ORIGINAL ARTICLE

Food pattern analysis over time: unhealthful eating trajectories predict obesity

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Background: Analysis of dietary patterns is prominent in nutrition literatures, yet few studies have taken advantage of multiple repeated measurements to understand the nature of individual-level changes over time in food choice, or the relation between these changes and body mass index (BMI).

Objective: To investigate changes in eating patterns at the individual level across three exam periods, and to prospectively examine the relation of eating trajectories to BMI at the cohort level.

Design: The study included 3418 participants at baseline. Clinically measured BMI and dietary intake were assessed during three exam periods between 1991 and 2001 using a validated food frequency questionnaire. An individual's eating trajectory across exam periods was analyzed using sequence analysis, and then used to estimate outcomes of continuous BMI and categorical obesity status. Ordinary least squares regression models with robust standard errors were adjusted for socio-economic and demographic confounders, baseline BMI and baseline eating.

Results: A total of 66.2% ($n = 1614$) of participants change their diet pattern during the study period, 33.8% ($n = 823$) remain stable. After accounting for potential confounders, an unhealthful trajectory is significantly associated with a 0.42 kg m^{-2} increase in BMI (confidence interval (CI): 0.1, 0.7). Those with an unhealthful trajectory are 1.79 times more likely to be overweight (relative risk ratio, 95% CI: 1.1, 2.8) and 2.4 times more likely to be obese (relative risk ratio, 95% CI: 1.3, 4.4). Moreover, a number of specific diet transitions between exams are predictive of weight gain or loss.

Conclusion: Contextualizing an individual's current eating behaviors with an eye towards diet history may be an important boon in the reduction of obesity. Although it may not be realistic for many people to shift from the least to most healthful diet, results from this study suggest that consistent movement in an overall healthier direction is associated with less weight gain.

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Introduction

The analysis of patterns of food choice (sometimes referred to as dietary pattern analysis) has been an important means to examine links between food consumption and a range of health conditions, including obesity;[1] gastric adenocarcinoma;[2] type 2 diabetes;[3] metabolic syndrome;[4] prostate cancer risk;[5] and atherosclerosis and carotid artery stenosis.[6,7] In a pattern analysis, classification techniques such as factor (FA) or cluster analysis (CA) are typically used to reduce the complexity of the wide variety of foods that individuals eat into a parsimonious set of food patterns. Yet there have been few studies in the population health or social scientific literatures that have taken advantage of multiple repeated measurements in order to understand the nature of individual-level change over time. Moreover, few of these longitudinal studies examine the relationship between changes in patterns of food choice and body mass index (BMI) status.[8–11]

Measures of self-reported food consumption have been collected from subjects over time in prospective cohort studies such as the National Health and Nutrition Examination Survey;[12] the Framingham Heart Study;[13] Nurses' Health Study;[14] Health Professionals' Follow-up Study;[15] the Multinational Monitoring of Trends and Determinants in Cardiovascular Disease Study (MONICA);[11] the Whitehall II study;[3] the Baltimore Longitudinal Aging Study;[1] the NHLBI National Growth and Health Study;[16] the Multi-Ethnic Study of Atherosclerosis (MESA);[7] and the Swedish Mammography Cohort (SMC).[8,9] Despite this abundance of longitudinal data, much of the research that informs our knowledge of links between diet and health is based upon

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cross-sectional study designs. This limits our knowledge of how changes in diet are related to changes in health status.

To address this gap, the primary aims of this study were to examine how individuals change their patterns of food choice over time using data from three survey panels between 1991 and 2001, and then to demonstrate the utility of diet change measures constructed by sequence-analytic methods to predict BMI/obesity status. Support was found for the hypothesis that diet change in a generally unhealthful direction over time would predict higher BMI. In a sensitivity analysis of the main findings, several particularly healthful and unhealthful discrete diet transitions were then identified. Although most medical professionals would welcome a change in the patient's eating behavior from a very unhealthful to a very healthful diet, this is often impractical. Results from this study provide fresh insight that less drastic diet changes can be effective in BMI reduction.

