associated with higher FFM [47]. Our results support this finding and indicate that adherence to the "plant-based dietary pattern" is associated with higher FFMI. Legumes, vegetables and fruits intake are mutual components in three plant-based dietary pattern groups of PCA, PLS and RRR. Legumes consumption was positively associated with lower body fat and higher fat free mass, based on previous study. This may due to its protein content and justify our results [48]. In other hand, vegetables intakes which are highly recommended in Mediterranean diet can improve skeletal muscle health and FFM [49]. The underlying mechanism may be related to plant-based nutrients since a study on women indicated that consumption of plant-based nutrients, including vitamin C, magnesium, potassium, and carotenoids, is important in maintaining fat-free mass [50]. This effect could be due to their anti-oxidant or anti-inflammatory properties, as oxidative stress and inflammation have been suggested as possible mechanisms of sarcopenia [51–53]. However, in contrast to previous studies [54, 55], our results revealed no association between other anthropometric measurements, including BMI and waist-to-hip ratio, with any dietary pattern in any statistical methods.

Moreover, our findings showed that the plant-based dietary pattern identified with PLS is also inversely associated with DBP but not SBP. The previous meta-analysis of clinical trials and observational studies found that plant-based dietary patterns (vegetarian, DASH, and Mediterranean) are effective at reducing BP [56–58]. Improved endothelial functions can be attributed to the plant-based dietary pattern [59]. First, less animal content, which has been linked to less inflammation [56, 60, 61]. Second, consuming foods high in nitrites and flavonoids increases nitric oxide levels, dilates blood vessels, enhances endothelial functions, and lowers blood pressure [62]. Another potential mechanism is that plant-based dietary patterns are rich in potassium, and increased potassium intake reduces BP and the risk of strokes [63] via vasodilation, increased glomerular filtration rate, and decreased renin, renal sodium reabsorption, reactive oxygen species production, and platelet aggregation [64]. Low fat dairy (rich in calcium) and dark green vegetables (rich in magnesium and potassium) may

Table 4 Odds ratios and 95% confidence intervals for cardiometabolic risks and tertiles factor scores were derived using principal component analysis, reduced-rank regression, and partial least-squares ($n = 376$)

