Joint temporal dietary and physical activity patterns: associations with health status indicators and chronic diseases

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ABSTRACT

Background: Diet and physical activity (PA) are independent risk factors for obesity and chronic diseases including type 2 diabetes mellitus (T2DM) and metabolic syndrome (MetS). The temporal sequence of these exposures may be used to create patterns with relations to health status indicators.

Objectives: The objectives were to create clusters of joint temporal dietary and PA patterns (JTDPAPs) and to determine their association with health status indicators including BMI, waist circumference (WC), fasting plasma glucose, glycated hemoglobin, triglycerides, HDL cholesterol, total cholesterol, blood pressure, and disease status including obesity, T2DM, and MetS in US adults.

Methods: A 24-h dietary recall and random day of accelerometer data of 1836 participants from the cross-sectional NHANES 2003–2006 data were used to create JTDPAP clusters by constrained dynamic time warping, coupled with a kernel k-means clustering algorithm. Multivariate regression models determined associations between the 4 JTDPAP clusters and health and disease status indicators, controlling for potential confounders and adjusting for multiple comparisons.

Results: A JTDPAP cluster with proportionally equivalent energy consumed at 2 main eating occasions reaching ≤1600 and ≤2200 kcal from 11:00 to 13:00 and from 17:00 to 20:00, respectively, and the highest PA counts among 4 clusters from 08:00 to 20:00, was associated with significantly lower BMI ($P < 0.0001$), WC ($P = 0.0001$), total cholesterol ($P = 0.02$), and odds of obesity (OR: 0.2; 95% CI: 0.1, 0.5) than a JTDPAP cluster with proportionally equivalent energy consumed reaching ≤1600 and ≤1800 kcal from 11:00 to 14:00 and from 17:00 to 21:00, respectively, and high PA counts from 09:00 to 12:00.

Conclusions: The joint temporally patterned sequence of diet and PA can be used to cluster individuals with meaningful associations to BMI, WC, total cholesterol, and obesity. Temporal patterns hold promise for future development of lifestyle patterns that integrate additional temporal and contextual activities. *Am J Clin Nutr* 2022;115:456–470.

Keywords: temporal pattern, dietary patterns, physical activity patterns, obesity, BMI, waist circumference, adults, chrono-nutrition

Introduction

Diet (1) and physical activity (PA) (2) are modifiable risk factors when it comes to health. Both dietary and PA behaviors are expected to be interrelated, with potential synergistic effects on health status indicators (3–5). A systematic review to investigate the effect of the interaction of time, eating, and exercising on health showed that postmeal exercise may have a potential benefit on postprandial glycemic response compared with premeal exercise (5). This study demonstrated that the timing of diet and PA and their relation to each other in a day are related to health indicators and hold promise for the discovery of their joint patterns of activity and these patterns' links to health.

Both dietary and PA behaviors occur in a temporal context or "temporal pattern" including daily rhythms that begin and end throughout a day (6). Previous work to derive clusters representing 4 distinct temporal dietary patterns in a representative US sample showed that participants with energy-equivalent and evenly distributed eating occasions throughout a day had higher diet quality (7), lower mean BMI and odds of obesity, and smaller

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Supplemental Figure 1 and Supplemental Tables 1–19 are available from the "Supplementary data" link in the online posting of the article and from the same link in the online table of contents at https://academic.oup.com/ajcn/.

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Abbreviations used: CDTW, constrained band dynamic time warping; $CDTW_D$, dependent multivariate constrained band dynamic time warping; $CDTW_I$, independent multivariate constrained band dynamic time warping; DBHCA, density balanced hierarchical cluster agglomeration; DTW, dynamic time warping; EER, estimated energy requirement; EI, energy intake; FNDDS, Food and Nutrient Database for Dietary Studies; HbA1c, glycated hemoglobin; JTDPAP, joint temporal dietary and physical activity pattern; MetS, metabolic syndrome; NCHS, National Center for Health Statistics; PA, physical activity; PAC, physical activity count; PIR, poverty to income ratio; T2DM, type 2 diabetes mellitus; WC, waist circumference.