Subjects and methods

Study population
Subjects in this study are drawn from the Offspring cohort of the Framingham Heart Study, a population-based, longitudinal, observational cohort study that was initiated in 1948 to prospectively investigate risk factors for cardiovascular disease. Published reports provide details about sample composition and study design for all these cohorts.[17–19] Continuous surveillance and serial examinations of these cohorts by Framingham Heart Study physicians provide longitudinal data. The Offspring study enrolled 5124 individuals at inception; by exam cycle 5 (1991–95), 75% ($n = 3799$) of the cohort was intact. The members of this cohort are representative, in terms of age (median age of 54, ranging from mid-20s to 80s at baseline) and gender (53% F), of the overall population from which they are drawn. At baseline, participants tended to be fairly well educated (median of 13 years), and categorically overweight (median BMI of 26.7). Cohort members are geographically distributed across the country. Of these individuals, $\sim 90\%$ ($n = 3418$) completed a semi-quantitative food frequency questionnaire (FFQ) at Exam 5. At Exam 6 (1996–98), 89% ($n = 3143$) of the available cohort completed a FFQ, and 86% ($n = 3030$) completed an Exam 7 (1998–2001) FFQ. This study is concerned with those who completed a FFQ at all three exam cycles ($n = 2437$), and this group is used to describe diet pattern changes and to estimate statistical models of food pattern change on BMI status. The Harvard University Faculty of Arts and Sciences and Harvard Medical School institutional review boards approved this study.

Measures
The main outcomes of interest are clinically measured BMI status (continuous kg m^{-2}) at exam cycle 7, and a transformation of BMI into a categorical measure of obesity status (BMI $< 25 =$ normal weight; BMI $25–30 =$ overweight; BMI $> 30 =$ obese). The main variable of interest is a sequence of food patterns that captures the way members of the Offspring cohort change diet over time. Because $< 1\%$ ($n = 23$) of participants fell below the common 'low BMI' threshold of 18.5, no such category was used here, and these individuals are categorized in 'normal weight'.

To construct this measure, similarities in consumption of 127 food items measured by FFQ are used to classify eating into a parsimonious number of food patterns. These patterns are then used to construct two sequence measures that capture eating changes. The first sequence measure, 'transition', is a categorical measure that reports on all possible permutations of change between two exams. For instance, pattern A (Exam 5), pattern B (Exam 6) is classified as $A_{\text{Exam5}}B_{\text{Exam6}}$. The second measure, 'trajectory', is a three-exam extension of the two-exam 'transition' measure. This measure characterizes the overall direction of diet change by cross-classifying food pattern sequences against a Dietary Guidelines Adherence Index (DGAI) score.[20] Here, the sequence of ABC consists of two transitions: 'AB', followed by 'BC'. Given that C can be objectively assessed as healthier than B or A, the general direction of trajectory ABC can be designated 'healthful' as opposed to CBA, or CBB, which would be characterized as 'unhealthful'. In this manner, the trajectory measure can describe the relative healthiness of the food pattern trajectory (that is, 'healthful', 'unhealthful', 'mixed direction', 'no change').

As food consumption is known to vary by demographic attributes and socio-economic status, potential confounders include gender (dichotomous), age (years) and educational attainment (total years in school). Baseline BMI (exam cycle 5) is included to account for the possibility that individuals of subsequent high BMI were heavier at baseline; baseline food pattern was included for similar reasons.

Food pattern analysis procedure
FFQ measurement is a relatively inexpensive and reliable data collection method for identifying and assessing food patterns in epidemiological research. A benefit of food pattern analysis is the ability to account for correlations that may exist between foods, food groups, or nutrient-nutrient interactions.[21,22] Classification techniques such as FA or CA are commonly applied to data gathered by FFQ to describe a population. Although a far more thorough treatment of these techniques can be found elsewhere, a short explanation of differences in these techniques may be useful.[21,23] Briefly, FA treats the multitude of foods constituting the diet as the unit of analysis, yielding a set of factor scores that (as a set) enable comparability among individuals in a population. The goal of CA is to minimize differences within each group while maximizing the differences across groups. Both FA[1,15] and CA[6,24,25] techniques have been shown to provide reproducible and valid food patterns using FFQ data. Yet as a recent review found, there is no single 'best' data classification procedure or algorithm for food

pattern analysis, and there is little work to employ hybrid techniques.[23]

One shortcoming of the valuable body of food pattern analysis is the relative paucity of research that attempts to assess change over time in food patterns. It is useful to estimate a deviation in food pattern inclusion from a baseline to subsequent time point;[11] to estimate separate food patterns at each point in time and use FA on an average consumption measure across repeated measures;[15] and to compare mean intakes of food groups within food patterns at multiple time points.[8,9] However, such strategies do not allow for easy commensuration of food patterns over time, because factor loadings are not easily comparable across time points. In contrast, this study utilizes a hybrid procedure that involves pooling all repeated measurements, and then submitting this pooled population to FA and CA. Distilling data in this manner establishes bounds on the range of what this population eats during the time period in question, holds the food patterns constant over time and yields a discrete diet pattern for each individual at each time point. In doing so, we can examine regularities in how individuals change what they consume between measurement points.

