Gaussian Graphical Models Identified Food Intake Networks among Iranian Women with and without Breast Cancer: A Case-Control Study

Samira Sadat Fereidani, Fatemeh Sedaghat, Hassan Eini-Zinab, Zeinab Heidari, Saba Jalali, Elahe Mohammadi, Farah Naja, Mojan Assadi & Bahram Rashidkhani

NUTRITION AND CANCER
2021, VOL. 73, NO. 10, 1890–1897
https://doi.org/10.1080/01635581.2020.1820051

Gaussian Graphical Models Identified Food Intake Networks among Iranian Women with and without Breast Cancer: A Case-Control Study

Samira Sadat Fereidani[a], Fatemeh Sedaghat[b,c], Hassan Eini-Zinab[a], Zeinab Heidari[a], Saba Jalali[a], Elahe Mohammadi[d], Farah Naja[e], Mojan Assadi[f], and Bahram Rashidkhani[a]

[a]Department of Community Nutrition, Faculty of Nutrition Sciences and Food Technology, National Nutrition and Food Technology Research Institute, Shahid Beheshti University of Medical Sciences, Tehran, Iran; [b]Department of Basic Medical Sciences, Faculty of Nutrition Sciences and Food Technology, National Nutrition and Food Technology Research Institute, Shahid Beheshti University of Medical Sciences, Tehran, Iran; [c]Mehr Fertility Research Center, Guilan University of Medical Sciences, Rasht, Iran; [d]Department of Nutrition, Kalkhal University of Medical Sciences, Khalkhal, Iran; [e]Department of Nutrition and Food Sciences, Faculty of Agricultural and Food Sciences, American University of Beirut, Beirut, Lebanon; [f]Department of Oncology, Shahid Madani Hospital, Alborz University of Medical Science, Karaj, Iran

ABSTRACT

Background: Dietary patterns may be an important predictor of breast cancer risk. However, they cannot completely explain the pairwise correlations among foods. The purpose of this study is to compare food intake networks derived by Gaussian Graphical Models (GGMs) for women with and without breast cancer to better understand how foods are consumed in relation to each other according to disease status.
Methods: A total of 134 women with breast cancer and 267 hospital controls were selected from referral hospitals of Tehran, Iran. Dietary intakes were evaluated by using a validated 168 food-items semi-quantitative food frequency questionnaire. GGMs were applied to log-transformed intakes of 28 food groups to construct outcome-specific food networks.
Results: Among cases, a main network containing intakes of 12 central food groups (vegetables, fruits, nuts and seeds, olive oil and olive, processed meat, sweets, salt, soft drinks, fried potatoes, pickles, low-fat dairy, pizza) was detected. In controls, a main network including six central food groups (liquid oils, vegetables, fruits, sweets, fried potatoes and soft drinks) was identified.
Conclusions: The findings of this study revealed a difference in GGM-identified networks graphs between cases and controls. Overall, GGM may provide additional understanding of relationships between diet and health.

ARTICLE HISTORY
Received 31 July 2019
Accepted 29 August 2020

Introduction

Breast cancer is the most prevalent cancer in women both in the developed and less developed world (1). Furthermore, it is the cancer that causes the highest mortality amongst females, resulting in about half a million total deaths each year worldwide (2). Although Breast cancer is thought to be a disease of the developed world, almost 50% of breast cancer cases and 58% of deaths occur in less developed countries (3). There are various genetic and well-established environmental factors associated with Breast cancer risk (4, 5). Among environmental factors, diet has been considered as an important modifiable exposure (6). However, the complexity of dietary intake, eg., consumption of food in different combinations, makes it difficult to examine the role of specific food groups or foods in the development of diseases (7). So far, epidemiologic studies addressing the role of diet in breast cancer development have mostly examined dietary intake in terms of dietary patterns (7–12), single nutrients or nutrient patterns (13–16). Dietary pattern analysis is a preferred method for describing dietary intake. Two frequently used methods to derive dietary patterns are principal component analysis (PCA) and cluster analysis (CA) (17). PCA has been of particular interest because it compresses food groups according to the correlation or covariance between original variables into a number of uncorrelated patterns named factors or components (18).

CONTACT Bahram Rashidkhani rashidkhani@yahoo.com No 46, Hafezi Street, Farahzadi Boulevard, Sharak Ghods, P.O. Box 1981619573, Tehran, Iran.

Supplemental data for this article can be accessed at https://doi.org/10.1080/01635581.2020.1820051.

There are, however, a few draw backs in the use of existing methods of dietary pattern analysis, such as the subjective choices made during data analysis (19), difficulties in interpretation of identified patterns (18, 19) and lack of association between these patterns and health (20). Second, dietary patterns cannot completely explain the pairwise correlations among food variables. If they are independent of the effect of other food groups, pairwise correlations among food groups can be more informative (21).

