



A Cross-Sectional Study on Dietary Patterns Derived From Principal Component Analysis and Their Association with Body Mass Index Among Extreme BMI Females in Iraq

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Abstract

The purpose of this study was to characterize dietary patterns using principle component analysis (PCA) and examine their association with extreme Body Mass Index categories and age groups among adult women. A sample of 100 females from 4 age groups, i.e., late adolescence, early reproductive age, peak reproductive age and perimenopausal age was subjected to cross-sectional design. Researchers gathered information on the sociodemographic, reproductive and health-related characteristics and food intake was assessed using a 105-item FFQ, a food-frequency questionnaire. PCA with varimax rotation was applied to obtain dietary patterns. Five dietary patterns were identified, accounting for 35.77% of variance. The dietary pattern scores were compared according to BMI and age categories by means of inferential statistics and Spearman correlation analysis. The two dietary patterns of sweet snack/sugar and western starchy/fast food were statistically significantly associated with BMI group as $p = 0.004$ for both. Nonetheless, both patterns had weak negative correlation with BMI. We didn't find any relationships between dietary patterns and age groups or BMI \times age interactions. As per the findings, dietary behaviour of this population is complex and multidimensional. It also has a weak association with BMI. It indicates chances of behavioural adaptation and under-reporting. Also, it suffers from cross-sectional limitations.

Keywords: dietary patterns, PCA, BMI, age groups, FFQ, obesity, nutritional epidemiology

Introduction

Dietary intake is widely recognized as a complex, multidimensional exposure shaped by biological, behavioral, environmental, and socioeconomic determinants. Contemporary nutritional epidemiology has increasingly shifted from single-nutrient approaches toward whole-diet approaches, as dietary patterns better reflect real-world eating behavior and cumulative metabolic exposure. Studies and dietary guidelines frameworks consistently indicate that a dietary pattern consisting of whole grains, unsaturated fats, fruits, and vegetables helps lower body mass index (BMI) and cardiometabolic risk. In contrast, a diet that is high in refined grains, added sugars, and ultra-processed foods leads to obesity (WHO, 2023).

The multivariate technique dietary pattern research often uses is Principal Component Analysis (PCA). It summarizes large food datasets that are correlated with each other into a smaller number of interpretable patterns. Recent methodological and epidemiological studies show that PCA-derived patterns, such as the "Western" and "Healthy/prudent" diets, are highly reproducible across populations, although the percentage of variance explained is usually modest due to dietary diversity. Systematic reviews indicate that PCA remains a common exploratory tool for nutritional epidemiology despite problems with subjectivity in food grouping and the use of rotation methods (Schulz et al., 2021).

The most popular anthropometric index in obesity studies remains the body mass index due to its simplicity and large-scale applicability. But in observational studies, the association between dietary patterns and BMI is inconsistent. Most evidence from large umbrella reviews and cohort studies suggests that "Western dietary patterns" are generally associated with higher BMI, while "healthy/prudent patterns" are associated with lower BMI and adiposity measures. Despite this, cross-sectional studies frequently report weak, inverse, or non-significant associations, attributable to reverse causation, behavioral change after weight gain, and under-reporting of unhealthy foods by the overweight. (Schwingshackl et al., 2021).

Age is another key factor in food habits and body make-up. Nutritional Epidemiologic literature shows that food requirements vary across life stages and depend on multiple factors, such as metabolic demand, reproductive demand, and lifestyle evolution. Women at different reproductive phases, such as adolescence, peak reproductive years, and perimenopause they witness a change in energy balance, hormonal regulation, and dietary habits. Nonetheless, there is limited evidence on how dietary patterns differ by age group and BMI category within the same population, for example, from cross-sectional designs examining interaction effects. (Schulz et al., 2021).

In addition, the international nutrition literature increasingly highlights the presence of underweight and obesity among the same populations, which is termed the “double burden of malnutrition”. This is especially characteristic of transitional populations where dietary patterns are rapidly changing. According to systematic evidence, different dietary patterns are related to both extremes of the BMI (Body Mass Index) distribution. Therefore, it is essential to focus on the extreme ends of the BMI distribution, rather than on being overweight and obesity only. Essential tools for capturing complex nutrition–health relationships in malnourished populations are dietary pattern approaches. (USDA NESR, 2020; WHO, 2023).