Statistical analysis of food pattern sequences
The central focus of this study concerns the propensity of individuals to change from one pattern of food choice to another during the three exam cycles. Two techniques are used to describe these changes. First, a transition probability matrix is first used to report on the chance that an individual in food pattern A will shift to pattern B in the following exam cycle. The [xttrans] procedure in Stata MP/11 calculates the probability that $x_{i,t+1} = v_2$ given that $x_{it} = v_1$ by counting transitions.[26] A reported probability in the matrix aggregates transitions from both Exam 5 to Exam 6, and Exam 6 to Exam 7.

The second procedure is a sequence analysis of the precise sequence of change between food patterns (that is, food pattern $A_{Exam5} \rightarrow B_{Exam6} \rightarrow C_{Exam7}$ = sequence ABC) in order to tabulate frequency of trajectories. Although sequence analysis is mainly used in examining DNA sequences, it has been adapted for population health and social scientific applications, including research on health over the life course.[27,28] However, to the best of authorial knowledge, it has not been applied to individual or population-level analysis of changes in food choices.

Food pattern sequences are then used as predictors in evaluating BMI and obesity status at the final time point (Exam 7). A multivariate regression framework is used to estimate BMI (continuous) and obesity (categorical) as outcomes of interest. The key predictor of interest is a food pattern trajectory variable. Models adjust for variation in measures of socio-demographic interest (sex, education, age), as well as baseline BMI and baseline food pattern. In a subsequent sensitivity analysis, the entire set of 49 possible transitions between two periods is used to assess the relationship between each of these transitions and BMI. This allows for the evaluation of the contributions of specific diet changes within one's broader diet trajectory.

Results

Food pattern enumeration
The dietary pattern analysis procedure consists of a three-stage process of refinement, the first two stages of which categorize food items, and the last of which categorizes people. The first stage groups foods ($n = 127$) according to categories of nutritional equivalence. Here, for instance, oranges and grapefruits are classified as nutritionally similar by American Dietetic Association guidelines. In the second stage, these nutritionally equivalent food groups ($n = 40$) are analyzed for similarities in co-occurrence of consumption (using principal components FA); this procedure yields a small number ($n = 7$) of latent factors. The set of factors explains 46.4% of the variance in eating; variance in previous research has ranged from 15 to 93%.[23] In the third stage, a set of factor scores are used as input variables in a CA. Here, people are clustered (using a κ-means algorithm) into seven non-overlapping groups according to individual's factor score similarity. The quality of this clustering solution is assessed by cross-classification with DGAI score, and by assessment of the mean levels of foods captured within each of the seven clusters. A more detailed treatment of this procedure is published elsewhere.[29]

The seven empirically derived patterns are: 'meat and soda', 'sweets', 'alcohol and snacks', 'light', caffeine-avoidant', 'offsetting', and 'healthier'. Pattern names were subjectively chosen according to food groups that characterize each pattern, and can be described by average DGAI score, with 'meat and soda' (lowest) to 'healthier' (highest). Table 1 describes the identifying food items of the other patterns in more detail.

Food pattern sequences
A transition probability matrix of food pattern change (Table 2) reports that across all patterns, there is a greater probability that an individual will remain in the same pattern than change to a different one at the subsequent exam—ranging from 30.6%, who remain with 'sweets', to 59.5%, who remain with 'healthier'. The most durably persistent patterns are 'alcohol and snacks' (61.1% are likely to remain), 'healthier' (59.5%) and 'meat and soda' (52.3%). In contrast, the most temporary food patterns are 'light eating' (39.3%) and 'sweets' (30.6%). Patterns between the extremes are 'caffeine-avoidant' (43.4%) and 'offsetting' (44.5%). Individuals are most likely to exhibit transition to a 'healthier' pattern over all others.