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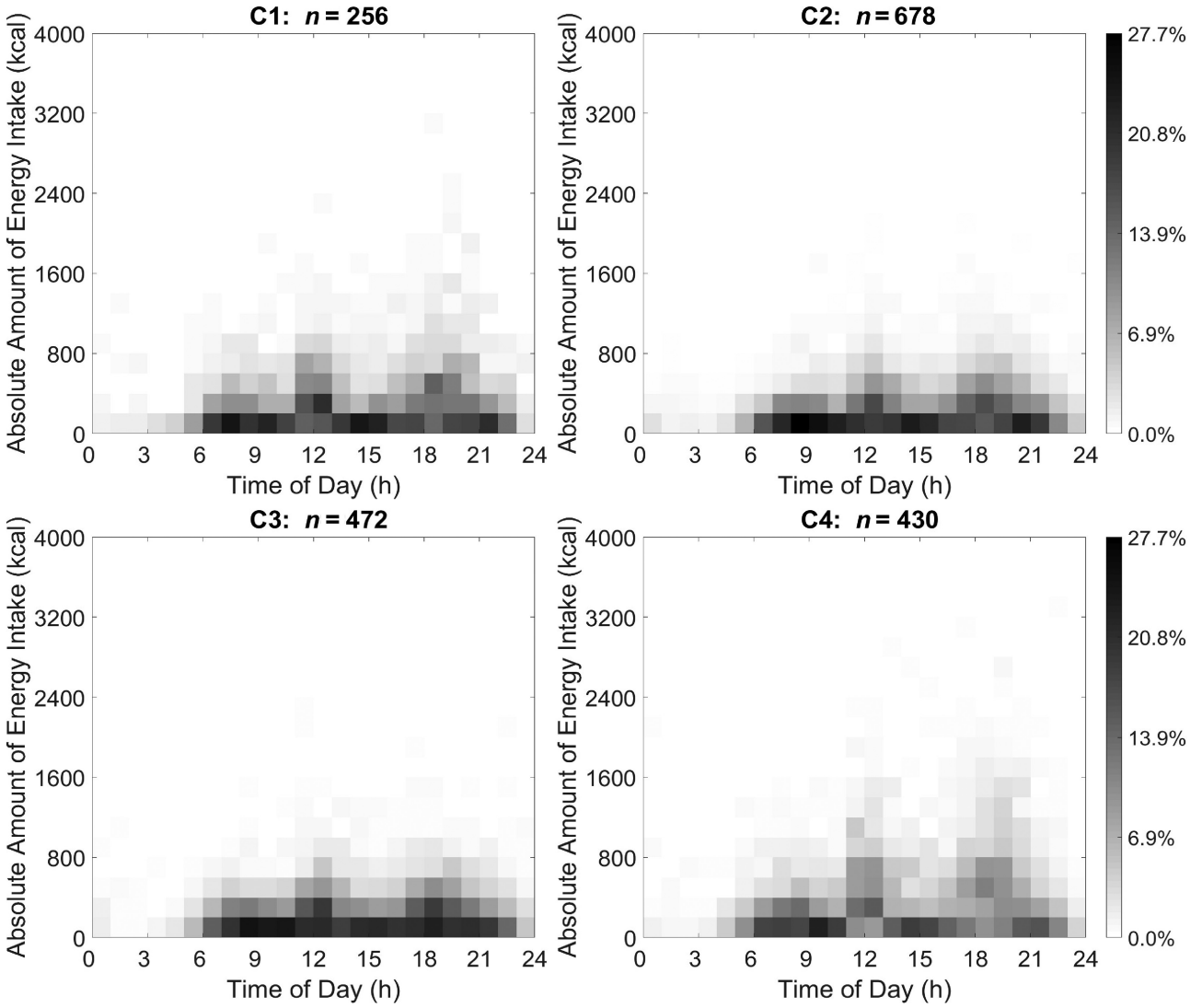

FIGURE 1 EI heat maps representing 4 distinct JTDPAPs for US adults aged 20–65 y drawn from NHANES 2003–2006 (C1: $n = 256$; C2: $n = 678$; C3: $n = 472$; C4: $n = 430$). Distribution of 1836 participants' EI in 4 JTDPAP clusters generated through the dependent constrained band dynamic time warping method is shown. The absolute EI ranging from 0 to 4000 kcal (*y* axis) ranging from 00:00 to 24:00 at the hourly level (*x* axis) for nonpregnant US adults aged 20–65 y as drawn from NHANES 2003–2006 is depicted. The proportion of participants in each of 4 JTDPAP clusters reporting EI is represented through shading ranging from 0.0% to 27.7% of participants. Darker shading represents a greater percentage of participants in the cluster reporting the same amount of EI at that time. C1, Cluster 1; C2, Cluster 2; C3, Cluster 3; C4, Cluster 4; EI, energy intake; JTDPAP, joint temporal dietary and physical activity pattern.

waist circumference (WC) (8) than those with other temporal dietary patterns exhibiting 1 energy intake (EI) peak sometime in a day. Similarly, novel work integrating PA and corresponding timing throughout the day generated "temporal PA patterns." Findings showed that those with the lowest PA counts (PACs) from 06:00 to 23:00 had significantly higher mean BMI and larger mean WC than those with higher PACs at either an early time (08:00–11:00) or later time (16:00–21:00) of the day (9).