		BMI (kg/m^2)		WC (cm)		FMI		FFMI	
		Crude	**Model1**	**Crude**	**Model1**	**Crude**	**Model1**	**Crude**	**Model1***
		OR (95%CI)	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**
PCA									
Factor 1	T1	Ref.							
	T2	1.01 (0.61,1.66)	1.02 (0.58,1.77)	0.87 (0.51,1.49)	1.05 (0.58,1.89)	1.60 (0.96,2.67)	1.97 (1.12,3.49)	0.85 (0.51,1.40)	0.89 (0.51,1.55)
	T3	1.53 (0.92,2.54)	1.42 (0.82,2.44)	1.17 (0.70,1.98)	1.25 (0.72,2.20)	3.19 (1.90,5.36)	3.50 (2.00,6.12)	1.42 (0.86,2.35)	1.37 (0.80,2.34)
Factor 2	T1	Ref.							
	T2	1.19 (0.72,1.96)	1.21 (0.70,2.09)	0.77 (0.45,1.31)	0.85 (0.48,1.50)	0.76 (0.46,1.25)	0.77 (0.45,1.33)	1.31 (0.80,2.16)	1.31 (0.76,2.26)
	T3	1.06 (0.64,1.75)	1.02 (0.59,1.77)	0.90 (0.53,1.51)	0.95 (0.54,1.68)	0.83 (0.51,1.37)	0.89 (0.51,1.53)	1.35 (0.82,2.23)	1.20 (0.69,2.08)
Factor 3	T1	Ref.							
	T2	0.89 (0.54,1.46)	0.99 (0.57,1.74)	0.77 (0.45,1.31)	0.84 (0.46,1.51)	0.92 (0.56,1.51)	1.08 (0.62,1.88)	0.83 (0.51,1.37)	0.79 (0.45,1.39)
	T3	0.96 (0.58,1.59)	1.33 (0.76,2.33)	1.00 (0.59,1.68)	1.06 (0.60,1.87)	0.83 (0.51,1.37)	0.96 (0.55,1.66)	0.89 (0.54,1.46)	1.14 (0.66,1.98)
RRR									
Factor1	T1	Ref.							
	T2	1.65 (1.00,2.73)	1.49 (0.86,2.58)	1.43 (0.84,2.42)	1.25 (0.55,2.82)	1.68 (1.01,2.78)	1.79 (1.03,3.09)	1.42 (0.86,2.34)	1.24 (0.72,2.13)
	T3	1.44 (0.88,2.38)	1.23 (0.71,2.14)	1.16 (0.67,1.98)	1.53 (0.68,3.46)	1.88 (1.13,3.12)	1.96 (1.13,3.42))	1.31 (0.79,2.16)	1.05 (0.60,1.81)
PLS									
Factor 1	T1	Ref.							
	T2	1.36 (0.82,2.24)	1.16 (0.68,2.00)	1.29 (0.76,2.19)	1.21 (0.54,2.72)	1.47 (0.89,2.43)	1.49 (0.87,2.56)	1.17 (0.71,1.93)	1.01 (0.58,1.73)
	T3	1.31 (0.80,2.16)	1.18 (0.68,2.04)	1.29 (0.76,2.19)	1.95 (0.86,4.41)	1.76 (1.06,2.91)	1.91 (1.10,3.32)	1.44 (0.87,2.38)	1.28 (0.74,2.21)
Factor 2	T1	Ref.							
	T2	1.36 (0.82,2.26)	1.58 (0.91,2.74)	1.02 (0.60,1.73)	0.80 (0.47,1.37)	1.15 (0.70,1.90)	1.32 (0.77,2.27)	1.11 (0.68,1.83)	1.19 (0.69,2.04)
	T3	0.98 (0.60,1.61)	1.08 (0.62,1.87)	0.97 (0.57,1.65)	0.82 (0.48,1.40	0.77 (0.46,1.27)	0.84 (0.48,1.45)	1.03 (0.62,1.69)	1.07 (0.62,1.85)
		SBP (mmHg)		DBP (mmHg)		FBS (mmol/L)		HDL_C (mmol/L)	
PCA									
Factor 1	T1	Ref.							
	T2	1.58 (0.56,4.47)	1.99 (0.54,7.32)	1.63 (0.78,3.43)	1.41 (0.59,3.35)	1.95 (0.60,6.31)	4.05 (0.84,19.33)	1.31 (0.64,2.67)	1.54 (0.69,3.43)
	T3	1.38 (0.50,3.79)	1.25 (0.36,4.26)	0.85 (0.39,1.85)	0.57 (0.24,1.36)	0.48 (0.11,2.09)	0.42 (0.06,2.65)	1.07 (0.56,2.04)	1.31 (0.65,2.62)
Factor 2	T1	Ref.							
	T2	1.10 (0.41,2.94)	1.68 (0.51,5.45)	1.28 (0.63,2.56)	1.75 (0.77,3.98)	0.35 (0.09,1.36)	0.29 (0.05,1.53)	0.60 (0.30,1.18)	0.60 (0.28,1.25)
	T3	0.84 (0.31,2.30)	1.09 (0.32,3.66)	0.37 (0.16,0.87)	0.50 (0.19,1.30)	0.38 (0.11,1.30)	0.36 (0.08,1.62)	1.28 (0.65,2.54)	1.26 (0.60,2.66)
Factor 3	T1								
	T2	1.01 (0.41,2.47)	0.80 (0.25,2.56)	0.81 (0.37,1.73)	1.12 (0.45,2.78)	1.43 (0.43,4.73)	1.22 (0.27,5.45)	0.70 (0.36,1.35)	0.87 (0.41,1.82)
	T3	0.32 (0.10,1.06)	0.53 (0.14,1.98)	0.97 (0.46,2.01)	1.36 (0.57,3.25)	0.90 (0.23,3.51)	1.18 (0.24,5.61)	1.00 (0.50,2.01)	1.01 (0.47,2.16)
RRR									
Factor1	T1								