Recently, Gaussian graphical models (GGM) were introduced as a complementary approach for dietary pattern analysis (21). These are graphical methods exploring conditional independence structure in the data by taking into account the pairwise correlation among two variables controlling for others (21, 22). In addition, the main advantage of GGM patterns is their ability to show how foods are consumed in different combinations, which might be important to interpret the eating pattern of the population (21).

The aim of the current study is to apply GGMs in order to identify specific dietary intake networks among Iranian breast cancer patients and their corresponding control subjects for further understanding the interrelation between food intakes and comparing these relationships among cases and controls. To the best of our knowledge, this is the first study that explores GGM-identified networks among dietary intake of Breast cancer patients.

Methods

Study Design and Sample

This study is a hospital-based case-control study, which included 136 female cases aged over 30 years who had been hospitalized at two referral cancer hospitals in Tehran province, Iran. Cases were women with a histo-pathologically confirmed diagnosis of breast cancer within the past 6 mo, with no history of other cancers. Eligible cases were all incident cases of breast cancer who did not undergo any cancer treatments at the time of interview. Controls ($n = 272$) were selected from female patients with the same age range who were admitted to the same hospitals as the cases for acute, non-neoplastic conditions that, to our knowledge, are unrelated to diet.

The exclusion criteria for controls were any history of cancer or benign breast disease, pregnancy or breast-feeding, and special dietary habits. Six controls and 2 cases were excluded from the study because their reported energy intakes were outside the range of ±3 standard deviation (SD) from the mean energy intakes of the study population. Finally, data from 134 cases and 266 controls were analyzed. The ethical committee of Shahid Beheshti University of Medical Sciences approved the study protocols and procedures.

Dietary Assessment

Information regarding the dietary habits of the cases in the year prior to diagnosis and of the controls in the year before the interview was collected by trained dietitians through private face-to-face interview using a valid and reliable semi-quantitative 168-food item food frequency questionnaire (FFQ) (23). Frequency of consumption for each food item was assessed on a daily, weekly, monthly or yearly basis. Data were transformed to daily frequencies. Using a manual for household measures, dietary intake was calculated in terms of grams of food intake/day (24). USDA and Nutrition Composition of Iranian Foods were used to analyze energy and nutrient content of foods (25). Nutrients Composition of Iranian Foods was used for foods or food ingredients that were not available in the USDA database (eg., traditional breads). The 168 FFQ food items were grouped 28 food groups including salt, as salt is considered an independent risk factor for non-communicable disease (26) and other food items/groups which are hypothesized to modify the risk of breast cancer (supplementary Table 1). For each woman, the daily intake of each food group was calculated by summing the intakes of individual food items within that group.

Other Measurements

Anthropometric measurements and other questionnaires were administered by trained dietitians during the same interview. Weight was measured to the nearest 100 gram using a digital scale (Seca, Germany) as subjects were wearing lightweight clothing with no shoes. Height was measured to the nearest 5 mm using a tape meter fixed to a wall. Body mass index (BMI) was calculated as a ratio of weight (kg) to the square of height (m). Physical activity was assessed using a valid and reliable questionnaire (27). Participants' demographic characteristics, lifestyle, and clinical information was collected using a multi-component questionnaire, which included questions about age (years), age at first pregnancy (years), education (illiterate, less than diploma, diploma and more), breast cancer family history (yes, no), marital status (single, married, divorced, widow), and smoking (yes, no).

Table 1. Characteristics of Iranian breast cancer cases (134) and controls (266).

Characteristics	Cases ($n = 134$)	Controls ($n = 266$)	p-value*
Age, (y)[a]	49.49 ± 10.68	47.13 ± 10.08	0.03
BMI, (kg/m2)[b]	29.47 (7.30)	28.54 (7.65)	0.11
first pregnancy age, (y)[b]	20.00 (8)	20.00 (5)	0.40
Number of deliveries	2/0 (3/0)	2/0 (2/0)	0.76
Physical activity, (Met.h/day)[b]	32.10 (6.15)	31.47 (6.03)	0.64
Daily energy intake, (kcal)[b]	2467.77 (89.015)	2549.63 (1068.66)	0.07
Marital status[c]			
Single	9 (7)	16 (6)	0.93
Married	105 (79)	206 (77)	
Divorced	5 (4)	13 (5)	
Widow	14 (10)	31 (12)	
Educational level[c]			0.31
Illiterate	13 (10)	24 (9)	
Less than diploma	55 (42)	134 (50)	
Diploma and more	62 (48)	108 (41)	
Smoking status[c]			1.00
Yes	4 (3)	9 (3)	
No	129 (97)	257 (97)	
Breast Cancer family history[c]			0.17
Yes	11(8)	12(4)	
No	123(92)	254(96)	

*$p \leq 0.05$ considered as significant. Statistically significant P-values are reported in bold.
[a]Mean ± SD was reported for variables with normal distribution (t-test).
[b]Median (IQR) was reported for variables without normal distribution (mann-whitney).
[c]Number (percent) was reported for qualitative variables (chi square and fisher test).