The present study aims to identify major dietary patterns using principal component analysis (PCA) based on 105 food items in the food-frequency questionnaire (FFQ). It will also assess the association between these major dietary patterns and extreme BMI categories and age groups in adult females. The impact of age on the association between dietary patterns and body mass index (BMI) was also examined. The study includes sociodemographic, reproductive, and health variables to contextually interpret dietary behavior among the study population.

2. Materials And Methods

2.1 Study Design

A cross-sectional analytical method was used in this research to identify dietary patterns using principal component analysis (PCA) and to assess their associations with extreme body mass index (BMI) categories and age groups among adult females. Nutritional epidemiologists favor cross-sectional designs because the same individuals are assessed simultaneously for dietary exposure and health outcomes. The STROBE Guidelines for Observation Studies were adhered to in the present study to ensure transparency and minimize personal bias.

Research that uses cross-sectional dietary designs is especially suitable for the exploratory identification of underlying dietary structures rather than for causal inference. According to contemporary epidemiological literature, PCA is helpful in capturing complex dietary behaviors, such as eating patterns, that cannot be assessed by single nutrients. Nonetheless, measures of directional exposure can be considered valid from the outset of the study. (Hu, 2002; Schulze & Martinez-Gonzalez, 2021).

2.2 Study Population and Reproductive Period Classification

A total of 100 female subjects from varied reproductive and life stages. Participants were categorized into late-adolescent, early-reproductive, mid-reproductive, and para-menopausal age groups. An analysis of women was undertaken to cover physiological and hormonal differences that may affect dietary intake and metabolic status throughout the female life course.

In nutritional epidemiology, the inclusion of females across various reproductive phases is important because hormonal variation, reproductive transitions, and aging affect energy balance, fat distribution, and dietary behavior. Recent studies indicate that food consumption patterns differ significantly across reproductive stages due to modifications in metabolic rate and hormonal regulation (Garcia et al., 2026).

2.3 Sampling Procedure and Eligibility Criteria

A non-probability sampling technique based on accessibility and volunteerism was used to recruit participants. The method is often used in exploratory nutritional studies when the goal is to identify patterns rather than infer the population. To assess the validity of the analysis, this was the inclusion criteria.

Participants with missing or incomplete food-frequency questionnaire (FFQ) responses were excluded from the analysis to reduce information bias. Although non-probability sampling limits external validity, it is widely used in PCA-based dietary pattern research because it is well-suited to exploratory factor extraction in heterogeneous populations (Newby & Tucker, 2004).

2.4 Sociodemographic, Clinical, and Reproductive Data Collection

A structured questionnaire was used to collect data. The predictors were age, marital status, educational level, and illness history. Where appropriate, clinical conditions including hypertension, hypercholesterolemia, and polycystic ovary syndrome were documented. To characterize population heterogeneity and possible confounders, these variables were added.

Reproductive characteristics were age at first procreative act, number of children, and age at last childbirth. Reproductive history can influence long-term dietary behavior, metabolic regulation, and adiposity development in women; therefore, each of these variables is important in nutritional epidemiology. (Slattery, 2010; Micha et al., 2021).

2.5 Anthropometric Measurement and BMI Classification

The body mass index (BMI) was calculated using the standard formula: weight in kilograms divided by height in meters squared. BMI is widely used in epidemiological studies as a proxy for adiposity and nutritional status, which is why it is chosen as the primary anthropometric indicator.

The participants were categorized into extreme BMI groups, namely underweight and obese categories, to enable a comparison of dietary patterns at nutritional extremes. Even though BMI does not distinguish fat mass from lean mass,

it is still a widely accepted nutritional indicator for populations in epidemiological studies. (WHO, 2023; Emdin et al., 2020).