Table 4 (continued)

		BMI (kg/m^2)		WC (cm)		FMI		FFMI	
		Crude	**Model1**	**Crude**	**Model1**	**Crude**	**Model1**	**Crude**	**Model1***
		OR (95%CI)	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**	**OR (95%CI)**
	T2	2.32 (0.74,7.24)	1.82 (0.46,7.18)	1.91 (0.92,3.97)	1.52 (0.66,3.51)	1.24 (0.41,3.74)	1.14 (0.30,4.31)	0.75 (0.38,1.50)	0.82 (0.39,1.74)
	T3	2.54 (0.85,7.52)	2.26 (0.64,7.97)	0.76 (0.34,1.69)	0.57 (0.23,1.40)	0.23 (0.04,1.17)	0.12 (0.01,1.10)	1.20 (0.62,2.33)	1.47 (0.70,3.09)
PLS									
Factor 1	T1								
	T2	1.57 (0.52,4.74)	1.67 (0.46,6.06)	0.96 (0.47,1.98)	0.78 (0.34,1.79)	0.63 (0.20,1.98)	0.65 (0.17,2.53)	0.72 (0.35,1.46)	0.69 (0.32,1.47)
	T3	2.00 (0.71,5.57)	1.61 (0.48,5.34)	0.47 (0.21,1.02)	0.36 (0.14,0.88)	0.16 (0.03,0.78)	0.06 (0.007,0.66)	1.03 (0.53,2.00)	1.15 (0.54,2.41)
Factor 2	T1								
	T2	0.58 (0.21,1.61)	0.73 (0.22,2.39)	1.14 (0.53,2.43)	1.77 (0.72,4.31)	0.94 (0.29,3.07)	1.15 (0.28,4.71)	1.97 (0.99,3.93)	1.78 (0.84,3.79)
	T3	0.71 (0.27,1.85)	0.78 (0.24,2.51)	0.92 (0.42,1.98)	1.42 (0.57,3.53)	0.58 (0.15,2.17)	0.60 (0.21,2.99)	1.58 (0.81,3.06)	1.39 (0.67,2.88)
		TC (mmol/L)		LDL_C (mmol/L)		HOMA-IR		CMI	
PCA									
Factor 1	T1								
	T2	1.22 (0.59,2.51)	0.71 (0.30,1.70)	0.83 (0.42,1.67)	0.77 (0.35,1.70)	1.26 (0.62,2.56)	1.25 (0.57,2.76)	2.08 (0.98,4.44)	2.14 (0.93,4.95)
	T3	1.16 (0.59,2.27)	0.89 (0.41,1.89)	0.95 (0.51,1.80)	0.83 (0.41,1.67)	0.99 (0.52,1.89)	0.99 (0.49,2.00)	1.16 (0.61,2.20)	1.16 (0.57,2.33)
Factor 2	T1								
	T2	1.67 (0.82,3.39)	1.59 (0.70,3.62)	0.85 (0.43,1.69)	0.83 (0.38,1.80)	1.52 (0.75,3.09)	1.51 (0.69,3.27)	1.16 (0.58,2.32)	1.17 (0.54,2.51)
	T3	1.22 (0.61,2.44)	1.29 (0.58,2.86)	1.11 (0.59,2.09)	1.43 (0.70,2.93)	0.86 (0.45,1.63)	0.81 (0.40,1.65)	1.42 (0.73,2.77)	1.39 (0.67,2.90)
Factor 3	T1								
	T2	1.63 (0.85,3.13)	1.69 (0.78,3.67)	1.40 (0.73,2.65)	1.31 (0.62,2.74)	1.25 (0.64,2.42)	1.06 (0.50,2.23)	0.87 (0.44,1.71)	0.94 (0.43,2.03)
	T3	0.53 (0.24,1.14)	0.73 (0.31,1.72)	0.95 (0.48,1.88)	0.99 (0.46,2.12)	0.94 (0.48,1.83)	0.84 (0.40,1.77)	0.84 (0.42,1.68)	0.97 (0.45,2.08)
RRR									
Factor1	T1								
	T2	1.40 (0.67,2.93)	1.07 (0.46,2.50)	0.86 (0.43,1.71)	0.77 (0.35,1.69)	1.02 (0.51,2.07)	0.85 (0.39,1.82)	1.15 (0.56,2.32)	1.06 (0.49,2.30)
	T3	1.68 (0.85,3.31)	1.33 (0.61,2.90)	0.95 (0.50,1.78)	0.95 (0.46,1.96)	0.85 (0.45,1.62)	0.89 (0.43,1.85)	1.28 (0.66,2.47)	1.23 (0.59,2.57)
PLS									
Factor 1	T1								
	T2	1.68 (0.81,3.48)	1.96 (0.85,4.51)	1.16 (0.58,2.31)	1.48 (0.69,3.17)	1.13 (0.55,2.33)	1.08 (0.50,2.36)	1.27 (0.61,2.62)	1.44 (0.66,3.17)
	T3	1.29 (0.65,2.55)	1.02 (0.45,2.29)	0.87 (0.46,1.66)	0.94 (0.45,1.97)	0.81 (0.43,1.53)	0.82 (0.39,1.68)	1.17 (0.61,2.26)	1.13 (0.54,2.35)
Factor 2	T1	Ref.							
	T2	0.98 (0.49,1.94)	1.05 (0.48,2.31)	0.77 (0.39,1.51)	0.69 (0.32,1.49)	1.26 (0.64,2.49)	1.17 (0.56,2.44)	1.91 (0.93, 3.92)	1.88 (0.85,4.18)
	T3	0.72 (0.36,1.46)	0.92 (0.41,2.05)	0.93 (0.48,1.78)	1.23 (0.59,2.56)	1.08 (0.56,2.10)	0.91 (0.44, 1.89)	1.04 (0.54,2.02)	0.89 (0.43,1.86)
		CRP (mg/L)		PAI (ng/ml)		Galectin (ng/ml)		MCP (ng/ml)	
PCA									
Factor 1	T1								