Yet, the combination of the timing of both dietary EI and PA throughout a 24-h day simultaneously and investigation of their joint relation with health status indicators are not known. To fill this gap, this study describes the creation of "joint temporal dietary and PA patterns" (JTDPAPs), or the chronological succession of energy from dietary intake and varying PACs over time. Therefore, study objectives were to *1*) create clusters of JTDPAPs using modern data-driven distance-based clustering algorithms, and *2*) investigate the association between JTDPAP clusters and primary health status indicators including BMI, WC, and odds of being obese, as well as secondary health status indicators including fasting plasma glucose, glycated hemoglobin (HbA1c), triglycerides, HDL cholesterol, total cholesterol, blood pressure, and disease status including T2DM and MetS, among US adults. JTDPAPs are hypothesized to be linked with health status indicators and disease status among US adults aged 20–65 y using NHANES 2003–2006.

Methods

Participants and data set

NHANES is a cross-sectional survey that is carried out by the National Center for Health Statistics (NCHS) of the US CDC to assess the US noninstitutionalized civilian population's

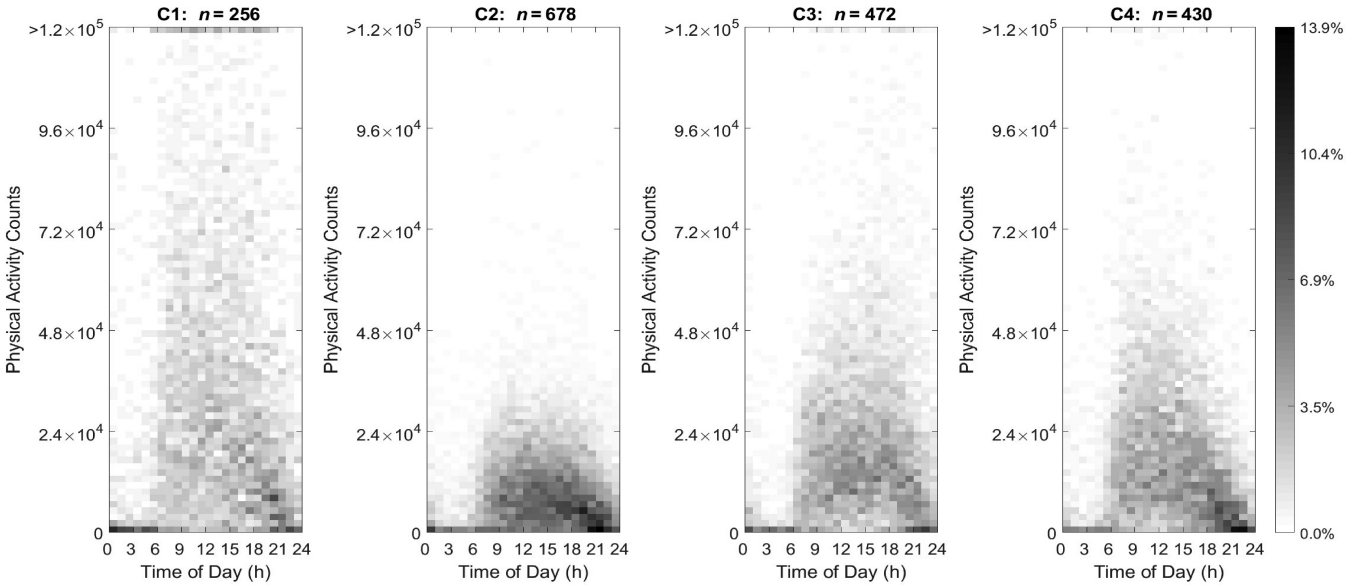

FIGURE 2 PA heat maps representing 4 distinct JTDPAPs for US adults aged 20–65 y drawn from NHANES 2003–2006 (C1: $n = 256$; C2: $n = 678$; C3: $n = 472$; C4: $n = 430$). Distribution of PA of 4 JTDPAP clusters generated through the dependent constrained band dynamic time warping method is shown. PACs ranging from 0 cph to 1.2×10^5 cph (y axis, truncated) ranging from 00:00 to 24:00 (x axis) for US adults aged 20–65 y as drawn from NHANES 2003–2006 are depicted. The proportion of participants in each of 4 JTDPAP clusters reporting PA is represented through shading ranging from 0.0% to 13.9% of participants. Darker shading represents a greater percentage of participants in the cluster reporting the same number of PACs at that time. cph, counts per hour; C1, Cluster 1; C2, Cluster 2; C3, Cluster 3; C4, Cluster 4; JTDPAP, joint temporal dietary and physical activity pattern; PA, physical activity; PAC, physical activity count.

health and nutritional status. The participants of NHANES are selected using a complex, multistage sampling design. Selected participants undergo an in-person household interview, a physical health examination, and a phone follow-up interview. Participants' sociodemographic information was collected during the in-person household interview, which included age, sex, race/ethnicity, and poverty to income ratio (PIR), using questionnaires. All participants consented to completing the survey approved by the NCHS Research Ethics Review Board (10).