2.6 Dietary Assessment Using FFQ

The dietary intake was measured using a semiquantitative FFQ of 105 food items. The FFQ comprises the major food groups, including fruits, vegetables, cereals, milk products, meat, and processed foods, such as snacks and drinks. Participants report on the frequency with which they consume the product during a reference period. The FFQ instrument is popular in nutritional epidemiology due to its ability to capture long-term rather than short-term dietary patterns. It is generally regarded as appropriate for dietary pattern analysis when used in conjunction with multivariate statistical methods such as principal component analysis. (Saravia, L., et al. 2021).

2.7 Data Processing and Standardization

All dietary data values were coded and standardized before analyzing using z-scores. To maintain comparability between food groups measured on different scales, standardization was performed. It prevents variables with high variance from exerting a very high weight on the PCA results. The data was checked for thoroughness and checked for accuracy.

To ensure each food group contributes equally to the extraction of underlying dietary structures, standardization is an important step in PCA-based dietary studies. This process improves the stability and interpretability of derived dietary patterns. (Slattery, 2010; Hu et al., 2022).

2.8 Principal Component Analysis (PCA)

To enhance interpretability and minimize correlation among extracted components, we derived dietary patterns using principal component analysis (PCA). The Kaiser–Meyer–Olkin measure and Bartlett’s test of sphericity were used to evaluate whether the dataset was sufficient for PCA.

Five components were retained based on eigenvalues greater than 1, inspection of the scree plot, and interpretability criteria. Dish products with factor loadings of at least $|0.30|$ were considered meaningful contributors. In nutritional epidemiology, PCA is one of the most exploited exploratory methods, which can detect latent dietary structures in complex food data. (Schulze & Martinez-Gonzalez, 2021; Newby & Tucker, 2004).

2.9 Dietary Pattern Scoring

Food intake variables and their corresponding factor loadings were used to calculate individual dietary pattern scores for participants via a weighted linear combination. In statistical analyses, scores indicating how much subjects adhered to each dietary pattern were treated as continuous variables.

Using dietary pattern scoring allows quantification of an individual’s adherence to each defined pattern. It can also allow comparisons across demographic and anthropometric groups. Statistical programs to translate the factor structure into usable exposure variables are widely used in PCA-based nutritional epidemiology. (Hu, 2002).

2.10 Statistical Analysis

SPSS Software was used to perform statistical analyses. Summary statistics were used to summarize the sociodemographic and clinical characteristics. The differences in dietary pattern scores across various BMI and age groups were tested using an appropriate parametric/non-parametric test, based on data distribution.

To assess correlations between BMI and dietary pattern scores, Spearman’s rank correlation was used. Moreover, we performed a two-way analysis to assess the interaction of BMI category and age group. Statistical significance was considered to be $p < 0.05$.

According to the latest methodological literature, it is advisable to use a combination of group comparison and correlation-based methods in dietary pattern analysis. (Micha et al., 2021).

3. Results And Discussion

3.1 Sociodemographic and Health Characteristics

There was a total of 100 females in the study, further segregated into four reproductive age groups. 20% were late adolescents, 30% were in early reproductive age, 30% were in peak reproductive age, and 20% were perimenopausal. This balanced distribution will help assess dietary behavior across different reproductive life stages, which are significant in nutritional epidemiology for the physiological and hormonal variations that affect energy intake and body composition.

The body mass index (BMI) variable had a polarized distribution, with an interquartile range, indicating that 50 percent of participants were underweight and 50 percent were obese, indicating a clear dual burden of malnutrition. The trend points to a process of nutritional change which is marked by the coexistence of calorie deficiency and obesity since the shift to a processed diet. (GBD 2020; WHO, 2023).

Most respondents (78%) were university graduates or higher. People with higher levels of education may be more knowledgeable about diet than those with lower levels of education. Nonetheless, it has been suggested that education

alone may not guarantee more healthy dietary behavior. This is due to the impact of environmental determinants and behavior determinants on food choice.(Micha et al., 2021).