Table 4 (continued)

		BMI (kg/m^2)		WC (cm)		FMI		FFMI	
		Crude	Model1	Crude	Model1	Crude	Model1	Crude	Model1*
		OR (95%CI)	OR (95%CI)	OR (95%CI)	OR (95%CI)	OR (95%CI)	OR (95%CI)	OR (95%CI)	OR (95%CI)
	T2	0.89 (0.54,1.46)	1.01 (0.57,1.81)	1.56 (0.70,3.45)	1.91 (0.78,4.65)	0.69 (0.24,2.01)	0.64 (0.20,2.07)	0.95 (0.48,1.88)	1.08 (0.51,2.30)
	T3	0.70 (0.42,1.15)	0.65 (0.37,1.14)	1.64 (0.78,3.44)	1.46 (0.65,3.24)	0.56 (0.17,1.76)	0.66 (0.19,2.31)	0.70 (0.37,1.35)	0.65 (0.32,1.29)
Factor 2	T1								
	T2	1.15 (0.69,1.91)	1.16 (0.66,2.05)	0.56 (0.26,1.22)	0.73 (0.31,1.69)	1.25 (0.43,3.61)	1.37 (0.42,4.50)	1.02 (0.52,2.01)	0.89 (0.43,1.86)
	T3	0.59 (0.36,0.98)	0.56 (0.31,1.00)	0.66 (0.31,1.39)	0.73 (0.32,1.65)	0.75 (0.24,2.34)	0.89 (0.26,3.05)	1.05 (0.55,2.00)	0.99 (0.49,2.00)
Factor 3	T1								
	T2	0.92 (0.56,1.51)	1.06 (0.59,1.88)	1.54 (0.73,3.24)	1.69 (0.71,4.01)	1.14 (0.41,3.20)	0.86 (0.27,2.69)	0.86 (0.45,1.66)	0.91 (0.43,1.90)
	T3	1.47 (0.89,2.44)	1.33 (0.75,2.36)	1.15 (0.54,2.41)	0.94 (0.40,2.19)	1.05 (0.32,3.45)	0.86 (0.22,3.26)	0.74 (0.38,1.46)	0.67 (0.32,1.40)
RRR									
Factor1	T1								
	T2	1.41 (0.85,2.34)	1.43 (0.80,2.54)	0.76 (0.35,1.67)	0.74 (0.31,1.74)	0.96 (0.31,2.97)	1.20 (0.34,4.17)	0.54 (0.27,1.08)	0.61 (0.29,1.28)
	T3	0.69 (0.42,1.13)	0.69 (0.39,1.22)	1.25 (0.61,2.55)	1.47 (0.64,3.34)	0.55 (0.18,1.61)	0.70 (0.21,2.30)	0.82 (0.43,1.57)	0.84 (0.41,1.71)
PLS									
Factor 1	T1								
	T2	1.12 (0.68, 1.86)	1.16 (0.65,2.04)	0.71 (0.32, 1.56)	0.85 (0.36,1.99)	0.67 (0.20, 2.06)	0.67 (0.19,2.31)	0.76 (0.38, 1.52)	0.89 (0.42,1.85)
	T3	0.53 (0.32,0.88)	0.46 (0.25,0.82)	1.08 (0.53, 2.22	1.27 (0.56,2.88)	0.32 (0.10,0.98)	0.38 (0.11,1.29)	0.72 (0.37,1.37)	0.68 (0.33,1.38)
Factor 2	T1								
	T2	1.01 (0.61,1.67)	0.91 (0.52,1.61)	0.91 (0.43,1.94)	0.93 (0.41,2.13)	0.86 (0.30,2.47)	1.39 (0.40,4.79)	0.54 (0.27,1.06)	1.07 (0.52,2.20)
	T3	0.78 (0.47,1.29)	0.76 (0.43,1.34)	0.79 (0.37,1.71)	0.70 (0.30,1.66)	0.92 (0.29,2.95)	0.89 (0.26,3.06)	0.99 (0.51,1.91)	0.62 (0.30,1.27)