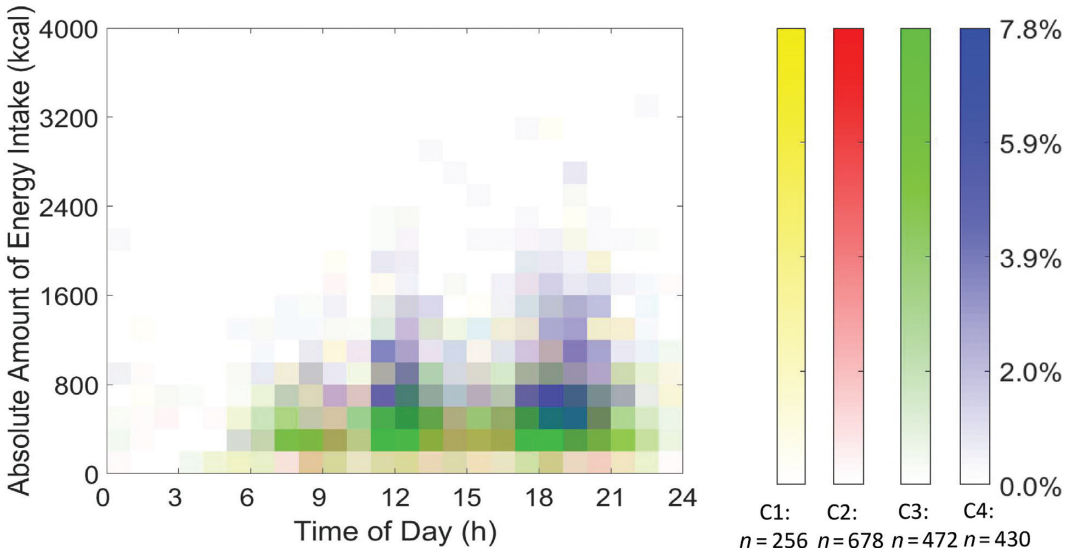

FIGURE 3 The largest EI heat maps representing 4 distinct JTDPAPs for US adults aged 20–65 y drawn from NHANES 2003–2006. Heat maps (distribution) of the highest EI of 1836 participants in 4 JTDPAP clusters (C1: $n = 256$; C2: $n = 678$; C3: $n = 472$; C4: $n = 430$). The clusters were generated through the dependent constrained band dynamic time warping method for nonpregnant US adults aged 20–65 y as drawn from NHANES 2003–2006. The absolute EI (blocks in heat map) is characterized by amount (y axis: ranging from 0 to 4000 kcal) ranging from 00:00 to 24:00 at the hourly level (x axis). The shading of blocks (ranging from 0.0% to 7.8%) represents the proportion of participants in each cluster whose highest EI is characterized by the corresponding amount and timing. Darker shading represents a greater percentage of participants in the cluster reporting the same amount of EI at that time. C1, Cluster 1; C2, Cluster 2; C3, Cluster 3; C4, Cluster 4; EI, energy intake; JTDPAP, joint temporal dietary and physical activity pattern.

