Research Square

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Seven-year trends in dietary patterns and their association with hyperglycemia risk in a Chinese city: a comparative analysis of two cross- sectional surveys (2014–2021)

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Abstract

Background

Rapid nutritional transitions in low- and middle-income countries have raised concerns about deteriorating glycemic health. However, evidence linking temporal changes in dietary patterns to hyperglycemia risk remains limited.

Methods

Two cross-sectional surveys were conducted in Jiangyin, China, in 2014 (n = 639) and 2021 (n = 577). Dietary patterns were identified using principal component analysis. Logistic regression was used to examine associations between dietary pattern scores and hyperglycemia, adjusting for sex, age, income, and education.

Results

Three dietary patterns were extracted. Pattern 1 (traditional cereal-vegetable-meat) and Pattern 2 (plant protein-fruit-vegetable) scores decreased from 2014 to 2021, while Pattern 3 (fast food-pastry) scores increased (all $P < 0.001$). Hyperglycemia risk was 65% higher in 2021 versus 2014 (adjusted OR = 1.65, 95% CI: 1.15–2.38, $P = 0.007$). Pattern 1 was protective against hyperglycemia (adjusted OR = 0.62, 95% CI: 0.50–0.76, $P < 0.001$), while Pattern 3 was a risk factor (adjusted OR = 1.90, 95% CI: 1.61–2.27, $P < 0.001$). Pattern 2 showed no significant association.

Conclusions

Over seven years, dietary structure in this Chinese city shifted toward Westernization, coinciding with increased hyperglycemia risk. These findings highlight the need for public health policies to counteract unfavorable dietary transitions in rapidly developing regions.

Introduction

Within the landscape of global public health governance, many low- and middle-income countries, including China, are undergoing a rapid nutritional transition. This shift is typically characterized by a move away from traditional cereal- and vegetable-based diets towards Westernized or highly processed dietary patterns high in fat, refined sugars, and animal products [1–3]. Concurrently, the prevalence of metabolic diseases, particularly hyperglycemia and type 2 diabetes, has risen steadily, posing a major threat to socioeconomic development [4]. Elevated blood glucose is not only a core feature of metabolic syndrome but also a key driver of cardiovascular disease, renal failure, and neurological disorders [5]. Despite notable advances in glucose-lowering drug development, biomedical interventions alone have

been unable to curb the population-wide rise in disease burden [6]. Hence, identifying protective and risk factors related to diet, a fundamental source of glycemic variability, has become a priority in preventive medicine [7].

In nutritional epidemiology, traditional analytical approaches have often focused on single nutrients or isolated food groups, such as red meat intake, dietary fiber, or sugar-sweetened beverages. While such studies offer clear biological mechanistic insights, they do not readily capture the synergistic or antagonistic effects of combined foods consumed in real-life settings [8]. Recognizing this limitation, dietary pattern analysis as a holistic approach has gained increasing attention [9]. To overcome the constraints of single-nutrient studies, statistical techniques such as principal component analysis (PCA) have been widely adopted to derive dietary patterns, which are now internationally accepted for evaluating overall dietary preferences and intake structures [10]. This dimension reduction approach based on food frequency data not only provides more realistic estimates of individual dietary exposure but also yields more robust evidence for examining non-linear relationships between complex dietary habits and chronic disease risk [11].

Despite extensive cross-sectional evidence linking dietary patterns to glucose metabolism, showing that “vegetable-fruit-legume” patterns are protective while “processed meat-sweets” patterns increase risk [12–14], several critical gaps remain. First, most studies rely on single-point dietary assessments, overlooking the dynamic shifts in eating habits over time. In reality, economic development, rising incomes, globalized food markets, and urbanization substantially alter population-level food preferences and availability [15, 16], yet evidence on how such changes affect long-term glycemic status is insufficient. Second, existing literature rarely integrates dietary pattern identification, temporal trend analysis, and association testing with health outcomes in a coherent framework; the logical links among these three elements are often broken [17]. Third, the structure and direction of dietary transitions may vary markedly across regions and stages of economic development, necessitating context-specific analyses based on local data [18].