Abbreviations: PCA: principle component analysis; RRR: reduced-rank regression; PLS: partial least-squares; BMI: Body Mass Index; WC: Waist Circumference; FFMI: Fat-Free Mass Index; FMI: Fat Mass Index; SBP: Systolic Blood Pressure; DBP: Diastolic Blood Pressure; HDL_C: High-Density Lipoprotein Cholesterol; TC: Total Cholesterol; LDL_C: Low-Density Lipoprotein Cholesterol; HOMA Index: Homeostatic Model Assessment Index; CMI: cardiometabolic index; hs CRP: High-Sensitivity C-Reactive Protein; PAI-1: Plasminogen Activator Inhibitor 1; MCP-1: monocyte chemoattractant protein; OR: odds ratio; CI: confidence interval

Binary logistic regression was used

Tertile 1 consider as a reference group

Data are presented as odds ratio (OR) and 95% CI (95% confidence interval)

Model 1: Adjusted for age, energy intake, BMI, physical activity

*BMI considered as collinear and this variable adjusted for Age, physical activity, and total energy intake

be responsible for the negative association between DBP and following plant-based dietary pattern from PLS [65]. Salty foods and fast foods (rich in sodium) intakes were higher in subjects following the plant-based diet derived from PLS. this may be the reason that why the SBP had not significantly any changes in this study [66].

Our research also revealed a link between lower FBS and the "plant-based dietary pattern" discovered by PLS. Similarly, a marginally significant inverse association was seen between a dietary pattern identified by RRR and FBS. This dietary pattern was characterized by dark green vegetables, legumes, red and orange vegetables, and fruits. In numerous studies, intake of these food groups has been linked with decreased fasting and postprandial blood glucose [67–69]. Antioxidants, fiber, polyunsaturated fatty acids, and micronutrients are abundant in plant-based diets. Intakes of dietary antioxidants might improve glucose metabolism by decreasing glucose absorption, increasing insulin secretion, and improving insulin sensitivity [70]. Dietary fiber reduces glucose absorption and has a beneficial effect on glucose metabolism [71]. Additionally, several micronutrients, including magnesium and vitamin C, also have a role in the regulation of glucose metabolism and improving insulin sensitivity [71]. However, despite the similarity in the content of the food groups, the "plant-based dietary pattern" determined by PLS and RRR, and not PCA, was inversely associated with FBS. As it mentioned in Table 2, the intake of grains, potatoes, are increasing in the plant-based dietary pattern from PCA. Previous studies emphasized on the adverse effects of refined grains intake and prevalence of type-2 diabetes [72]. On the other side, Iranian population are likely preferred to consume refined grains more than the whole grains and this justify not existing the association between FBS and plant-based dietary pattern derived from PCA [73]. In addition, consumption of egg and mayonnaise was higher in individuals following the plant-based diet from PCA. This also may justify the results [74]. So In line with this finding, an absence of an association between healthy dietary patterns derived from PCA and FBS was reported [75].