Next, a sequence analysis enables identification of individuals who change patterns during all the three exam cycles, and allows for classification of the kind and frequency

Table 1 Food groups that characterize eating patterns

Meat and Soda	Sweets	Alcohol and Snacks	Light	
n = 1494	n = 811	n = 1298	n = 915	
DGAI = 7.29 (2.11 s.d.)	DGAI = 8.03 (2.27 s.d.)	DGAI = 8.31 (2.24 s.d.)	DGAI = 8.36 (1.89 s.d.)	
Highest in	Highest in	Highest in	Highest in	
Sweet caffeine bevs	Refined grains	Beer	N/A	
Non-calorie caffeine bevs	High-fat dry/cheese	Wine		
High-fat dairy bevs	Low-fat dairy product	Liquor	Lowest in	
Butter/cream	Soup	Salty/fatty snacks	Vit-A rich veg	Refined grains
High-fat meat	High-fat sweets	Shellfish	Vit-C rich veg	Soft veg fats
Low-fat meat	Low-fat desserts		High-fiber veg	High-fat dry/cheese
Mixed proteins	High-fat desserts		Other veg	Low-fat sweets
High-fat poultry			High-fat fruits	Salty/fatty snacks
Eggs			Other fruits	Mixed proteins
			High-fat health foods	Legumes
Lowest in	Lowest in	Lowest in	Low-fat health foods	Eggs
Non-calorie decaffeine bevs	N/A	N/A	Whole grains	

Caffeine-avoidant		Offsetting		Healthier	
n = 1093		n = 1631		n = 2349	
DGAI = 9.41 (2.41)		DGAI = 9.67 (2.28)		DGAI = 11.95 (1.94)	
Highest in		Highest in		Highest in	
Sweet decaffeine bevs		Non-fat dairy bevs		Vit-A rich veg	
Non-calorie decaffeine bevs		High-fat health foods		Vit-C rich veg	
Low-fat health food		Whole grains		High-fiber veg	
		Refined grains		Other veg.	
		Soft veg. fats		Vit-C rich fruits	
		Low-fat sweets		High-fat fruits	
		Snacks, salty/fatty		Other fruits	
				Low-fat poultry	
				Fish	
				Legumes	
Lowest in		Lowest in		Lowest in	
Non-calorie caffeine bevs		High-fat poultry		Beer	
				High-fat meat	

Abbreviations: bevs, beverages; DGAI, Dietary Guidelines Adherence Index score; Veg., vegetables; Vit, vitamin. Summary statistics reported on pooled measurements across exams 5–7. The seven eating patterns are described here by listing outlying food groups within each pattern. Two of the patterns ('sweets', 'alcohol and snacks') did not contain low-consumption food groups relative to the other five patterns; these are denoted with 'N/A' for 'not applicable'. Similarly, the 'light' eating pattern did not contain any food groups that were extraordinarily high relative to the other patterns.

of food pattern sequences. The [sq] algorithms implemented in Stata MP/11 were used to perform these analyses.[30] A measure of diet health (DGAI score, with a range of 1–20) describes the direction of pattern change over time. The mean score within each pattern ranges from 7.29 (2.11 s.d.) for 'meat and soda' to a score of 11.95 (1.93 s.d.) for those in the 'healthier' group.

Given the permutation of possible food pattern sequences, there are seven ways to remain consistently within the same food pattern (that is, 'sweets, sweets, sweets'). In this sample, individuals improve diet health in 71 different ways (for instance: 'meat and soda', to 'light', then 'healthier'); in mixed directions in 147 ways (that is, 'healthier', 'light', 'offsetting'); and decline in 72 ways (that is, 'healthier', 'alcohol and snacks', 'meat and soda'). Tabulation of trajectory direction frequencies suggests that there is significantly more change over time in the food patterns consumed during this 10-year period (66.2%, n = 1614) than there is stability (33.8%, n = 823).