Using two cross-sectional surveys conducted in 2014 and 2021 within the same community-based population, the present study systematically addressed the following three objectives. First, we identified major dietary patterns through PCA and tested the suitability of factor analysis. Second, we compared changes in dietary pattern scores over the seven-year period to quantify temporal shifts in dietary structure. Third, we used multivariable logistic regression models to assess associations between dietary patterns and hyperglycemia risk, presenting results both unadjusted and adjusted for demographic and socioeconomic variables.

Through these analyses, we aim to elucidate the potential impact of dietary pattern transitions on glucose metabolism. The findings may not only help clarify the mechanisms linking broad dietary structure to glycemic outcomes but also inform targeted nutritional intervention strategies and public health guidelines for populations experiencing rapid socioeconomic transitions.

Methods

Study design and population

This study was conducted in Jiangyin City, Jiangsu Province, based on two cross-sectional surveys carried out in 2014 and 2021. A multistage stratified cluster random sampling method was used. Specifically, three townships or subdistricts were randomly selected from Jiangyin City. From each selected township or subdistrict, two villages or neighborhood committees were randomly chosen. Finally, 75 households were randomly selected from each village or neighborhood committee, and all permanent residents who had lived locally for six months or longer were included.

Inclusion criteria were: (1) having lived in the local area for at least six months at the time of the survey; (2) age 18 years or older; and (3) availability of complete data from the food frequency questionnaire, demographic information, physical measurements, and blood glucose tests. Exclusion criteria included abnormal daily energy intake (< 500 kcal or > 4000 kcal), as well as pregnant or lactating women. A total of 1,216 participants were included in the final analysis, with 639 from the 2014 survey and 577 from the 2021 survey, allowing for an assessment of changes in the relationship between dietary patterns and blood glucose levels over time.

Data collection and laboratory measurements

A standardized questionnaire was administered through face-to-face interviews by trained and certified interviewers. Information collected included age, sex, occupation, education level, annual household income, and smoking status. Dietary intake over the past year was assessed using a validated food frequency questionnaire covering more than 100 food items [19, 20]. Food models were used to help participants recall and estimate the average frequency and portion size of each food consumed. Raw food items were aggregated according to the food coding and classification rules specified in the study manual.

Fasting venous blood (10 mL) was collected from all participants in the morning on the survey day. Blood samples were centrifuged at 4℃ within two hours of collection to separate serum, which was then sent to the laboratory for uniform testing. Fasting plasma glucose (FPG) was measured using the hexokinase method and used as the outcome variable. According to the 2020 guidelines for the prevention and treatment of type 2 diabetes in China, glycemic status was defined as follows: normal glucose, FPG < 6.1 mmol/L; impaired fasting glucose (prediabetes), 6.1 mmol/L ≤ FPG < 7.0 mmol/L; newly diagnosed diabetes, FPG ≥ 7.0 mmol/L. In this study, impaired fasting glucose and newly diagnosed diabetes were collectively defined as "hyperglycemia."

Dietary pattern identification

Dietary patterns were identified via PCA based on food frequency data. First, the dietary data for all food groups were standardized, followed by the Kaiser-Meier-Olkin (KMO) test and Bartlett's test of sphericity. If the results met the criteria of KMO > 0.5 and Bartlett's test $P < 0.05$, factor analysis could be performed. Then, based on eigenvalues > 1, combined with the inflection point of the scree plot using the elbow method, and considering both the cumulative contribution rate and the interpretability of the factors, the number of retained factors (dietary patterns) was determined. After varimax orthogonal rotation, foods with an absolute factor loading > 0.4 were retained in the respective dietary pattern. Finally, the factor score for each individual in each dietary pattern was calculated.

Statistical analysis

A database was established using Microsoft Excel 2024. Statistical analyses were performed to evaluate temporal trends and the association between dietary habits and health outcomes. Baseline characteristics between the 2014 and 2021 cohorts were compared using Chi-square tests for categorical variables, presented as n (%), and non-parametric tests for continuous variables, presented as median with interquartile range (IQR). Temporal shifts in dietary pattern scores over the seven-year period were analyzed to identify significant evolution in population habits. Logistic regression models were employed to calculate odds ratios (ORs) and 95% confidence intervals (CIs) to evaluate the risk of elevated blood glucose. Model 1 represented the unadjusted crude association, while Model 2 was adjusted for potential confounders including sex, age, income, and education level. All statistical tests were two-sided, and a p-value < 0.05 was considered to indicate statistical significance. All statistical analyses were performed using R software (version 4.5.2).