Table 1. Sociodemographic and clinical characteristics (n = 100)

Variable	Category	n	%
Age group	Late adolescents	20	20
	Early reproductive age	30	30
	Peak reproductive age	30	30
	Perimenopausal age	20	20
BMI group	Underweight	50	50
	Obese	50	50
Marital status	Single	61	61
	Married	38	38
	Divorced	1	1
Education	University/institute	55	55
	Higher education	23	23
Medical condition	None	75	75
	Present	25	25
Menarche age	12–14 years	87	87
	Others	13	13
Children	No children	66	66
	Has children	34	34

The dual burden of malnutrition we see now is in line with global nutrition transition trends, where both underweight and obesity co-exist within the same population. The latest Global Burden of Disease Study (GBD 2020) indicates that the impact of dietary risks on BMI-related outcomes has now reached an astounding first magnitude worldwide. WHO reports have similarly confirmed that obesity and undernutrition increasingly overlap in transitional societies, thanks to the rapid westernization of diets and economic direction (WHO, 2023).

The population exhibits a dual burden of malnutrition, with an equal percentage of underweight and obese individuals. According to the patterns highlighted above, there is a global nutritional transition toward more energy-dense foods. There is overall demand for more energy-dense foods. However, undernutrition persists in the subpopulation.

Higher educational attainment may lead to greater awareness and dietary reporting behavior, thereby impacting self-reported intake in FFQ-based analyses. Studies have demonstrated that dietary quality generally improves with education. In epidemiological studies, education displays a strong inverse relationship with ‘bad’ dietary choices.

Table 2. Key population health indicators

Indicator	Category	n	%
BMI distribution	Underweight	50	50
	Obese	50	50
Medical status	No disease	75	75
	Any disease	25	25
Reproductive status	No children / N/A	66	66
	With children	34	34

3.2. Principal Component Analysis (PCA) and Variance Explained

The study utilized PCA to determine dietary patterns in the population. According to eigenvalues and interpretability standards, five components were extracted. The five retained components accounted for 35.77% of the variance, reflecting a moderate dimensionality reduction characteristic of FFQ-based dietary studies.

The first component had a variance of 8.28%, followed by 8.77% for the second, 7.25% for the third, 5.90% for the fourth, and 5.57% for the fifth. The cumulative variance increased to 35.77%, thereby confirming that the dietary behavior of the studied population is distributed across multiple dietary patterns of moderate strength and not dominated by any single pattern.

Table 1. Total variance explained by PCA

Pattern	Variance (%)	Cumulative (%)
P1	8.28	8.28
P2	8.77	17.05
P3	7.25	24.31
P4	5.90	30.20
P5	5.57	35.77

3.3. Dietary Patterns Identified

According to dietary patterns identified by principal component analysis (PCA) of the 105-item food frequency questionnaire (FFQ). The extracted patterns revealed very heterogeneous dietary behaviors in the study subjects. It consisted of healthy, mixed, processed, and traditional dietary patterns.

The first pattern was characterized by the presence of mushrooms, fruit (tinned, dried and fresh), avocado, legumes (baked beans), corn, berries, broccoli and fish. The second pattern refers to a dietary pattern of sweet snacks/sugary dominated by chocolate products, biscuits, toffees, sugar added to tea, crisps, ice cream, and hot chocolate. The third pattern consisted of a Western starchy/fast-food dietary structure comprised of foods like pizza, burgers, chips, lasagne, sponge cake, fruit juice and potato-based foods. The fourth pattern involved fruits, eggs, yogurt, cottage cheese, dairy desserts, tahini and brown bread (fruit-dairy/egg pattern). The fifth pattern was the most traditional mixed cooked-food pattern, incorporating rice, pasta, noodles, chicken, vegetables, cheese & garlic, etc.

The five patterns show that the population's dietary intake is multidimensional and reflects both health-promoting and energy-dense dietary behaviors.

