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Food pattern analysis over time: Unhealthful eating trajectories predict obesity

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Abstract

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, nor the relation between these changes and 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 3 418 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. OLS regression models with robust standard errors adjusted for socioeconomic and demographic confounders, baseline BMI, and baseline eating.

Results—66.2% (n=1 614) 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 (CI: 0.1, 0.7). Those with an unhealthful trajectory are 1.79 times more likely to be overweight (RRR, 95% CI: 1.1, 2.8), and 2.4 times more likely to be obese (RRR, 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. While 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.

CONFLICT OF INTEREST
There are no conflicts of interest.

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Keywords

obesity; diet change; sequence analysis; diet patterns; population health; social behavior

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 clustering or factor analysis 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 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 (NHANES)[12]; the Framingham Heart Study (FHS)[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 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. While most medical professionals would welcome a change in patient 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 (FHS), 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 FHS physicians provide longitudinal data. The Offspring study enrolled 5 124 individuals at inception; by exam cycle 5 (1991–95), 75% (N=3 799) 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, approximately 90% (n=3 418) completed a semi-quantitative food frequency questionnaire (FFQ) at Exam 5. At Exam 6 (1996–98), 89% (n=3 143) of the available cohort completed a FFQ, and 86% (n=3 030) completed an Exam 7 (1998–2001) FFQ. This study is concerned with those who completed a FFQ at all three exam cycles (n=2 437), 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 less than 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 $A_{Exam5}B_{Exam6}$ 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 (i.e. ‘healthful’, ‘unhealthful’, ‘mixed direction’, ‘no change’).

Because food consumption is known to vary by demographic attributes and socioeconomic 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 factor (FA) or cluster analysis (CA) are commonly applied to data gathered by FFQ to describe a population. While 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 food frequency questionnaire data. Yet as a recent review finds, 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 factor analysis 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 factor and cluster analysis. 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 (i.e. *Food Pattern* $A_{Exam5} \rightarrow B_{Exam6} \rightarrow C_{Exam7}$ = Sequence *ABC*) in order to tabulate frequency of trajectories. While 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 factor analysis); 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 prior research has ranged from 15% to 93%[23]. In a third stage, the set of factor scores are used as input variables in a cluster analysis. Here, people are clustered (using a k-means algorithm) into seven non-overlapping groups according to individuals' 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 & soda,' 'sweets,' 'alcohol & 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 & 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 & snacks' (61.1% are likely to remain), 'healthier' (59.5%), and 'meat & 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 transition to a 'healthier' pattern over all others.

Next, a sequence analysis enables identification of individuals who change patterns during all three exam cycles, and allows for classification of the kind and frequency 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 SD) for 'meat & soda' to a score of 11.95 (1.93 SD) for those in the 'healthier' group.

Given the permutation of possible food pattern sequences, there are 7 ways to remain consistently within the same food pattern (i.e. 'sweets, sweets, sweets'). In this sample, individuals improve diet health in 71 different ways (for instance: 'meat & soda,' to 'light,' then 'healthier'); in mixed directions in 147 ways (i.e. 'healthier,' 'light,' 'offsetting'); and decline in 72 ways (i.e. 'healthier,' 'alcohol & snacks,' 'meat & soda'). Tabulation of trajectory direction frequencies suggests that there is significantly more change over time in the food patterns consumed during this ten-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 & soda' to 'sweets' to 'offsetting' moves in a healthful direction; 23.4% (n=570) change in this manner. An individual who changes from 'caffeine-avoidant' to 'alcohol & snacks' to 'meat & soda' is considered to move in a less healthful direction; 17.5% (n=426) 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 while no group loses weight, those in the 'healthful' trajectory gain the least (0.56 kg/m^2, 2.37 SD). Those in the 'no change' trajectory gain 0.67 kg/m^2 (2.4 SD); those in the 'mixed' trajectory gain 0.75 kg/m^2 (2.22 SD); and those in the 'unhealthful' trajectory on average gain 1.03 kg/m^2 (2.39 SD). To summarize, more people change food patterns than stay consistent. Of those individuals who change patterns during this ten-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. While 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, while 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 & soda', 'alcohol & 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 (i.e. healthful, unhealthful, mixed direction, no change). This 'trajectory direction' measure is constructed using the set of observed 3-exam sequences (i.e. *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 socioeconomic confounders, individuals with an unhealthful trajectory have a 0.42 kg/m^2 increase in BMI (Table 4). Relative to those who follow a 'meat & soda' pattern at baseline, 'light' eaters tend to have a lower BMI. While younger individuals tend to have slightly lower BMI, neither educational background nor gender is statistically significant; prior 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 to 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 (RRR=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). Due to 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, while 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 & soda', 'caffeine-avoidant' to 'alcohol & snacks', 'offsetting' to 'light') are associated with increased BMI. The finding that transitions in a healthful direction among the three least-healthy 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 ten-year period. The frequency of change between individuals’ patterns of choice during three exam measurements was examined, and the types of diet trajectories used as predictors of weight status. While 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 likelihood 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 participants’ life course, when conventional wisdom leads us to expect food choices are relatively stable. While 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 (i.e. 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 prior research in the Swedish Mammography Cohort (SMC) which 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 FHS 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 approximately 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 while a leap from a ‘light’ to ‘healthier’ diet may not be feasible for many individuals, incremental change from 'light' to 'caffeine-avoidant', 'caffeine-avoidant' to 'healthier' has measurable returns to weight loss.

An unexpected finding was that some transitions in a relatively healthful direction ('meat & soda' to 'sweets' and 'sweets' to 'alcohol & 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 prior work. While 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 closer reflects reality. The decision not to stratify the cohort by sex prior to 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.