Ethical Approval

The data used in this study were derived from the Jiangsu Provincial Nutrition and Health Surveillance and Monitoring Project. All procedures followed the ethical guidelines of the Declaration of Helsinki. The study protocol was approved by the Medical Ethics Committee of the Jiangsu Provincial Center for Disease Control and Prevention (Approval No. JSCDC2014236; JSJK2024-B036-01). Written informed consent was obtained from all participants prior to enrollment, and they were informed of their right to withdraw from the survey at any stage without providing a reason.

Results

Comparison of baseline characteristics between 2014 and 2021

The baseline characteristics of the study population in 2014 (N = 639) and 2021 (N = 577) are compared in Table 1. Significant temporal differences were observed in several demographic and socioeconomic indicators, most notably a significant increase in the proportion of male participants from 48.5% to 56.2% ($P = 0.008$) and a slight but statistically significant rise in median age from 55 [39, 65] to 56 [44, 68] years ($P < 0.001$). Economic status shifted profoundly ($P < 0.001$), characterized by a sharp increase in the high-income group from 31.3% in 2014 to 80.9% in 2021, while the low-income proportion fell from

20.0% to 4.7%. Educational attainment also improved significantly (P = 0.002), with the percentage of participants holding a junior college degree or higher rising from 6.9% to 12.8%. In contrast, no significant differences were detected between the two periods regarding ethnicity (P = 0.183), occupational distribution (P = 0.057), marital status (P = 0.118), or smoking prevalence (P = 0.109).

Association between survey year and risk of elevated blood glucose

Furthermore, logistic regression analysis was conducted to evaluate the association between the survey year and the risk of elevated blood glucose (Table 2). In the unadjusted model (Model 1), the year 2021 was associated with a significantly higher risk of blood glucose compared to 2014 (OR = 1.67, 95% CI: 1.24–2.24, P < 0.001). This association remained statistically significant in Model 2 after adjusting for sex, age, income, and education level, with an adjusted OR of 1.65 (95% CI: 1.15–2.38, P = 0.007).

Identification and characterization of major dietary patterns via principal component analysis

The suitability of the data for factor analysis was confirmed by a KMO index of 0.783 and a Bartlett's test of sphericity (P < 0.001), both indicating that the dataset was appropriate for PCA. Based on the criterion of eigenvalues > 1 and the elbow method principle (Figure 1), three major dietary patterns were extracted, which collectively accounted for a substantial proportion of the total variance (43.3%). Food groups with absolute factor loadings > 0.400 were used to characterize and name each pattern. Pattern 1, characterized by high loadings for red meat (0.840), vegetables (0.780), cereals (0.666), fish and seafood (0.568), and eggs and egg products (0.566), was identified as traditional cereal-vegetable-meat pattern. Pattern 2, defined by strong loadings for legumes and soy products (0.678), fruits (0.600), nuts (0.579), and milk and dairy products (0.426), was labeled as the plant protein-fruit-vegetable pattern. Pattern 3, which showed prominent loadings for instant/fast foods (0.729) and pastries and snacks (0.591), was designated as the convenient fast food-pastry pattern (Table3)

Temporal trends and significant shifts in dietary pattern scores (2014–2021)

The temporal changes in dietary pattern scores between 2014 and 2021 are illustrated in Figure 2. Significant shifts were observed across all identified patterns over the seven-year period (all P < 0.001). Specifically, the scores for pattern 1 and pattern 2 exhibited a marked decline from 2014 to 2021. Conversely, the scores for pattern 3 showed a significant upward trend during the same period, reflecting a substantial evolution in the dietary habits of the study population.