Table 2. Identified dietary patterns

Pattern	Suggested name	Main high-loading foods
Pattern 1	Mixed fruit–vegetable / varied pattern	Mushrooms, tinned fruits, dried fruits, avocado, baked beans, corn, strawberries, peaches, grapes, broccoli, fish
Pattern 2	Sweet snacks / sugary pattern	Chocolate bars, sweet biscuits, toffees, sugar added to tea, nuts, chocolate squares, ketchup, crisps, hot chocolate, ice cream
Pattern 3	Western starchy / fast-food pattern	Roasted potato, buns, ready sponge cake, boiled/mashed potato, lasagne, hot chocolate, chips, pizza, fruit juice, beefburger
Pattern 4	Fruit–dairy / egg pattern	Apple, cottage cheese, orange, eggs, melon, banana, dairy desserts, tahini, brown bread, low-fat yogurt
Pattern 5	Traditional mixed cooked-food pattern	Carrot, pasta, macaroni/noodles, cheese, garlic, butter, tomatoes, onions, white rice, sweet peppers, chicken

3.4 Association Between Dietary Patterns, BMI, and Age

Analysis of the data showed that two dietary patterns were significantly associated with BMI category: sweet snacks/sugary pattern (code P2) and western fast-food pattern (code P3); $p = 0.004$. However, the association was negative, indicating that higher BMI was associated with lower reported intake of these patterns.

There were no significant associations found between dietary patterns and ages. There were no significant interaction effects of BMI and age either. Spearman correlation analysis showed that BMI is weakly inversely related to P2 ($\rho = -0.198$) and P3 ($\rho = -0.237$), whereas the remaining patterns are not correlated.

Table 3. Association between dietary patterns, BMI, and age

Pattern	BMI group p	Age p	BMI×Age p	Spearman ρ
P1	0.578	0.441	0.279	-0.083
P2	0.004	0.837	0.334	-0.198*
P3	0.004	0.500	0.069	-0.237*
P4	0.452	0.222	0.292	-0.088
P5	0.338	0.383	0.933	-0.003

*Significant at $p < 0.05$

The identification of five dietary patterns in this study indicates that the population's dietary structure is highly heterogeneous. The patterns extracted consisted of healthy (fruit-vegetable, fruit-dairy), traditional (cooked-food), and energy-dense (sweet snacks, western fast-food) dietary structures. The moderate variance explained (35.77%) is consistent with findings from FFQ-based PCA studies, which typically range from 25% to 40% due to the complexity of human food intake.

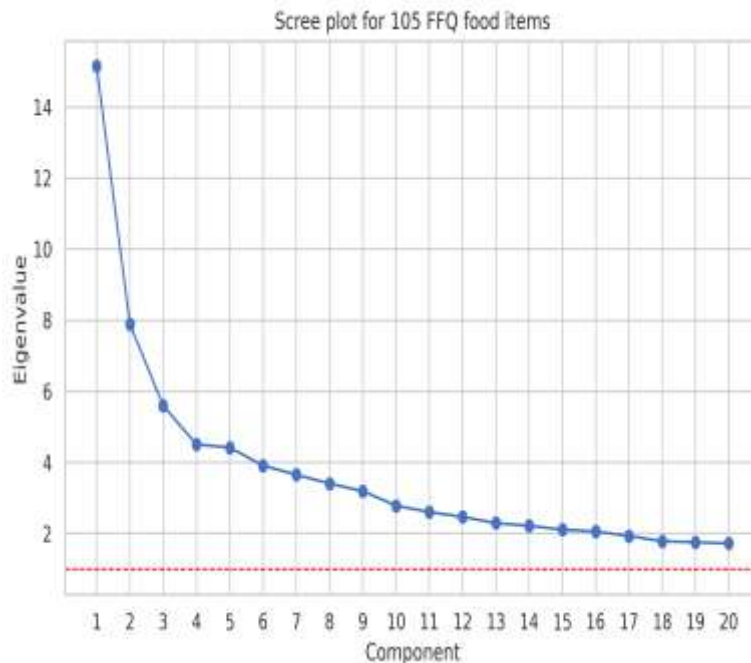
Recent dietary epidemiology literature confirms that diet does not often cluster into a dominant pattern; instead, it reflects overlapping behavioral structures. Still, the PCA analyses consistently demonstrate the “Western” and “healthy/prudent” dietary patterns across large populations, including North Americans/or Western Europeans, as well as Japanese. It must be noted that the composition of these patterns varies across contexts and cultures. This finding lends support to the present study and verifies that the patterns identified reflect genuine dieting behavior, rather than an artifact of statistical testing. (Schulze & Martinez-Gonzalez, 2021).