Statistical Methods

All analyses were performed using the Statistical Package for Social Sciences software version 18 (SPSS Inc., Chicago, IL, USA), and a two-sided p-value < 0.05 was considered significant. To compare general characteristics of all participants, t-test, Mann-Whitney and Pearson Chi-Square were used.

GGMs were used to derive dietary intake networks of cases and controls on 28 food groups separately. GGM analysis was run in R (version 3.4.3, R). Gaussian assumption for GGM was visually assessed applying a histogram and box plot. In order to improve normality, dietary data were log-transformed [ln (g/d + 1)] (21). A sparse inverse covariance (precision) matrix was estimated from the log-transformed data using graphical lasso (least absolute shrinkage and selection operator) in R package "glasso"(21). The optimum value for the regularization parameter λ was assessed in the "huge" package by specifying a sequence of λ values (0.60–0.10) in a decreasing order for sparsity. In order to obtain an adequately sparse correlation matrix, λ value of 0.30 was chosen by the maximum likelihood estimation of the graphical models and was applied for all analyses. The final networks in cases and controls consisted of vertices and edges. Vertices showed food groups, and edges show conditional dependencies between food groups. Positive partial correlations were shown with continuous lines whereas negative partial correlations were represented by broken lines. Correlation coefficients with an absolute value of 0.2 or greater represented a strong relationship. Moreover, the thickness of the edges was proportional to the strength of the correlations. A network was considered to be made up of three or more edges. There would be no connection between vertices if there was no conditional independence between food groups. Food groups, which had high correlation with a greater number of other food groups (4+) were considered as central food groups (21).

Results

Table 1 shows the characteristics of participants at baseline. Cases were significantly older than controls. BMI, physical activity, daily energy intake, marital status, number of deliveries, educational level, breast cancer family history and smoking status were not significantly different between cases and controls.

The mean intakes of the food groups (g/d) derived from the 168-food item FFQ in this case-control study are shown in Table 2.

Among cases (Figure 1), a main network consisted of intakes of 12 central food groups (vegetables, fruits, nuts and seeds, olive oil and olive, processed meat, sweets, soft drinks, salt, pickles, low-fat dairy, pizza and fried potatoes). Vegetables intake had strong correlation with the intakes of whole grains, fruits, nuts and seeds and fish and sea food. Olive oil and olive intake had strong correlation with the intakes of nuts and seeds and whole grains, while there was a strong inverse correlation between intakes of olive oil and olive and boiled potatoes. Processed meat intake had a

Table 2. Dietary intakes of 28 food groups used to derive dietary networks among cases and controls in this study[a].

Food groups	Cases (n= 134)	Controls (n= 266)	p-value
Processed meat, g/d	4.7 ± 9.6	3.4 ± 5.5	0.02
Fried potatoes, g/d	6.3 ± 10.3	5.9 ± 6.9	0.51
Mayonnaise, g/d	2.8 ± 3.1	2.5 ± 4.1	0.93
Sweets, g/d	49.7 ± 32.3	44.8 ± 31.1	0.13
Liquid oils, g/d	22.1 ± 24.6	22.3 ± 26.6	0.49
High fat dairies, g/d	137.3 ± 176.0	139.8 ± 180.8	0.55
Red meat, g/d	22.0 ± 16.6	23.2 ± 17.7	0.91
Whole grains, g/d	88.3 ± 86.6	97.3 ± 91.6	0.27
Solid oils, g/d	19.9 ± 18.0	18.0 ± 19.5	0.46
Pickles, g/d	23.5 ± 30.7	25.6 ± 32.6	0.18
Egg, g/d	19.9 ± 26.1	20.3 ± 16.9	0.59
Soft drinks, g/d	43.0 ± 95.4	31.8 ± 69.4	0.20
Low fat dairies, g/d	621.3 ± 408.3	711.6 ± 448.6	0.85
Vegetables, g/d	364.8 ± 191.2	386.1 ± 163.4	0.02
Fruits, g/d	472.5 ± 206.5	523.3 ± 231.0	0.11
Legumes, g/d	29.4 ± 21.5	33.7 ± 26.9	0.02
Salt, g/d	5.9 ± 3.6	5.8 ± 3.8	0.90
Fish and sea foods, g/d	13.2 ± 23.2	14.7 ± 16.6	0.66
Olive oil and olive, g/d	3.0 ± 5.6	3.3 ± 5.5	0.91
Condiments, g/d	3.9 ± 3.9	4.1 ± 4.2	0.24
Refined grains, g/d	278.9 ± 119.2	310.4 ± 172.6	≥ 0.01
Snacks, g/d	30.4 ± 35.0	39.2 ± 80.1	0.02
Coffee, g/d	739.7 ± 522.8	785.6 ± 540.0	0.72
Poultry, g/d	56.5 ± 39.9	58.9 ± 43.3	0.65
Nuts and nuts and seeds, g/d	10.8 ± 11.9	12.7 ± 12.9	0.44
Organ meat, g/d	5.6 ± 6.7	5.7 ± 11.8	0.29
Boiled potatoes, g/d	18.8 ± 14.2	24.6 ± 22.8	0.01
Pizza, g/d	8.0 ± 14.8	6.7 ± 14.8	0.49