Association between dietary patterns and the risk of elevated blood glucose

The association between the identified dietary patterns and the risk of elevated blood glucose was evaluated using logistic regression models. As illustrated in the forest plot (Figure 3), pattern 1 served as a significant protective factor, with both crude (OR = 0.60, 95% CI: 0.49–0.73, P < 0.001) and adjusted odds ratios (OR = 0.62, 95% CI: 0.50–0.76, P < 0.001) remaining below 1.0, suggesting that higher adherence to this pattern is linked to a reduced risk of glucose abnormalities. In contrast, pattern 2 showed no statistically significant correlation with blood glucose levels. Conversely, pattern 3 was

identified as a strong risk factor. Participants with higher scores in this pattern exhibited a substantially increased likelihood of elevated blood glucose, with an adjusted odds ratio of approximately 1.90 (95% CI: 1.61–2.27, $P < 0.001$).

Discussion

Based on two cross-sectional surveys conducted in 2014 and 2021, this study systematically delineates the seven-year evolution of dietary patterns among community residents in Jiangyin and their subsequent impact on glycemic health. Our findings reveal a striking trend: despite significant gains in household income and educational attainment, scores for the “traditional cereal-vegetable-meat pattern” declined, while the “fast food-pastry pattern” saw a substantial rise. During the same period, the risk of hyperglycemia increased by 65%. This observation aligns closely with the macro-trends of Chinese nutritional transition; the prevalence of diabetes in China has surged from 7.53% in 2005 to 13.7% in 2023 [21], a trajectory that parallels the rapid penetration of Westernized diets [22].

Pattern 1 (traditional cereal-vegetable-meat pattern) demonstrated a significant inverse correlation with glycemic risk (OR = 0.62). Although red meat exhibited a high factor loading (0.840) within this pattern, its essence lies in the balanced integration of diverse food groups, with high loadings maintained for vegetables (0.780) and cereals (0.666). This reflects the traditional Chinese nutritional philosophy of “balance between grains, vegetables, and livestock” [23]. Such a balanced structure confers protection through multiple pathways: vegetable fibers delay carbohydrate absorption, resistant starch from grains enhances insulin sensitivity, and moderate animal protein increases satiety [24]. Notably, the score for this pattern dropped significantly between 2014 and 2021, even as the high-income population segment grew from 31.3% to 80.9%. This highlights a “transition paradox”, wherein economic prosperity, rather than naturally leading to healthier eating habits, may paradoxically accelerate the erosion of traditional balanced diets [25]. Countering this trend therefore calls for systemic policy interventions beyond what economic growth or individual health education alone can achieve.

Interestingly, Pattern 2 (comprising soy products, fruits, nuts, and dairy) showed no significant association with glycemic risk. This contradicts much of the existing literature, which typically suggests that plant-based and dairy-rich diets reduce diabetes risk by approximately 25% [26]. Three factors may explain this discrepancy. First, a threshold effect may exist; as consumption levels for Pattern 2 declined in this study, intake may have fallen below the minimum protective threshold [27]. Second, internal heterogeneity within food groups may introduce confounding, as the glycemic impact of different fruits and nuts varies significantly [28]. Third, the high prevalence of lactose intolerance among Chinese adults may result in effective dairy intake being much lower than reported, while the added sugars in commercially available flavored dairy products could negate any inherent benefits [29].

Pattern 3 (fast food and pastries) was robustly associated with an increased risk of hyperglycemia, a finding consistent with global evidence. A dose-response relationship exists between high consumption of ultra-processed foods and diabetes risk [30]. The underlying mechanisms involve high-fructose corn

syrup and refined carbohydrates triggering glucose fluctuations, trans-fats inducing lip toxicity, and a lack of dietary fiber exacerbating chronic inflammation [31]. The synchronized rise in Pattern 3 scores and hyperglycemia risk over the seven-year period suggests a potential causal link. When coupled with the evidence that increasing energy intake during dinner correlates with a 44% higher risk of hyperglycemia [32], it becomes clear that the Westernization of dietary structures is a primary driver of deteriorating glycemic health [33].