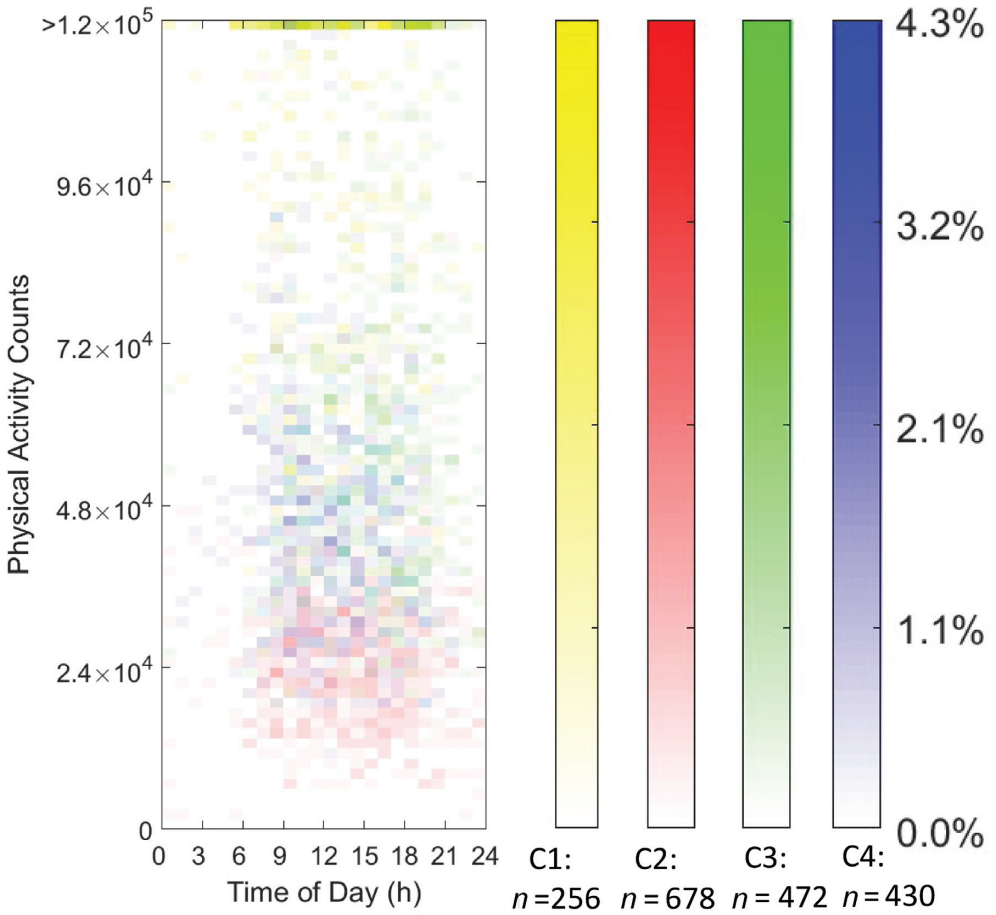

FIGURE 4 The largest PA heat maps representing 4 distinct JTDPAPs for US adults aged 20–65 y drawn from NHANES 2003–2006. Heat maps (distribution) of the highest PA of participants in 4 JTDPAP clusters (C1: $n = 256$; C2: $n = 678$; C3: $n = 472$; C4: $n = 430$). The clusters were generated through the dependent constrained band dynamic time warping method for US adults aged 20–65 y as drawn from NHANES 2003–2006. The PA (blocks in heat map) is characterized by counts (y axis: ranging from 0 cph to 1.2×10^5 cph, truncated) ranging from 00:00 to 24:00 at the hourly level (x axis). The shading of blocks (ranging from 0.0% to 13.9%) represents the proportion of participants in each cluster whose highest PAC is characterized by the corresponding amount and timing. Darker shading represents a greater percentage of participants in the cluster reporting the same number of PACs at that time. cph, counts per hour; C1, Cluster 1; C2, Cluster 2; C3, Cluster 3; C4, Cluster 4; JTDPAP, joint temporal dietary and physical activity pattern; PA, physical activity; PAC, physical activity count.

Analytic sample

NHANES 2003–2006 was used owing to the availability of hip-worn PA accelerometer data. The analytic sample only included nonpregnant US adults ages 20–65 y with ≥1 reliable 24-h weekday dietary recall and 1 valid weekday accelerometer record. The temporal dietary and PA behaviors of pregnant women and participants outside of the age range are expected to entail unique life stage patterns and were excluded. Participants with missing sociodemographic, anthropometric, and health status indicator data were also excluded. Therefore, the study sample included 1836 participants (**Supplemental Figure 1**).

Dietary data assessment

The USDA Automated Multiple-Pass Method was used to collect 2 dietary recalls (11) detailing all the foods that participants reported consuming during a 24-h period, including information on the time of intake, amount, and type of each food, and detailed food descriptions (12). One valid dietary 24-h recall that met the minimum criteria in NHANES (12) with nonzero EI was used in this study. Previous research has found that weekdays and weekend days of dietary intake can differ (13). For this first attempt to generate JTDPAPs, weekday dietary recalls were chosen to maintain the largest possible sample; the first recall was used if it was for a weekday, otherwise, the second weekday recall was used. Each participant's EI for all reported foods and beverages was determined using the USDA Food and Nutrient Database for Dietary Studies (FNDDS) for 2003–2004 data (USDA FNDDS, version 2.0) and 2005–2006 data (USDA FNDDS, version 3.0). The duration time of the eating occasions was not available in NHANES, but 15 min/occasion was applied based on a previous study (14) so that energy reported at a time of eating was divided by 15 min to determine the energy per minute and applied to each minute within the 15-min eating occasion. Dietary data from the chosen valid weekday recall were also used to determine total EI over the entire day.