[a]Mean ± SD was reported for variables with normal distribution (t-test).

strong correlation with the intake of pizza. In addition, the intakes of processed meat and snacks were conditionally dependent on intake of pizza. Soft drinks intake had a strong correlation with the intakes of sweets and solid oils. Fish and sea foods intake had a strong correlation with the intakes of poultry and pickles. Pickles intake had a strong correlation with the intakes of refined grains, fish and pizza. High fat dairies intake had a strong correlation with the intakes of organ meat, fried potatoes and sweets. Also, there was a strong correlation between the intake of fried potatoes and boiled potatoes and there was a strong negative correlation between intakes of solid oils and liquid oils.

In controls (Figure 2), a main network consisted of six central food groups: liquid oils, vegetables, fruits, sweets, soft drinks and fried potatoes. Liquid oils intake had a strong correlation with the intake of legumes, while there was a strong inverse correlation between the intakes of liquid oils and solid oils. In addition, the intakes of poultry and legumes were conditionally dependent on the intake of liquid oils. Fruits intake had strong correlation with the intakes of nuts and seeds and vegetables. Moreover, intakes of whole grains and fruits were conditionally dependent on intake of vegetables. Sweets intake had a strong correlation with the intake of coffee. Fried potatoes intake had a strong correlation with the intakes of boiled potatoes and refined grains. Moreover, there was a strong correlation between intakes of mayonnaise and red meat.

Discussion

In this analysis, GGMs identified health status (breast cancer)-specific networks, each consisting of a principal network. On both principal networks, vegetables, fruits, sweets, and fried potatoes were central food groups, underlining their potential key role in determining dietary behavior. In this study, GGM was used to derive dietary intake networks in cases and controls. In cases, a main network consisted of intake of nine central food groups: vegetables, fruits, nuts and seeds, olive oil and olive, sweets, processed meat, salt, soft drinks and fried potatoes. In controls a principal network consisted of five central food groups: liquid oils, vegetables, fruits, sweets and fried potatoes. Network of cases showed more conditional dependencies between intakes of food groups compared to the network in controls. Central food groups are key features since they explain primary structure of dietary behavior of our subjects. The consumption of majority of food groups are independently related to the consumption of these central foods. Processed meat and soft drinks (which are unhealthy foods) were central to the cases' network and not to the controls' network. In other words, cases seemed to eat less healthfully than controls. Another observation is that unhealthy foods seem to be closer related to each other and there are few correlations or mostly negative correlations relating healthful and unhealthful foods. These results are in line with our findings in previous study showing that an unhealthy dietary pattern might be associated with higher risk of breast among Iranian women (28).

This is the first study that uses GGM to derive dietary intake networks among breast cancer patients. To our knowledge, there are only 2 studies in nutrition science that have used GGM to derive dietary intake networks, both in a healthy, German adult population (21, 29). One of this studies (21), dietary intake data of 10780 males and 13,340 women in EPIC cohort study was used to derive food networks. And the other one (29), dietary intake data of 815 adults was used to derive meal networks. In comparison to PCA, GGM offer complementary, not interchangeable information (21). Even though both methods are based on correlations, fundamental differences compromise their comparability. A previous investigation by our group showed that, by using