Despite these insights, several limitations must be acknowledged. Dietary data were derived from food frequency questionnaires, which are susceptible to recall bias [34]. While two cross-sectional snapshots reveal trends, they cannot establish temporal causality. Furthermore, the dietary patterns extracted via PCA are sample-specific, requiring caution when generalizing the results [35]. Vital confounders such as physical activity, sleep, and psychological stress were also not included. Future research should utilize continuous glucose monitoring to assess individual glycemic responses more precisely and integrate gut microbiota analysis to explore how dietary patterns influence metabolism through the microbiome. Additionally, regional studies based on the diverse “eight great traditions” of Chinese cuisine would provide a more localized basis for nutritional interventions.

Conclusion

This study underscores a marked Westernization of dietary structures in Jiangyin and its detrimental impact on glycemic health. The protective influence of traditional balanced diets is being undermined by the proliferation of fast food and pastries, proving that economic development does not automatically translate into improved health outcomes. In rapidly developing middle-income regions, nutritional interventions must move beyond individual education to reshape the broader food environment. This includes tax regulations on ultra-processed foods, subsidies for healthy options, and the cultural revitalization of traditional healthy eating. Transforming the goal from “eating enough” to “eating well” is essential to curbing the escalating diabetes epidemic.

Abbreviations

PCA
Principal component analysis
FPG
Fasting plasma glucose
KMO
Kaiser-Meier-Olkin
OR
Odds ratios
CI
Confidence intervals

Declarations

Ethics approval and consent to participate

The study protocol was approved by the Medical Ethics Committee of the Jiangsu Provincial Center for Disease Control and Prevention (Approval No. JSCDC2014236; JSJK2024-B036-01). Written informed consent was obtained from all participants prior to enrollment, and they were informed of their right to withdraw from the survey at any stage without providing a reason.

Consent for publication

Not applicable.

Availability of data and materials

All data analyzed during this study are included in this article.

Competing interests

The authors declare that they have no competing interests.

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Authors' Contributions

MG, PL and YM conceived and designed the study. YM, PL and JC conducted the data gathering. YM performed data analysis. YM and MG wrote the manuscript. All authors read and approved the final manuscript.

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Not applicable.

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Tables

Table 1
Comparison of baseline characteristics of the study population between 2014 and 2021

Demographic Characteristics	2014	2021	p-value
Sex			0.008
Male	310 (48.5)	324 (56.2)	
Female	329 (51.5)	253 (43.8)	
Age	55 [39, 65]	56 [44, 68]	< 0.001
Income			< 0.001
Low	128 (20.0)	27 (4.7)	
Middle	254 (39.7)	83 (14.4)	
High	200 (31.3)	467 (80.9)	
Unknown	57 (8.9)	0 (0.0)	
Ethnicity			0.183
Han	632 (98.9)	575 (99.7)	
Other	7 (1.1)	2 (0.3)	
Education Level			0.002
Junior high school or below	495 (77.5)	425 (73.7)	
Senior high/Vocational school	100 (15.6)	78 (13.5)	
Junior college/Vocational college	21 (3.3)	45 (7.8)	
Bachelor's degree or above	23 (3.6)	29 (5.0)	
Occupation			0.057
Manual labor	198 (31.0)	143 (24.8)	
Office-based/Mental labor	117 (18.3)	102 (17.7)	
Unemployed/Retired	278 (43.5)	292 (50.6)	
Other	46 (7.2)	40 (6.9)	
Marital Status			0.118
Married	610 (95.5)	539 (93.4)	
Notes: Data are presented as n (%) or median [IQR]			

Demographic Characteristics	2014	2021	p-value
Unmarried	29 (4.5)	38 (6.6)	
Smoking Status			0.109
Non-smoker	492 (77.0)	466 (80.8)	
Smoker	147 (23.0)	111 (19.2)	
Notes: Data are presented as n (%) or median [IQR]			

Table 2
Logistic regression analysis of the association between survey year and the risk of blood glucose

Analysis Model	OR (95% CI)	p-value
Model 1 (Unadjusted)	1.67 (1.24–2.24)	< 0.001
Model 2 (Adjusted for sex, age, income, and education level)	1.65 (1.15–2.38)	0.007