TABLE 1 Characteristics of clusters representing joint temporal dietary and physical activity patterns of US adults aged 20–65 y as drawn from the NHANES, 2003–2006[1]

Characteristics	Total, *n*	Cluster 1	Cluster 2	Cluster 3	Cluster 4	*P* value[2]
Total	1836	256 (14.0)	678 (36.9)	472 (25.7)	430 (23.4)	
Survey year						0.19
2003–2004	895 (49.3)	131 (54.0)	338 (51.2)	222 (45.5)	204 (48.0)	
2005–2006	941 (50.7)	125 (46.0)	340 (48.8)	250 (54.5)	226 (52.0)	
Sex						<0.0001*
Male	933 (49.5)	197 (73.4)	226 (32.0)	202 (39.8)	308 (70.3)	
Female	903 (50.5)	59 (26.6)	452 (68.0)	270 (60.2)	122 (29.7)	
Race/ethnicity						0.09
Mexican American	389 (8.4)	54 (10.0)	142 (7.6)	107 (8.9)	86 (8.1)	
Other Hispanic	57 (3.2)	11 (4.5)	16 (2.6)	18 (3.9)	12 (2.6)	
Non-Hispanic white	910 (71.5)	127 (71.0)	325 (69.3)	229 (71.7)	229 (74.5)	
Non-Hispanic black	385 (10.5)	56 (11.3)	149 (11.4)	96 (10.0)	84 (9.4)	
Other	95 (6.4)	8 (3.2)	46 (9.1)	22 (5.5)	19 (5.4)	
Age group, y						<0.0001*
20–34	560 (29.4)	122 (44.9)	138 (20.0)	162 (32.5)	138 (29.8)	
35–49	623 (38.2)	93 (37.2)	193 (34.8)	173 (40.1)	164 (41.4)	
50–65	653 (32.4)	41 (18.0)	347 (45.2)	137 (27.3)	128 (28.8)	
Household PIR						0.007*
0–0.99	288 (9.9)	39 (10.5)	136 (13.2)	57 (7.2)	56 (7.8)	
1.00–2.99	427 (18.0)	62 (19.3)	161 (20.4)	116 (17.2)	88 (14.6)	
2.00–2.99	280 (15.9)	40 (17.6)	111 (16.0)	73 (16.9)	56 (13.4)	
3.00–3.99	277 (17.1)	39 (14.3)	94 (17.3)	79 (18.7)	65 (16.9)	
4.00–4.99	168 (11.1)	24 (11.0)	50 (9.1)	39 (9.8)	55 (15.3)	
≥5.00	396 (28.1)	52 (27.3)	126 (24.0)	108 (30.2)	110 (31.9)	
BMI[3]						<0.0001*
Underweight	24 (1.6)	4 (2.2)	10 (1.7)	6 (1.3)	4 (1.5)	
Normal weight	519 (31.1)	103 (43.1)	164 (28.0)	146 (34.4)	106 (24.7)	
Overweight	630 (33.5)	94 (36.9)	205 (28.4)	181 (37.3)	150 (34.5)	
Obese	663 (33.8)	55 (17.8)	299 (41.8)	139 (27.0)	170 (39.4)	

[1] Values are unweighted sample sizes and weighted percentages except for the total cluster size percentage. The percentages may not add up to 100% owing to rounding. *Significant difference: $P < 0.05$. PIR, poverty to income ratio.

[2] Rao–Scott F adjusted χ^2 test is a goodness-of-fit, 1-sided test. Analyses were adjusted for aspects of survey design including stratification, clustering, and weight.

[3] BMI: categories were classified based on the WHO (95).

PA assessment

PA accelerometers were used to quantify the PA of each participant. The accelerometers recorded vertical accelerations as "counts per minute," which represent the relative intensity of movements per minute (15), for 7 consecutive days after the health examination (16). Use of the accelerometer for >10 h/d was considered as a valid wear day (17). Previous research has determined that PA on weekdays or weekend days can differ (18). One random valid weekday was selected for each participant to ensure the selection probabilities for each weekday were equal (19). The random valid weekday of accelerometer data was also used to determine total PACs for the entire 24-h day. Because there is no gold standard to identify intensity levels and different cutoffs influenced estimates of PA intensity level, and specificity and sensitivity regarding health indicators (20, 21), the possible bias can be decreased by utilizing raw PACs, as in this study, rather than cutoffs or categorized intensity levels.