Furthermore, our findings from the PLS method indicate that a "plant-based dietary pattern" is associated with a decreased level of CRP. The literature on dietary patterns and CRP is inconclusive, with a meta-analysis suggesting the presence of an association [76], and another meta-analysis finding no such evidence [77]. Even though red meat and salty foods, green, red and orange vegetables, low fat dairy consumption is higher in plant-based dietary pattern derived from PLS but also intakes of fast foods, butter and margarines, sweetened beverages and snacks was lower in this group. In fact, it is proven that consumption of these food groups are associated with systemic inflammation and higher serum CRP [78]. There are some mechanisms describing the possible association between plant-based dietary patterns and a reduction in inflammation. The most significant explanation is that the trend toward decreased inflammation may be due to an array of nutrients and "nonnutritive" components of a vegetarian or plant-based diet [79]. Flavonoids, carotenoids, and phytochemicals, which are typically found in higher concentrations in individuals following vegetarian-based dietary patterns [80], may contribute to the observed attenuation of inflammation in vegetarian-based groups. In a study, even after adjusting for covariates such as vitamin C, vitamin E, carotenoids, and fruit and vegetable consumption, flavonoid intake was negatively correlated with blood CRP [81]. According to a hypothesis, the antioxidant properties of flavonoids can prevent LDL oxidation, which is an early inflammatory event in the development of atherosclerosis [82]. Similarly, carotenoids are potent scavengers of free radicals within the lipid bilayer and have been inversely associated with markers of inflammation [83, 84]. However, our results did not reveal any association between MCP-1 and any dietary pattern using any statistical methods.

Comparison of the PCA, RRR, and PLS

The second objective of the current study was to compare the results obtained by PCA to those of RRR and PLS for estimating diet-cardiometabolic risk factor association in overweight and obese Iranian women. Information obtained by PCA can give a clearer understanding of eating habits and dietary patterns within a specific population [85]. In this study, the patterns obtained by RRR and PLS shared some characteristics with the PCA-derived patterns that could relate to the actual food consumption in the population. For example, the first pattern of the RRR and PLS shared many food components with the PCA "plant-based dietary pattern". However, the RRR pattern did not include spices, olive oil, other vegetables, potatoes, and grains, and the first factor of PLS did not include spices and olive oil. The second factor of the PLS included many food groups similar to the "western dietary pattern" obtained by PCA, such as red meat, poultry, salty foods, sweetened beverages, fast foods, fish, and legumes. Previous studies on Iranian adults and adolescents also showed similar western and healthy dietary patterns (similar to our plant-based dietary patterns) [86, 87]. So, in line with the previous studies, our data showed that the dietary patterns derived by PCA provide a clearer understanding of dietary patterns within a specific population. This trait of the PCA can be used to formulate customized and context-sensitive nutrition interventions [8, 85, 88]. Moreover, in our study, the plant-based dietary pattern identified by RRR also tended to have an inverse association with FBS and a positive association with FFMI. Actually, our findings confirm previous evidence that PLS is more appropriate in identifying dietary patterns associated with cardiovascular diseases [89]. Another study also revealed that compared to the RRR and PCA, the western dietary pattern identified with PLS is more strongly associated with subclinical carotid atherosclerosis [6]. These findings could be explained by the fact that the patterns identified by PLS and RRR are derived from disease-associated responses while the factors obtained from PCA are more reflective of the dietary habits of a target population [90]. Indeed, in our study, the RRR-derived pattern explains a lower variation in the food group but a larger variation in the intermediate response variables. Compared to the RRR-derived, the PLS-derived patterns considerably better explain variation in food groups while explaining almost identical amounts of variation in intermediate response variables.