Another way to describe change is by movement in an objectively healthful or unhealthful direction. In terms of how food patterns are classified by dietary guidelines adherence index (DGAI) score, an individual who shifts from 'meat and soda' to 'sweets' to 'offsetting' moves in a healthful direction; 23.4% (n = 570) of individuals change in this manner. An individual who changes from 'caffeine-avoidant' to 'alcohol and snacks' to 'meat and soda' is considered to move in a less healthful direction; 17.5% (n = 426) of individuals exhibit transition in this manner. The remaining 25.4% (n = 618) shift in inconsistent directions (upwards, then downwards; or downwards, then upwards). Calculation of average BMI change between Exam 5 and 7 by trajectory (no change, healthful, unhealthful, mixed) reveals that although no group loses weight, those in the 'healthful' trajectory gain the least (0.56 kg m^{-2}, 2.37 s.d.). Those in the 'no change' trajectory gain 0.67 kg m^{-2} (2.4 s.d.); those in the 'mixed' trajectory gain 0.75 kg m^{-2} (2.22 s.d.); and those in the 'unhealthful'

Table 2 Transition probabilities of food patterns between exams

	Unhealthful→Healthful							
	M&S	S	A&S	L	C	O	H	Total
Unhealthful→Healthful								
Meat and Soda	52.3	8.3	6.6	8.5	4.8	9.3	10.3	100.0
Sweets	12.9	30.6	7.5	8.6	10.2	13.3	16.9	100.0
Alcohol and Snacks	8.4	3.9	61.1	3.6	3.0	4.2	15.7	100.0
Light	8.0	6.3	8.0	39.3	8.0	8.5	21.9	100.0
Caffeine-avoidant	8.4	8.1	6.5	9.7	43.9	7.4	16.1	100.0
Offsetting	10.6	7.3	6.3	6.5	9.1	44.5	15.8	100.0
Healthier	4.4	4.4	5.6	8.2	7.3	10.6	59.5	100.0
Total (%)	16.5	8.7	13.5	10.3	11.3	14.4	25.3	100.0

Abbreviations: M&S, meat and soda; S, sweets; A&S, alcohol and snacks; L, light; C, caffeine-avoidant; O, offsetting; H, healthier.

trajectory exhibit an average gain of $1.03 \, \mathrm{kg \, m^{-2}}$ (2.39 s.d.). To summarize, more people change food patterns than stay consistent. Of those individuals who change patterns during this 10-year period, most move in mixed directions. Of those who do change patterns between all three exams, a greater number move towards a healthful food pattern. Although all trajectories report weight gain over time, those in the 'healthful' trajectory gain the least.

Scrutiny of the 25 most common sequences offers a novel perspective on diet change (Table 3). Together, these sequences capture 49.4% ($n = 1205$) of individuals with diet information. Among consistent trajectories (no change), we observe weight gain in all sequences, with a notable exception that those who follow a 'light' pattern have 0.07-unit decrease in BMI. Among unhealthful and mixed-direction trajectories, all top sequences show weight gain, whereas among healthful eaters, those who transition from 'light' to 'healthier' have a 0.75-unit decrease in BMI. Consistency in 'healthier' eating is the most frequently observed sequence in this population. Among transitions in a mixed direction, the two most frequent (of 147 unique) mixed-direction sequences are those that vacillate between the 'offsetting' and 'healthier' pattern; namely, *OHO* and *HOH*. Among healthful transitions, the greatest numbers of people make transitions from 'offsetting to healthier' and 'sweets to healthier' patterns. Among downward transitions, there is most movement from 'healthier to offsetting', to 'light', and to 'caffeine-avoidant'. In examining gender differences in consistent food pattern sequences, women are most likely to adhere to 'healthier', 'light' and 'caffeine-avoidant' patterns. Men who eat consistently are most likely to adhere to 'meat and soda', 'alcohol and snacks' and 'sweets'. There is relative gender parity among those who adhere to the 'offsetting' food pattern.

Relationship between food trajectory and BMI
Multivariate regression models are used to evaluate a measure that indexes the direction of change (that is, healthful, unhealthful, mixed direction, no change). This

Table 3 Common food sequences (Exam 5→6→7)