Table 3
Factor loading matrix of major dietary patterns identified by principal component analysis

Food Groups	Pattern 1	Pattern 2	Pattern 3
Red meat	0.840		
Vegetables	0.780		
Cereals	0.666		
Eggs and egg products	0.566		
Fish and seafood	0.568		
Legumes and soy products		0.678	
Fruits		0.600	
Nuts		0.579	
Milk and dairy products		0.426	
Instant/Fast foods			0.729
Pastries and snacks			0.591
Tubers			
Poultry			

Figures

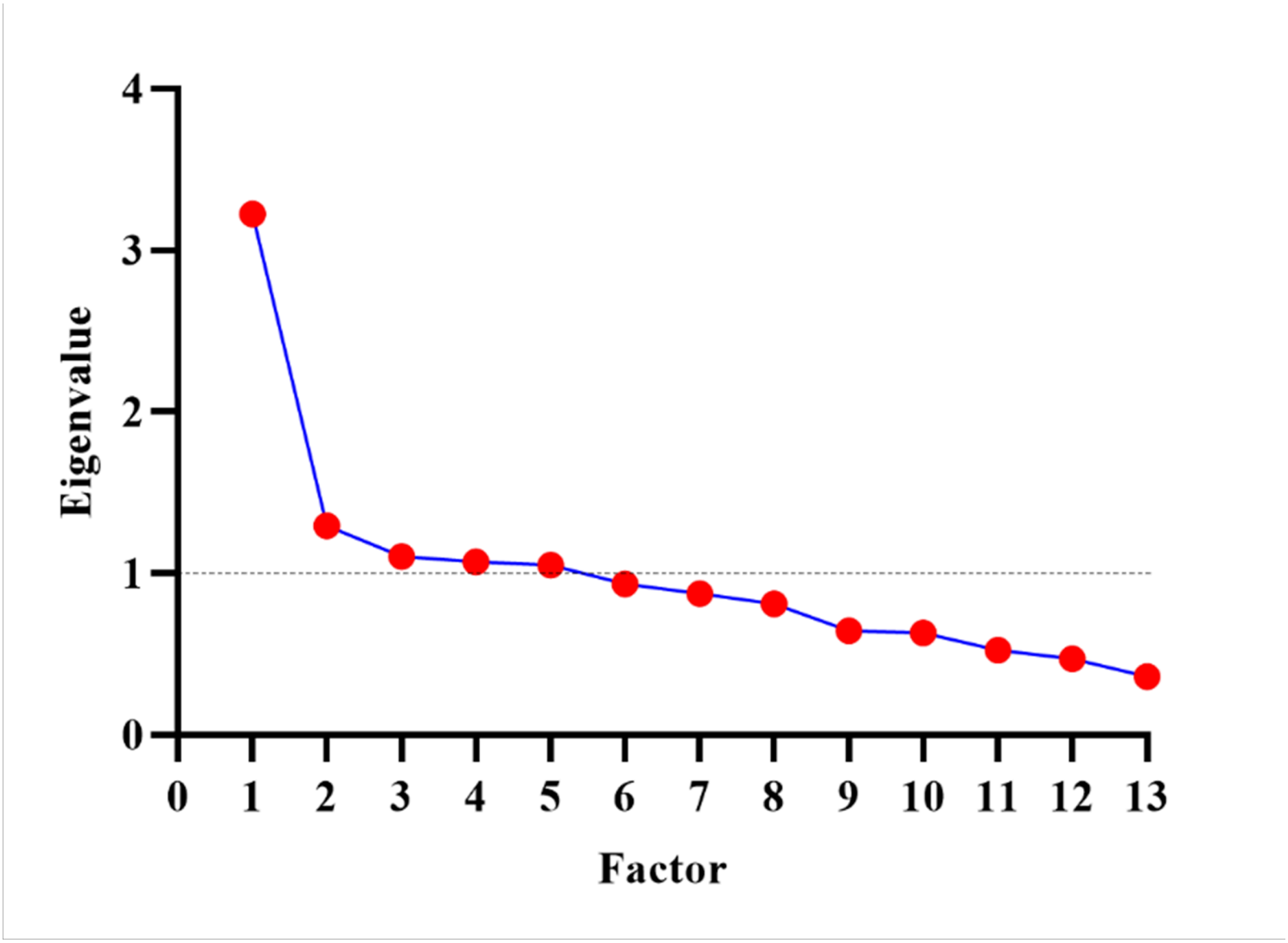

Figure 1

Scree plot of eigenvalues for dietary pattern identification.