Anthropometric assessment and laboratory tests

Health status indicators were included to study their associations with JTDPAPs. Height, weight, and WC were measured (22), and BMI was calculated. Blood samples of participants were obtained based on standardized protocols (23, 24). After 8.5–24 h of fasting, triglycerides were measured enzymatically (25, 26) and a hexokinase method was used to measure fasting plasma glucose with a Roche/Hitachi 911 in years 2003–2004 or a Roche Cobas Mira in years 2005–2006 (27, 28). HDL cholesterol, total cholesterol, and HbA1c were measured without regard to fasting or nonfasting state (29). A direct immunoassay method was used to measure HDL cholesterol (30) and total cholesterol was measured enzymatically (31, 32). The equipment to measure HDL cholesterol and total cholesterol in years 2005–2006 was different, but the method and location were the same as those in 2003–2004 (30, 32). The blood lipid measurements were standardized for NHANES according to the CDC's lipid standardization program (33) and corrected using the Solomon Lab quality controls (30, 32). HPLC was used to measure HbA1c by a Primus CLC 330 and Primus CLC 385 (Primus Corporation) in years 2003–2004 and a Tosoh A1c 2.2 Plus Glycohemoglobin Analyzer (Tosoh Medics, Inc.) in years 2005–2006 (34, 35). A mercury sphygmomanometer was used to measure ≤4 systolic and diastolic blood pressures (36): if only 1 measurement was recorded, the value used in this study was the only measurement; if multiple measurements were recorded, the mean of the multiple measurements excluding the first measure was used.

TABLE 2 Qualitative description of separate energy and PA pattern clusters representing joint temporal dietary and physical activity patterns of US adults aged 20–65 y as drawn from the NHANES, 2003–2006[1]

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
n (%)	256 (14.0)	678 (36.9)	472 (25.7)	430 (23.4)
Characteristics of EI patterns	Mean ± SEM EI is 2558 ± 69 kcal/d. Peaks in EI were at 2 main occasions reaching ≤1600 and ≤2200 kcal at 11:00–13:00 and 17:00–20:00 where 59.35% and 75.8% of the cluster consumed 0–600 kcal, respectively	Mean ± SEM EI is 1808 ± 28 kcal/d. Proportionally equivalent peaks in EI were at 2 main occasions reaching ≤1000 kcal at 11:00–14:00 and 17:00–20:00 where 79.5% and 81.3% of the cluster consumed 0–600 kcal, respectively	Mean ± SEM EI is 1817 ± 34 kcal/d. Proportionally equivalent peaks in EI were at 2 main occasions reaching ≤1000 kcal at 11:00–04:00 and 17:00–20:00 where 74.2% and 78.6% of the cluster consumed 0–600 kcal, respectively	Mean ± SEM EI is 3017 ± 46 kcal/d. Peaks in EI were at 2 main occasions reaching ≤1600 and ≤1800 kcal at 11:00–14:00 and 17:00–21:00 where 46.5% and 31.9% of the cluster consumed 200–800 kcal, respectively
Characteristics of PA patterns	Mean PA (SEM) is 5.7×10^5 (1.2×10^4) counts/d. Highest PACs reached $>1.2 \times 10^5$ cph and 92.2% of the cluster engaged in PACs between 1.8×10^4 and 3.6×10^4 cph between 08:00 and 20:00	Mean PA (SEM) is 1.7×10^5 (2.4×10^3) counts/d. Lowest PACs reached $\leq 3.8 \times 10^4$ cph and 98.1% of the cluster engaged in PACs between 0.3×10^4 and 1.2×10^4 cph between 09:00 and 22:00	Mean PA (SEM) is 3.4×10^5 (4.7×10^3) counts/d. High PACs reached $\leq 8.8 \times 10^4$ cph and 75.4% of the cluster engaged in PACs between 1.2×10^4 and 2.4×10^4 cph between 16:00 and 20:00	Mean PA (SEM) is 3.0×10^5 (5.0×10^3) counts/d. High PACs reached $\leq 6.2 \times 10^4$ cph and 58.6% of the cluster engaged in PACs between 1.2×10^4 and 2.4×10^4 cph between 09:00 and 12:00

[1] cph, counts per hour; EI, energy intake; PA, physical activity; PAC, physical activity count.

Disease status classification

Disease status included obesity, T2DM, and MetS. Obesity was classified as BMI (in kg/m^2) >30 (37). The number of participants with T2DM was determined by subtracting the number with type 1 diabetes from the total number of participants with diabetes. Diabetes was classified by participant self-reports of being told they had diabetes by a doctor or of taking medications that lowered glucose, or by fasting plasma glucose concentration ≥126 mg/dL or HbA1c ≥ 6.5% (38). Type 1 diabetes was classified when a participant reported being diagnosed with diabetes before being 30 y old and continuous insulin use since diagnosis (39). MetS was determined by ≥3 of 5 risk factors: *1*) WC > 102 cm for men or >88 cm for women; *2*) triglycerides >150 mg/dL; *3*) HDL cholesterol < 40 mg/dL for men or <50 mg/dL for women; *4*) hypertension (systolic blood pressure > 130/diastolic blood pressure > 85 mm Hg); or *5*) impaired fasting plasma glucose >110 mg/dL (40).