Sequence	n	%Male	%Female	ΔBMI (s.d.)
No change, n = 7 types				
HHH	247	23.5	76.5	0.82 (2.87)
AAA	159	66.0	34.0	0.83 (2.10)
OOO	135	49.6	50.4	0.24 (2.05)
MMM	130	63.1	36.9	0.95 (2.51)
CCC	67	46.3	53.7	0.68 (1.91)
LLL	53	34.0	66.0	−0.07 (1.79)
SSS	32	65.6	34.4	0.67 (2.29)
Unhealthful (decline), n = 72 types				
HHO	30	36.7	63.3	1.38 (1.72)
HOO	26	42.3	57.7	0.64 (3.76)
HHL	19	15.8	84.2	1.42 (2.20)
HCC	15	40.0	60.0	0.72 (2.28)
OOM	15	60.0	40.0	0.30 (2.31)
Mixed direction, n = 148 types				
OHO	24	45.8	54.2	0.07 (1.70)
HOH	22	18.2	81.8	0.57 (2.41)
HCH	15	13.3	86.7	0.41 (1.91)
Healthful (improvement), n = 71 types				
OHH	34	30.4	69.6	0.58 (2.04)
SHH	24	29.2	70.8	1.03 (2.48)
OOH	23	26.5	73.5	0.38 (2.02)
MHH	22	22.7	77.3	1.03 (2.85)
CHH	22	22.7	77.3	0.64 (2.03)
MMO	19	63.2	36.8	1.45 (2.07)
LHH	19	15.8	84.2	−0.75 (4.42)
AAH	18	72.2	27.8	1.00 (1.53)
CCH	18	27.8	72.2	0.27 (3.23)
AHH	17	52.9	47.1	1.16 (2.27)

Abbreviations: A&S, alcohol and snacks; ΔBMI (s.d.) reports mean difference in body mass index, standard deviation; C, caffeine-avoidant; H, healthier; L, light; M&S, meat and soda; O, offsetting; S, sweets. There are 298 unique food sequences; only the 25 most frequent are reported.

'trajectory direction' measure is constructed using the set of observed 3-exam sequences (that is, *MAS, HHM, OCO … n = 298*), and then used to predict Exam 7 BMI and obesity status. In the first analysis, continuous BMI is estimated using ordinary least squares regression with robust standard

errors. Models omitted 11% of cases ($n = 270$) due to missing observations on education. After holding baseline BMI and food pattern constant, and controlling for demographic and socio-economic confounders, individuals with an unhealthful trajectory have a $0.42 \, \mathrm{kg \, m^{-2}}$ increase in BMI (Table 4). Relative to those who follow a 'meat and soda'

Table 4 Multivariate OLS regression of food pattern trajectory on BMI at Exam 7

	β	95% CI
Female	0.184*	(−0.030–0.398)
Age (years)	−0.0451***	(−0.055−−0.035)
Education (years)	0.00137	(−0.043–0.045)
Baseline BMI (Exam 5)	0.962***	(0.930–0.993)
Baseline food pattern (Exam 5)		
Meat and soda (reference)	–	–
Sweets	0.0052	(−0.367–0.378)
Alcohol and snacks	0.0343	(−0.314–0.382)
Light	−0.481**	(−0.875−−0.087)
Caffeine-avoidant	−0.111	(−0.493–0.271)
Offsetting	−0.337**	(−0.664−−0.009)
Healthier	−0.038	(−0.418–0.342)
Exam 5→6→7 food pattern trajectory		
Consistent (reference)	–	–
Healthful (upwards)	−0.111	(−0.382–0.160)
Unhealthful (downwards)	0.416***	(0.109–0.723)
Mixed movement	0.14	(−0.108–0.388)

Abbreviations: β, parameter estimate; BMI, body mass index; CI, confidence interval; OLS, ordinary least squares. ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$. $R^2 = 0.81$. Sample includes ($n = 2158$) individuals.

pattern at baseline, 'light' eaters tend to have a lower BMI. Although younger individuals tend to have slightly lower BMI, neither educational background nor gender is statistically significant; previous BMI strongly predicts subsequent BMI.

Categorical BMI status is estimated using a multiple logistic regression specification with robust standard errors (Table 5). When the overweight and obese are compared with normal-weight individuals, we observe that overweight individuals are 1.79 times more likely than normal-weight individuals to have an unhealthful diet trajectory, and obese are 2.4 times more likely. This model specification adds additional value by showing that obese individuals are 2.1 times more likely to be women than men, and that the obese are 2.2 times less likely (relative risk ratio = 0.45) to follow an 'offsetting' diet.