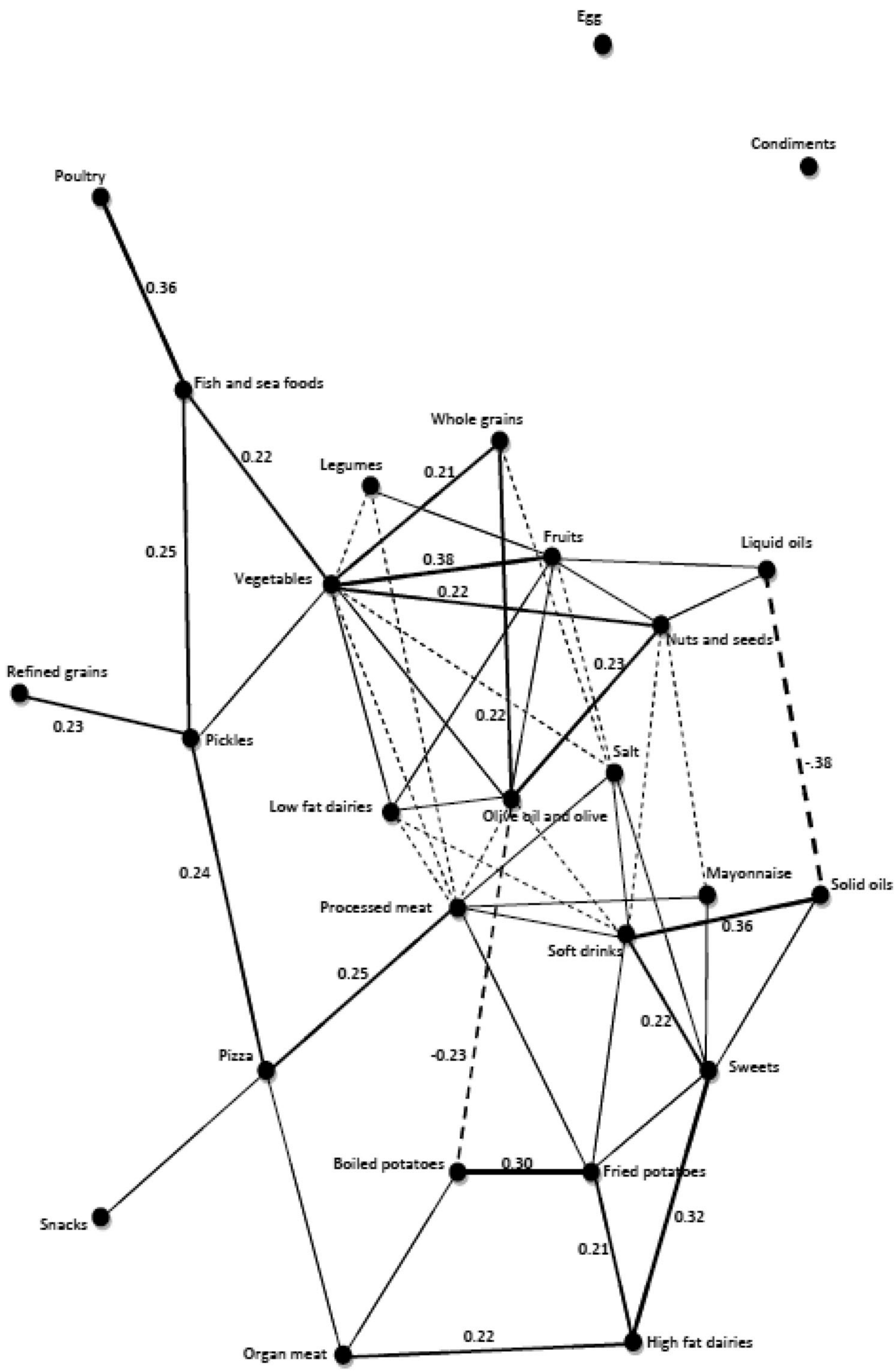

Figure 1. Dietary intake networks for cases, estimated by Gaussian graphical models. Vertices show foods/food groups, and edges show conditional dependencies between foods/food groups.

PCA, two major dietary patterns were identified in the same population and using the same dataset (28): The "Healthy" dietary pattern (loaded for high consumptions of fruits, vegetables, nuts and seeds, legumes, fish and sea foods, whole grains, liquid oils, olive oil and olive and lack of salt intake) vs. "Unhealthy" (loading on sweets, soft drinks, mayonnaise, solid oils, processed meat, fried potatoes and boiled potatoes, pickles and salt intake) (28). It is important to note that the findings of this study (one network) are not easily comparable to the PCA-derived dietary pattern results of our earlier investigation because in the PCA-derived patterns, the analysis was not stratified by health status. Furthermore,