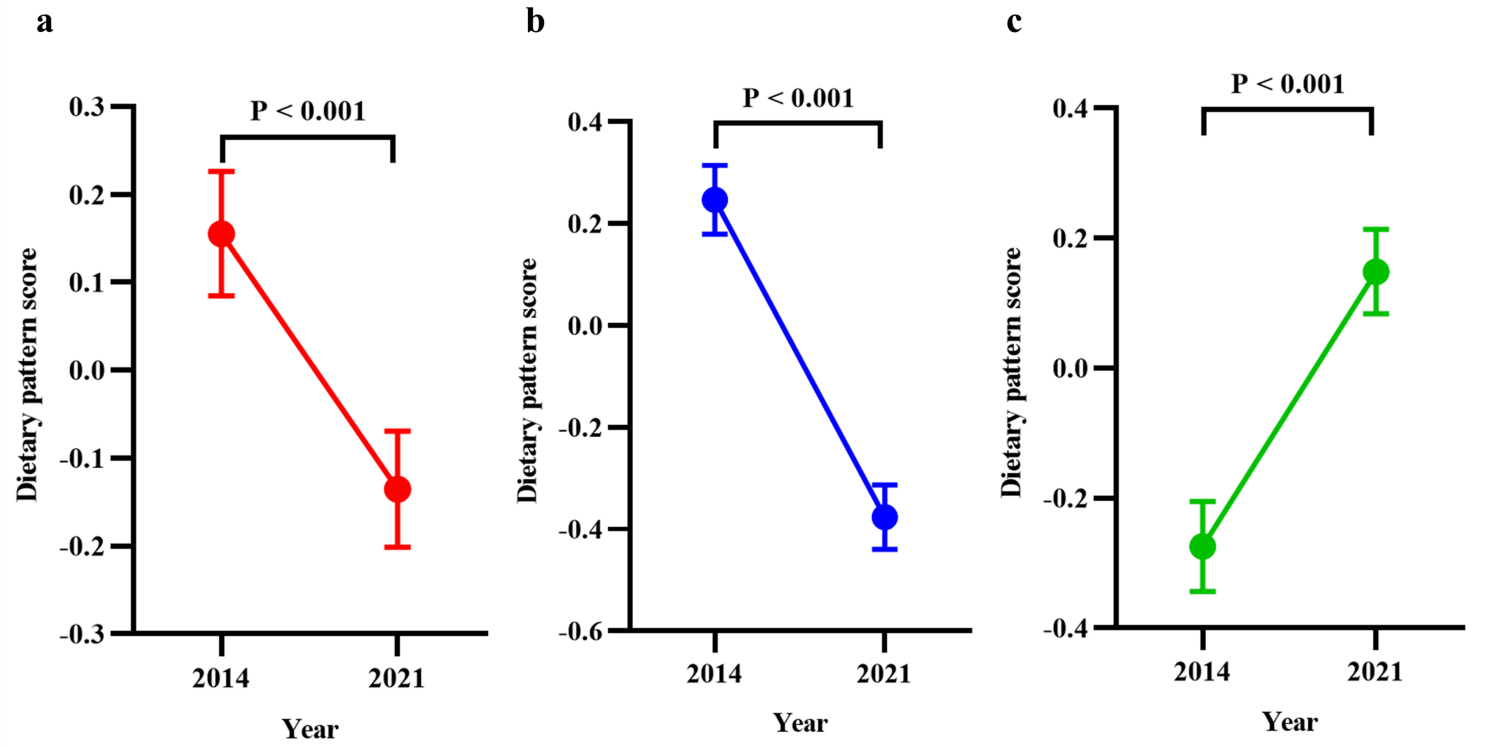

Figure 2

Changes in dietary pattern scores of the study population from 2014 to 2021.