Although the RRR-derived pattern had a larger variation in the intermediate response variables, PLS had more association with cardiometabolic-related risk factors. First, this could be because factor loadings of vegetables and fruit in our study showed that the intake of vegetables and fruit in RRR was lower than in PLS.

Second, PLS is more efficient with smaller sample sizes and non-normally distributed data. Our results confirm that PLS suggests more flexibility than RRR in exploratory analysis [89]. Moreover, based on our finding, PLS is more efficient in using the information about intermediate variables on the pathway to disease in identifying the dietary patterns, which may lead to the detection of cardiometabolic-related dietary exposures in the overweight and obese female population. Compared to PCA and RRR, PLS has been underutilized in nutritional epidemiology studies. Future studies which aim to identify the interrelationship between dietary patterns, intermediate risk factors, and disease outcomes can use this relatively novel method.

Strengths and limitations

The strength of our study is the use of three different statistical methods to determine the dietary patterns that may be associated with cardiometabolic-related risk factors. Some limitations should also be considered. First, FFQ was used to estimate dietary intake, which is prone to recall bias and potential omission of food groups [91]. Moreover under or over-reporting of dietary intake from the FFQ is possible and may bias dietary interpretation and compromise the accuracy of the associations observed [92]. However, FFQ is a valid and widely used tool to assess overall dietary consumption via dietary pattern methods [93]. Concerning the dietary patterns analyses, limitations arose from subjectivity in selecting food groups, determining the number of principal factors, and selecting which foods have large factor loadings [13]. There is also a higher risk of overlooking 'real' correlations and sensitivity to the relative scaling of the descriptor variables when using PLS [94]. Furthermore, since the sample size was relatively small and only composed of overweight and obese Iranian women, our findings should be used with caution in other populations. Additionally, although the nutrients used as response variables (carotenoids, fiber, and folic acid) have been consistently associated with cardiometabolic risk factors [17, 18, 95], they may not be the only nutrients with important physiological effects. Finally, our study has a cross-sectional design, which will restrict claims of causality.**Conclusion**.

In conclusion, PLS was found to be more appropriate in determining dietary patterns associated with cardiometabolic-related risk factors in obese Iranian women. In our study, higher adherence to the "plant-based dietary patterns" identified by PCA, RRR, and PLS was all associated with higher FFMI. The "plant-based dietary pattern" identified by PLS is also inversely associated with FBS, DBP, and CRP. Similarly, in addition to having a positive association with FFMI, the "plant-based dietary pattern" identified by RRR tended to have an inverse association with FBS. Overall, compared to PCA and RRR, the "plant-based dietary pattern" identified by PLS is associated with more cardiometabolic-related risk factors. Nevertheless, the advantage of PLS over PCA and RRR must be confirmed in future longitudinal studies with extended follow-up in different settings, population groups, and response variables.

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Author contributions
F-GH conceived and designed the study, performed analyses, and manuscript drafting. AH, ZK and MS.Y performed analyses, data interpretation and manuscript drafting. BB, and NS, and NB wrote the main manuscript text. All authors contributed to writing, reviewing or revising the paper. SA. K and Gh.J finalized the manuscript. All authors have approved the final article should be true. KH-M is the guarantor.

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Data availability
The datasets used and/or analyzed during the current study are available from the Khadijeh Mirzaei on reasonable request.

Declarations

Ethics approval and consent to participate
The present study was carried out in accordance to the ethical standards laid down in the 1964 Declaration of Helsinki. This investigation was also approved by the Ethics Committee of Tehran University of Medical Sciences, Tehran, Iran (with ethics number: IR.TUMS.MEDICINE.REC.1400.1515). All of the study participants signed a written consent form related to this study. Each individual was informed completely regarding the study protocol and provided a written and informed consent form before taking part in the study.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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