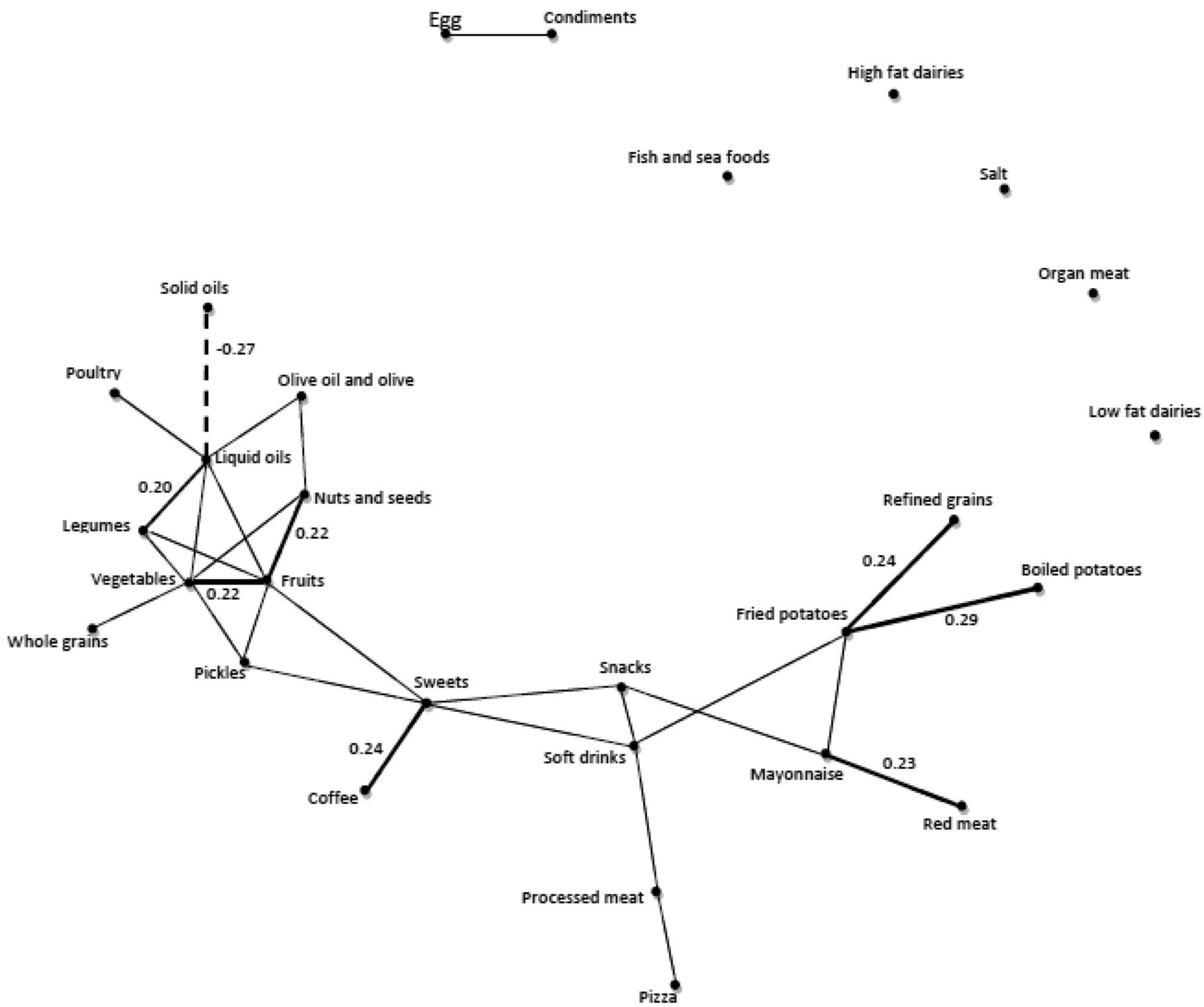

Figure 2. Dietary intake networks for controls, estimated by Gaussian graphical models. Vertices show foods/food groups, and edges show conditional dependencies between foods/food groups.

another difference between GGM dietary networks and PCA dietary patterns is that PCAs reduce variables in order to maximize the variance explained while GGM creates a graph of conditional dependence. Finally, another reason not to expect comparable findings between the two methods is that GGMs do not reflect the frequency of consumption. However, our results are in line with result obtained by Khalid Iqbal (21) showing that detected food networks might reflect true patterns. We showed that cases seemed to eat less healthfully than controls. Consistently, our previous investigation (28) using PCA showed that an unhealthy dietary pattern might be associated with higher risk of breast among Iranian women (same data set). The strength of GGMs is their ability to differentiate between direct and indirect associations among the food group consumption variables. GGMs take into account the indirect associations by computing a measure of conditional independencies between the food groups. This is an added advantage over PCA dietary patterns, which are based on the simple correlation matrix of the food groups. The removal of indirect effects when assessing pairwise correlations between 2 food groups is very important to understand how foods relate to each other (21).

The strengths of the current study were high participation rate (85%) and using a validated FFQ. In addition, all cases were affirmed histologically. To our knowledge, this is the first study that applies GGMs to derive dietary intake networks representing consumption patterns in Middle-Eastern population. Dietary habits of the Middle-Eastern population have their own unique features characterized by large portion sizes along with high consumption of refined grains (white rice and bread) and hydrogenated fats and a greater percentage of energy derived from carbohydrates (7). Furthermore, this is the first study that shows that the primary structure of dietary behavior of patients with cancer is different from that among controls with distinct central foods (processed meat and soft drinks).