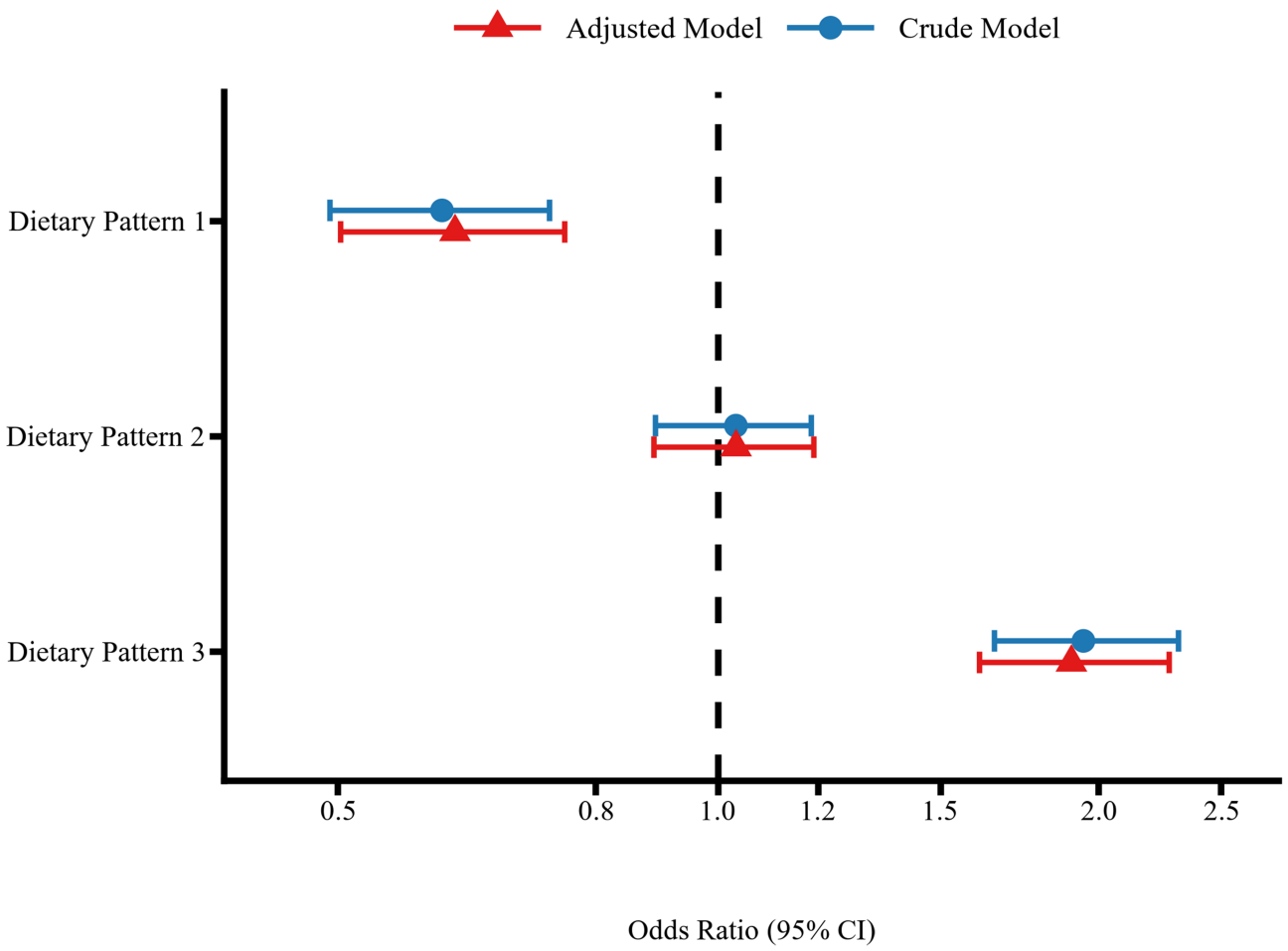

Figure 3

Forest plot of crude and adjusted odds ratios for the risk of blood glucose across three dietary patterns.