In a final set of sensitivity analyses, discrete diet transitions between the three exam cycles are used to assess subsequent weight status (Table 6). Because of collinearity with transitions between only two periods, baseline food pattern is omitted in both estimates. Model (a) reports that unhealthful transitions ('offsetting to 'caffeine-avoidant', 'healthier' to 'meat and soda') are associated with increased BMI, whereas healthful transitions ('light' to 'caffeine-avoidant', 'caffeine-avoidant' to 'healthier') are associated with decreased BMI. Turning to the next discrete transition (Model b), we observe that several transitions in an unhealthy direction ('light' to 'meat and soda', 'caffeine-avoidant' to 'alcohol and snacks', 'offsetting' to 'light') are associated with increased BMI. The finding that transitions in a healthful direction among the three least-healthy

Table 5 Multinomial logistic regression, food pattern trajectory on obesity status, Exam 7

	Overweight (BMI 25–30)		Obese (BMI > 30)	
	RRR	95% CI	RRR	95% CI
Female	1.217	(0.872–1.699)	2.106***	(1.334–3.324)
Age (years)	0.950***	(0.934–0.965)	0.919***	(0.899–0.941)
Education (years)	0.993	(0.924–1.067)	1.039	(0.943–1.145)
Baseline BMI (Exam 5)	2.668***	(2.394–2.973)	5.345***	(4.586–6.230)
Baseline Food Pattern (Exam 5)				
Meat and Soda (reference)	–	–	–	–
Sweets	0.965	(0.510–1.824)	1.387	(0.593–3.242)
Alcohol and Snacks	1.377	(0.812–2.335)	1.237	(0.588–2.602)
Light	0.962	(0.537–1.722)	0.544	(0.238–1.241)
Caffeine-avoidant	0.915	(0.503–1.663)	0.732	(0.332–1.615)
Offsetting	0.79	(0.464–1.347)	0.448**	(0.215–0.933)
Healthier	0.973	(0.567–1.670)	0.752	(0.352–1.608)
Exam 5→6→7 Food Pattern Trajectory				
Consistent (reference)	–	–	–	–
Healthful (upwards)	1.092	(0.716–1.667)	0.848	(0.466–1.542)
Unhealthful (downwards)	1.787**	(1.133–2.817)	2.401***	(1.298–4.442)
Mixed movement	1.491**	(1.015–2.188)	1.687*	(0.996–2.856)

Abbreviations: BMI, body mass index; CI, confidence interval; RRR, relative risk ratio. ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$. Outcome categories are estimated relative to 'normal' weight (that is, BMI < 25). Sample includes ($n = 2158$) individuals.

Table 6 Multivariate regression of discrete food pattern transitions on BMI status

	(a) Exam 5 → Exam 6		(b) Exam 6 → Exam 7	
	β	95% CI	β	95% CI
Female	0.147*	(−0.013–0.307)	0.006	(−0.148–0.160)
Age (years)	−0.0345***	(−0.043– −0.027)	−0.014***	(−0.022– −0.007)
Education (years)	−0.0104	(−0.043–0.023)	0.007	(−0.024–0.038)
Baseline BMI	0.972***	(0.949–0.995)	0.969***	(0.948–0.990)
Transition type				
(Exam 5 → Exam 6)				
Meat and Soda → Meat and Soda	(reference category)			
Light → Caffeine-avoidant (H)	−0.721**	(−1.388– −0.055)		
Caffeine-avoidant → Healthier (H)	−0.751**	(−1.421– −0.082)		
Offsetting → Caffeine-avoidant (U)	0.889***	(0.281–1.497)		
Healthier → Meat and Soda (U)	1.364**	(0.266–2.462)		
(Exam 6 → Exam 7)				
Meat and Soda → Meat and Soda			(reference category)	
Meat and Soda → Sweets (H)			0.742***	(0.217–1.267)
Sweets → Alcohol and Snacks (H)			1.124**	(0.067–2.181)
Light → Meat and Soda (U)			2.178***	(0.813–3.542)
Caffeine-avoidant → Alcohol and Snacks (U)			1.165***	(0.420–1.909)
Offsetting → Light (U)			0.564**	(0.013–1.116)
	n = 2477		n = 2318	
	$R^2 = 0.87$		$R^2 = 0.90$	

Abbreviations: β, parameter estimate; BMI, body mass index; CI, confidence interval; H, healthful transition; U, unhealthful transition. ***$P < 0.01$; **$P < 0.05$; *$P < 0.1$. Non-significant transitions omitted for table readability.

patterns are associated with increased BMI is somewhat unexpected. However, the finding that both healthful and unhealthful movement toward 'alcohol and snacks' is associated with increased BMI is notable. Taken together, examination of both sets of discrete transitions help to better explain the relationship between diet trajectory and BMI.