However, like other case–control studies, our study has some limitations. One of the study limitations was possibility of recall and selection bias due to the design of the study. However, we tried to minimize this limitation by selecting incident cases. Furthermore, because of the use of hospital-based patients as controls, the control sample may not be representative of the general population. In addition, the lack of precision of results due to small sample size is another limitation of our study similar to PCA patterns, GGM dietary patterns are a descriptive tool, not involving testing or inferential statistics and therefore not adjusted for confounders. However, like PCAs, results from GGM networks can be used in regression analysis as a measure of dietary exposure on health outcomes (30). Finally, a value of 0.30 which was chosen for the regularization parameter is a subjective decision. However, we chose this regularization parameter based on the maximum likelihood estimation and the same parameter was chosen for comparability purposes.

In conclusion, GGM networks have the ability of showing conditional independence between food groups which PCAs or simple correlation analyses do not. Network of cases showed more conditional dependencies between intakes of food groups compared to the network in controls due to two unhealthy foods playing as a central food groups. Processed meat and soft drinks (which are unhealthy foods) were central to the cases' network and not to the controls' network. The findings of this study suggested that breast cancer patients eat more un-healthfully than controls. Additional studies are warranted to confirm our findings.

Disclosure statement

Authors declare no conflict of interest.

Funding

This study was funded by the National Nutrition and Food Technology Research Institute, Shahid Beheshti University of Medical Sciences, Tehran, Iran.

References

1. Ferlay J, Soerjomataram I, Dikshit R, Eser S, Mathers C, Rebelo M, Parkin DM, Forman D, Bray F. Cancer incidence and mortality worldwide: sources, methods and major patterns in GLOBOCAN 2012. Int J Cancer. 2015;136(5):E359–86. doi:10.1002/ijc.29210
2. Torre LA, Bray F, Siegel RL, Ferlay J, Lortet-Tieulent J, Jemal A. Global cancer statistics, 2012. CA Cancer J Clin. 2015;65(2):87–108. doi:10.3322/caac.21262
3. Madeddu C, Gramignano G, Floris C, Murenu G, Sollai G, Maccio A. Role of inflammation and oxidative stress in post-menopausal oestrogen-dependent breast cancer. J Cell Mol Med. 2014;18(12):2519–29. doi:10.1111/jcmm.12413
4. Brennan SF, Cantwell MM, Cardwell CR, Velentzis LS, Woodside JV. Dietary patterns and breast cancer risk: a systematic review and meta-analysis. Am J Clin Nutr. 2010;91(5):1294–302. doi:10.3945/ajcn.2009.28796
5. Chang Y-J, Hou Y-C, Chen L-J, Wu J-H, Wu C-C, Chang Y-J, Chung K-P. Is vegetarian diet associated with a lower risk of breast cancer in Taiwanese women? BMC Public Health. 2017;17(1):800. doi:10.1186/s12889-017-4819-1
6. Lammert J, Grill S, Kiechle M. Modifiable lifestyle factors: Opportunities for (hereditary) breast cancer prevention - a narrative review. Breast Care (Basel). 2018;13(2):109–14. doi:10.1159/000488995
7. Karimi Z, Jessri M, Houshiar-Rad A, Mirzaei HR, Rashidkhani B. Dietary patterns and breast cancer risk among women. Public Health Nutr. 2014;17(5):1098–106. doi:10.1017/S1368980013001018
8. Sant M, Allemani C, Sieri S, Krogh V, Menard S, Tagliabue E, Nardini E, Micheli A, Crosignani P, Muti P, et al. Salad vegetables dietary pattern protects against HER-2-positive breast cancer: a prospective Italian study. Int J Cancer. 2007;121(4):911–4. doi:10.1002/ijc.22714
9. Butler LM, Wu AH, Wang R, Koh WP, Yuan JM, Yu MC. A vegetable-fruit-soy dietary pattern protects against breast cancer among postmenopausal Singapore Chinese women. Am J Clin Nutr. 2010;91(4):1013–9. doi:10.3945/ajcn.2009.28572
10. Demetriou CA, Hadjisavvas A, Loizidou MA, Loucaides G, Neophytou I, Sieri S, Kakouri E, Middleton N, Vineis P, Kyriacou K, et al. The mediterranean dietary pattern and breast cancer risk in Greek-Cypriot women: a case-control study. BMC Cancer. 2012;12(1):113. doi:10.1186/1471-2407-12-113
11. Shin S, Saito E, Inoue M, Sawada N, Ishihara J, Takachi R, Nanri A, Shimazu T, Yamaji T, Iwasaki M, et al. Dietary pattern and breast cancer risk in Japanese women: the Japan Public Health Center-based Prospective Study (JPHC Study). Br J Nutr. 2016;115(10):1769–79. doi:10.1017/S0007114516000684
12. Lu S, Qian Y, Huang X, Yu H, Yang J, Han R, Su J, Du W, Zhou J, Dong M, et al. The association of dietary pattern and breast cancer in Jiangsu, China: A population-based case-control study. PloS One. 2017;12(9):e0184453. doi:10.1371/journal.pone.0184453