The study discovered that two dietary patterns, which are sweet snacks/sugary and western fast-food, were significantly associated with BMI ($p = 0.004$). Nevertheless, both exhibit weak inverse correlations with BMI (P2 : $\rho = -0.198$; P3 : $\rho = -0.237$), suggesting that those with higher BMIs report lower intakes of these energy-dense dietary patterns.

According to classical nutritional epidemiology, it was always believed that a high intake of sugar and ultra-processed foods raises the risk of obesity. But more recent literature strongly makes the point that the inverse or weak association is common in diet. A large explanatory factor is reverse causation, that is, individuals with higher BMIs change their dietary intakes in response to having gained weight or being diagnosed with an obesity-related illness.

In addition, underreporting bias afflicts FFQ-based dietary assessment. People who are obese and overweight tend to under-report their consumption of socially undesirable foods such as sweets, fast food, and cola drinks. The correlations between our intake and our body size and weight that we expect are diminished and sometimes reversed. Recent studies show that people with higher BMI are more likely to misreport their diet, and this distorts the diet-disease relationship. (Micha et al., 2021; Schwingshackl et al., 2021).

Moreover, regulation of energy balance is dynamic, so cross-sectional snapshots of diet may not adequately capture the long-term dietary exposure that underlies the development of BMI. The known limitations of the disciplines of dietary epidemiology are the time discrepancy of the exposure and outcome.



The scree plot shows the eigenvalues corresponding to the extracted components resulting from a principal component analysis of 105 FFQ items. The component number is on the x-axis, and the eigenvalues, which are the measure of variance each component has, are on the y-axis.

A significant drop from Component 1 to Component 4 suggests that a small number of components explain a fairly large percentage of dietary variance. In particular, Component 1 has the highest eigenvalue (around 15), with a sharp drop in Components 2 and 3. After Component 5, the curve starts flattening; that is, the additional components have less explanatory power.

Referring to the dotted horizontal line representing the Kaiser criterion (eigenvalue = 1), components above this line are expected to be meaningful. Anything above this threshold will be considered useful in explaining variance.

The scree plot's elbow point and the Kaiser criterion indicated a solution retaining five components, representing the optimal number of dietary patterns. After the fifth component, the eigenvalues hover near or drop below the threshold. This indicates that additional components contribute very little meaningful variance, likely noise rather than interpretable dietary structures.

Conclusion

This study aimed to determine dietary pattern using a principal component analysis of food-frequency questionnaire (FFQ) items in adults. The FFQ was developed with 105 items, and 5 distinct FFQ patterns were identified for adult females using PCA. The identified groups were a mixed fruit-vegetable group, sweet snacks/sugary group, western starchy/fast-food group, fruit-dairy/egg group, and traditional cooked-food group, accounting together for 35.77% of the total dietary variation. The examined population's dietary behavior is heterogeneous, as evidenced by the moderate level of explained variance. These findings are in line with the global nutritional epidemiology studies.

The relationship between BMI and two energy-dense dietary patterns was significant but weak and inverse, meaning that higher-BMI individuals reported lower intake of sweet and fast-food items. The inconsistency with classical nutrition models is probably due to behavioral adjustment, changing your diet after your weight increase, and under-reporting bias in cross-sectional dietary studies. No association was found between dietary patterns and age groups.

Similarly, no interaction effect was observed between BMI and age. This suggests that dietary behavior in this population remains stable across reproductive life stages.

The findings suggest that dietary intake does not merely represent a risk factor. Dietary intake perhaps contains an important behavior that socio-psychologically determines a cultural concept. The relationship between dietary patterns and BMI was weak and inconsistent. This highlights the limitations of cross-sectional designs, which will capture long-term dietary exposure and its relationship with adiposity. These findings highlight the need for longitudinal cohort studies using objective dietary assessment methods to further elucidate the role of dietary patterns in body weight regulation.

In conclusion, PCA may have successfully identified relevant dietary structure. However, it only had a modest relationship with BMI. This modest relationship is likely due to behavioral reporting bias rather than dietary effects.

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