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Table 1

Food Groups That Characterize Eating Patterns

"Meat & Soda"	"Sweets"	"Alcohol & Snacks"	"Light"		"Caffeine-avoidant"	"Offsetting"	"Healthier"
n=1494	n=811	n=1298	n=915		n=1093	n=1631	n=2349
DGAI=7.29 (2.11 SD)	DGAI=8.03 (2.27 SD)	DGAI=8.31 (2.24)	DGAI=8.36 (1.89)		DGAI=9.41 (2.41)	DGAI=9.67 (2.28)	DGAI=11.95 (1.94)
Highest in:	Highest in:	Highest in:	Highest in: N/A		Highest in:	Highest in:	Highest in:
Sweet caf bevs	Refined grains	Beer				Non-fat dairy bevs	Vit-A Rich Veg
Non-cal caff bevs	High-fat dry/chse	Wine	Lowest in:		Sweet decaf bevs	High-fat health fds	Vit-C Rich Veg
High-fat dairy bevs	Low-fat dairy prod	Liquor			Non-cal decaf bevs	Whole Grains	Hi-fiber Veg
Butter/cream	Soup	Salty/fatty snacks	Vit-A Rich Veg	Refind grains	Low-fat health food	Refined grains	Other veg
Hi-fat meat	High-fat sweets	Shellfish	Vit-C Rich Veg	Soft veg fats		Soft veg fats	Vit-C Rich fruits
Low-fat meat	Low-fat desserts		Hi-fiber Veg	High-fat dry/chse		Low-fat sweets	High-fat fruits
Mixed proteins	High-fat desserts		Other veg	Low-fat sweets		Snacks, salty/fatty	Other fruits
High-fat poultry			High-fat fruits	Salty/fatty snacks			Low-fat poultry
Eggs			Other fruits	Mixed proteins			Fish
			High-fat health fds	Legumes			Legumes
Lowest in:	Lowest in: N/A	Lowest in: N/A	Low-fat health food	Eggs	Lowest in:	Lowest in:	
Non-cal decaf bevs			Whole Grains		Non-cal caff bevs	High-fat poultry	Lowest in:
							Beer
							Hi-fat meat

Abbreviations: DGAI, Dietary Guidelines Adherence Index score. Summary statistics reported on pooled measurements across exams 5-7. The seven eating patterns are described here by listing outlying food groups within each patten. Two of the patterns ('sweets', 'alcohol & snacks') did not contain low-consumption food groups relative to the other 5 patterns; these are denoted with 'n/a' for 'not applicable'. Similarly, the 'light' eating pattern did not contain any food groups which were extraordinarily high relative to the other patterns

Table 2

Transition Probabilities of Food Patterns Between Exams

		Unhealthful → Healthful							
		M&S	**S**	**A&S**	**L**	**C**	**O**	**H**	**Total**
Unhealthful	Meat & 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 & 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
Healthful	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

Table 3

Common Food Sequences (Exam 5 → 6 → 7)

No change, n=7 types				
seq.	**n=**	**%M**	**%F**	**Δ BMI (SD)**
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				
seq.	**n=**	**%M**	**%F**	**Δ BMI (SD)**
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				
seq.	**n=**	**%M**	**%F**	**Δ BMI (SD)**
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				
seq.	**n=**	**%M**	**%F**	**Δ BMI (SD)**
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: Δ BMI (SD) reports mean difference in body mass index, standard deviation; M, meat & soda; S, sweets; A, alcohol & snacks; L, light; C, caffeine-avoidant; O, offsetting; H, healthier. There are 298 unique food sequences; only the 25 most frequent are reported.

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 & soda (reference)	-	-
Sweets	0.0052	(−0.367 – 0.378)
Alcohol & 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; CI, confidence interval; BMI, body mass index. Sample includes (n=2 158) individuals.

*** $p<0.01$,

** $p<0.05$,

* $p<0.1$. $R^2=0.81$

Table 5

Multinomial Logistic Regression of Food Pattern Trajectory on Obesity Status at 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 & soda (reference)	-	-	-	-
Sweets	0.965	(0.510 – 1.824)	1.387	(0.593 – 3.242)
Alcohol & 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)
Unhealthul (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: RRR, relative risk ratio; CI, confidence interval; BMI, body mass index. Sample includes (n=2 158) individuals.

*** p<0.01,

** p<0.05,

* p<0.1. Outcome categories are estimated relative to ‘normal’ weight (i.e. BMI<25).

Table 6

Multivariate Regression of Discrete Food Pattern Transitions on BMI

	(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 & Soda → Meat & Soda	(ref. category)			
Light → Caf.Avoid (H)	−0.721**	(−1.388 – −0.055)		
Caf.Avoid → Healthier (H)	−0.751**	(−1.421 – −0.082)		
Offsetting → Caf.Avoid (U)	0.889***	(0.281 – 1.497)		
Healthier → Meat & Soda (U)	1.364**	(0.266 – 2.462)		
(Exam 6 → Exam 7)				
Meat & Soda → Meat & Soda			(ref. category)	
Meat & Soda → Sweets (H)			0.742***	(0.217 – 1.267)
Sweets → Alcohol & Snacks (H)			1.124**	(0.067 – 2.181)
Light → Meat & Soda (U)			2.178***	(0.813 – 3.542)
Caf.Avoid → Alcohol & Snacks (U)			1.165***	(0.420 – 1.909)
Offsetting → Light (U)			0.564**	(0.013 – 1.116)
	n = 2 477		n = 2 318	
	$R^2 = 0.87$		$R^2 = 0.90$	

Abbreviations: β, parameter estimate; CI, confidence interval; BMI, body mass index; H, healhtful transition; U, unhealthful transition.

*** p<0.01,

** p<0.05,

* p<0.1. Non-significant transitions omitted for table readability.