13. Chen P, Li C, Li X, Li J, Chu R, Wang H. Higher dietary folate intake reduces the breast cancer risk: a systematic review and meta-analysis. Br J Cancer. 2014;110(9):2327–38. doi:10.1038/bjc.2014.155
14. Matejcic M, de Batlle J, Ricci C, Biessy C, Perrier F, Huybrechts I, Weiderpass E, Boutron-Ruault MC, Cadeau C, His M, et al. Biomarkers of folate and vitamin B12 and breast cancer risk: report from the EPIC cohort. Int J Cancer. 2017;140(6):1246–59. doi:10.1002/ijc.30536
15. Edefonti V, Decarli A, La Vecchia C, Bosetti C, Randi G, Franceschi S, Dal Maso L, Ferraroni M. Nutrient dietary patterns and the risk of breast and ovarian cancers. Int J Cancer. 2008;122(3):609–13. doi:10.1002/ijc.23064
16. Ronco AL, de Stefani E, Aune D, Boffetta P, Deneo-Pellegrini H, Acosta G, et al. Nutrient patterns and risk of breast cancer in Uruguay. Asian Pac J Cancer Prev: APJCP. 2010;11(2):519–24.
17. Newby PK, Tucker KL. Empirically derived eating patterns using factor or cluster analysis: a review. Nutr Rev. 2004;62(5):177–203. doi:10.1301/nr.2004.may.177-203
18. Michels KB, Schulze MB. Can dietary patterns help us detect diet-disease associations? Nutr Res Rev. 2005;18(2):241–8. doi:10.1079/NRR2005107
19. Moeller SM, Reedy J, Millen AE, Dixon LB, Newby PK, Tucker KL, Krebs-Smith SM, Guenther PM. Dietary patterns: challenges and opportunities in dietary patterns research an Experimental Biology workshop, April 1, 2006. J Am Diet Assoc. 2007;107(7):1233–9. doi:10.1016/j.jada.2007.03.014
20. Hodge A, Bassett J. What can we learn from dietary pattern analysis? Public Health Nutr. 2016;19(2):191–4. doi:10.1017/S1368980015003730
21. Iqbal K, Buijsse B, Wirth J, Schulze MB, Floegel A, Boeing H. Gaussian graphical models identify networks of dietary intake in a German adult population. J Nutr. 2016;146(3):646–52. doi:10.3945/jn.115.221135
22. Villers F, Schaeffer B, Bertin C, Huet S. Assessing the validity domains of graphical Gaussian models in order to infer relationships among components of complex biological systems. Stat Appl Genet Mol Biol. 2008;7(1):1–37.
23. Asghari G, Rezazadeh A, Hosseini-Esfahani F, Mehrabi Y, Mirmiran P, Azizi F. Reliability, comparative validity and stability of dietary patterns derived from an FFQ in the Tehran Lipid and Glucose Study. Br J Nutr. 2012;108(6):1109–17. doi:10.1017/S0007114511006313
24. Ghafarpour M, Houshiar-Rad A, Kianfar H. The manual for household measures, cooking yields factors and edible portion of food. Tehran: Keshavarzi Press; 1999.
25. Esfahani FH, Asghari G, Mirmiran P, Azizi F. Reproducibility and relative validity of food group intake in a food frequency questionnaire developed for the Tehran Lipid and Glucose Study. J Epidemiol. 2010;20(2):150–8. doi:10.2188/jea.je20090083
26. Li Y, Luo R, Zhang PH. Progress on salt reduction and prevention of chronic non-communicable disease. Zhonghua Yu Fang Yi Xue Za Zhi. 2018;52(7):757–61. doi:10.3760/cma.j.issn.0253-9624.2018.07.016
27. Aadahl M, Jorgensen T. Validation of a new self-report instrument for measuring physical activity. Med Sci Sports Exerc. 2003;35(7):1196–202. doi:10.1249/01.MSS.0000074446.02192.14
28. Heidari Z, Jalali S, Sedaghat F, Ehteshami M, Rashidkhani B. Dietary patterns and breast cancer risk among Iranian women: a case-control study. Eur J Obstet Gynecol Reprod Biol. 2018;230:73–8. doi:10.1016/j.ejogrb.2018.09.018
29. Schwedhelm C, Knüppel S, Schwingshackl L, Boeing H, Iqbal K. Meal and habitual dietary networks identified through semiparametric Gaussian Copula graphical models in a German adult population. PloS One. 2018;13(8):e0202936. doi:10.1371/journal.pone.0202936
30. Iqbal K, Schwingshackl L, Floegel A, Schwedhelm C, Stelmach-Mardas M, Wittenbecher C, Galbete C, Knüppel S, Schulze MB, Boeing H, et al. Gaussian graphical models identified food intake networks and risk of type 2 diabetes, CVD, and cancer in the EPIC-Potsdam study. Eur J Nutr. 2019;58(4):1673–86. doi:10.1007/s00394-018-1714-1