Discussion

A set of seven empirically derived food patterns from an adult population was used to demonstrate the value of sequence analysis to assess the relationship between changes in food choice and health status during a 10-year period. The frequency of change between individuals' patterns of choice during three exam measurements was examined, and the types of diet trajectories were used as predictors of weight status. Although on average, no trajectory (healthful, unhealthful, mixed, no change) was linked with weight loss, those in the healthful trajectory showed the least weight gain. After controlling for potential confounders (sex, age, baseline BMI, baseline food pattern), support was found for the hypothesis that a decline in the relative healthfulness of food patterns would predict greater BMI and higher like-lihood of obesity. In addition, discrete diet transitions were identified that helped to explain changes in BMI. There is no known research that analyzes repeated food intake measurements using a sequence-analytic framework of this type to describe how individuals' food choices change over time, nor

work that attempts to link these transitions in food pattern to weight status.

One key finding involves the nature of consistency and change in how individuals shift eating patterns during a relatively short (10-year) period. Examination of frequent patterns shows that twice the proportion of people change what they eat as remain consistent. This is somewhat surprising, given that diet changes observed in this study occurred during a later phase of the participant's life course, when conventional wisdom leads us to expect food choices are relatively stable. Although a substantial body of research tends to focus upon drastic diet changes in the earlier-life transition from single to married life,[31,32] we also know that significant events within the marital sphere (that is, spousal mortality, divorce) can have adverse effects on eating.[32,33] This suggests benefit in further research that can address diet change over the life course with attention to important life transitions.

The results from the current study also harmonize with previous research in the Swedish Mammography Cohort that linked changes over time in food patterns to BMI change.[8] In the latter study, changes in women's diet between 1987 and 1997 (two time points) were analyzed; the effects of longitudinal diet change were most drastic in obese women. The present findings—that obese individuals in the Framingham Heart Study are more likely to have an unhealthful diet trajectory, and more likely to be women—are notable because the cohort includes both men and women, and the study was conducted using very different methods capturing three time points.

Sensitivity analyses showed that certain diet transitions were more likely than others to lead to weight change. A change from a 'caffeine-avoidant' to a 'healthier' pattern was associated with weight loss of $\sim 0.75\,kg\,m^{-2}$. Interestingly, however, a shift from 'light' to 'caffeine-avoidant' has nearly as much of an effect. One possible interpretation is that although a leap from a 'light' to 'healthier' diet may not be feasible for many individuals, incremental change from 'light' to 'caffeine-avoidant', and 'caffeine-avoidant' to 'healthier' has measurable returns to weight loss.

An unexpected finding was that some transitions in a relatively healthful direction ('meat and soda' to 'sweets' and 'sweets' to 'alcohol and snacks') were associated with weight gain. Considering that these three patterns were the lowest in objective diet health (DGAI score), it may be that diet change that falls short of a certain threshold is less effective. Further investigation of why people follow the eating patterns they do would help us to understand these discrete effects with more depth. Because of the dynamic nature of individual choice, it may be that some people ate poorly at earlier points in time and gained weight, which spurred their decision to more closely monitor diet and eat more healthfully at a later point in time. The present study design does not control for reverse causation of this type. Several aspects of the current study differ from some previous work. Although some research has excluded alcohol from the list of foods to be clustered,[13,24] this study includes alcohol consumption because of the belief that it closely reflects reality. The decision not to stratify the cohort by sex before clustering foods or people allows for the assessment of similarities in eating patterns between men and women, and how these similarities change over time.

As physicians attest, changing a patient's overall diet behavior is a difficult prospect, and previous research has shown that only one quarter of family physicians actively counsel patients on nutrition.[34] Moreover, the effectiveness of counseling can vary by style; recently, motivational interviewing has been associated with better nutrition-related health outcomes.[35,36] Still, it is debated how large of a diet change may be effective for weight loss in different types of patients. The findings in this study help to provide guidance in the area of behavior change, especially insofar as they concern the likelihood of dietary modification in an older patient population. The observation that a given patient is on a diet trajectory with a statistically significant chance of weight gain or loss can give clinicians greater confidence about the conditions under which a particular intervention may be of benefit. In conclusion, considering dietary habits as an evolving trajectory (rather than a fixed entity) helps to demonstrate how change in one health behavior is empirically associated with change in a marker of health status.

Conflict of interest

The author declares no conflict of interest.

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