Understanding meal patterns among pregnant and postpartum women according to BMI, weight change, and diet quality through food network analysis

AIMS

We aim to identify and compare meal-specific food networks among pregnant women with a high versus low diet quality. This knowledge could provide a basis for meal-based dietary advice during pregnancy, facilitating the achievement of a healthier diet among women during this critical period.

HYPOTHESES

We hypothesize observing healthy foods clustering together, with stronger correlations, and higher frequency of consumption among women with a higher diet quality, and unhealthier foods showing a similar relationship structure among women with lower diet quality. We expect the different meals (breakfast, lunch, dinner) to show different food groups and correlation structures.

METHODS

Food grouping

Foods were grouped into 40 categories based on USDA’s Food and Nutrient Database for Dietary Studies (FNDDS). Foods using FNDDS codes for mixed dishes were broken down into the different foods making up the mixed dish when the breakdown provided further information about the healthfulness of the food or the conceptualization of choice to consume such foods (e.g. meat, poultry, fish in gravy or sauce or creamed was separated into the animal protein component and the sauce component). FNDDS mixed dishes where the conceptualization of the choice would substantially be altered by breaking down into more foods or ingredients were left as mixed dishes and categorized based on similarity of ingredients or type of food (e.g. protein-based patties and loaves).

1. Methods to obtain networks (1):

Gaussian Graphical Models (GGMs) were used to *produce probabilistic graphs in which nodes represent variables and edges represent a relationship between the variables... A high-dimensional multivariate data set can have no or few 0 values, which would form very dense, less informative graphical representations of the networks. For this reason, regularization methods for covariance estimation are available. Regularization is achieved by choosing a penalty parameter (λ >0), which reduces the variance and helps avoid overfitting of the model (avoiding the false inclusion of edges)(2). Various methods are available for choosing the penalty parameter λ (3)**…Due to highly skewed data, the meal networks were derived through Semiparametric Gaussian Copula Graphical Models (SGCGMs), which is a nonparametric extension of GGMs. It performs the nonparanormal skeptic (Spearman/Kendall estimates preempt transformations to infer correlation) transformation in order to perform semiparametric analyses suited for highly skewed data (4, 5)…**For the analyses here presented, skeptic transformed inverse covariance matrices were estimated using the “huge” R package (6). The selection of the optimal penalization λ was performed with a fivefold cross-validated graphical lasso (glasso), which was run in R with the package “nethet” (7).*

1. Detect communities using the Louvain algorithm for community detection

In addition to weighed edges (direction and strength of correlations), weighed nodes will be used to represent frequency of consumption for each food group at each meal.

We will qualitatively describe and compare the networks. We will also calculate differences in modules using the Participation Coefficient (PC) and differences between modules using Clustering Coefficient (CC) and run GLMs to test these communities properties in both HEI groups.

References:

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