Measures for covariates

Variables to classify survey year (2003–2004 and 2005–2006) and variables based on self-reported information to classify sex (male or female), race/ethnicity, age group (20–34, 35–49, and 50–65 y), and PIR were created and used to adjust the models. Furthermore, BMI, total PACs per day, and energy misreporting were also accounted for in the models. Race/ethnicity was reported and classified as Mexican American, other Hispanic, non-Hispanic white, non-Hispanic black, and other including multirace. PIR was the reported household income divided by the federal poverty guideline for household income, and classified as 0–0.99 (under poverty threshold), 1–1.99, 2–2.99, 3–3.99, 4–4.99, and ≥5 (41). BMI was classified as underweight (<18.5), normal weight (18.5–24.9), overweight (25.0–29.9), and obese (>30.0) (37). Energy misreporting was considered as a potential confounder modeled as total EI divided by estimated energy requirement (EER) (42–44), where EER was calculated using equations for adults based on age, sex, height, weight, and PA level according to the Institute of Medicine (45). According to previous studies, the vast majority (96.5%) of the US NHANES participant sample (and representative of the US population as a whole) did not meet the Physical Activity Guidelines for Americans and, similarly, the mean PACs of the 4 clusters indicated a light activity level (17, 46). Therefore, a low PA level was applied in the calculation to determine the EER (coefficient for men = 1.11 and women = 1.12) (44). For each participant whose data are reported in the NHANES data, the NCHS creates a weight based on the selection process. Weights were constructed when combining survey cycles 2003–2006 and used in the models, so the results are representative of the US civilian, noninstitutionalized population at the midpoint of the 4 y of the study (47, 48). The survey design of NHANES included stratification and clustering, which were both accounted for in the regression models according to NCHS guidelines to increase the precision of survey estimates (49).

Creating JTDPAPs

Participants' diet and PA data from the NHANES were extracted as 2-dimensional time series of length 1440 (24 h × 60 min), the entries of which are 2-dimensional vectors consisting of EIs and PACs at the timing (min) indicated by their indexes. For instance, participant q is represented by a 2D time series $[x_1^{(q)}, x_2^{(q)}, \ldots, x_i^{(q)}, \ldots, x_M^q]$, where $x_i^{(q)} = [{}^{\mathrm{EI}_i^{(q)}}_{\mathrm{PAC}_i^{(q)}}]x_i^{(q)} = [{}^{EI_i^{(q)}}_{PAC_i^{(q)}}]$ is a 2D vector representing the EI and PAC at the ith minute of the day, and $M = 1440$ is the length of the time series. Distance-based clustering analysis was used to derive JTDPAPs; specifically,

TABLE 3 Adjusted regression model results for mean BMI with clusters representing joint temporal dietary and physical activity patterns of US adults aged 20–65 y as drawn from the NHANES, 2003–2006[1]

Adjusted models[2]	*n*, %	BMI,[3] kg/m^2	$\beta^4 \pm$ SE compared with Cluster 2	95% CI	Adjusted *P* value	$\beta^4 \pm$ SE compared with Cluster 3	95% CI	Adjusted *P* value	$\beta^4 \pm$ SE compared with Cluster 4	95% CI	Adjusted *P* value
Cluster 1	256 (14.0)	26.8 ± 0.3	−1.3 ± 0.6	−2.9, 0.4	0.17	0.5 ± 0.5	−0.8, 1.9	0.71	−3.1 ± 0.5	−4.6, −1.7*	<0.0001
Cluster 2	678 (36.9)	30.0 ± 0.3				1.8 ± 0.4	0.7, 3.0*	0.001	−1.8 ± 0.5	−3.3, −0.4*	0.01
Cluster 3	472 (25.7)	27.8 ± 0.3							−3.7 ± 0.5	−5.1, −2.2*	<0.0001
Cluster 4	430 (23.4)	29.5 ± 0.3									

[1] There were significant differences in mean BMI between Clusters 1 and 2, Clusters 1 and 4, Clusters 2 and 3, and Clusters 3 and 4 in the unadjusted model at $P < 0.05$ (see Supplemental Table 1).
*Significant difference: adjusted $P < 0.05$.
[2] Multiple linear regression models were used and were adjusted for survey year, age group, sex, race/ethnicity, poverty to income ratio, energy misreporting, and total physical activity counts per day.
[3] Values are mean ± SEM.
[4] β represents the difference of mean BMI between 2 compared clusters. Least square means were used to calculate the differences in mean BMI.

dynamic time warping (DTW) is a distance measure that was used to determine the pairwise distances between participants (50). Unlike the commonly used Euclidean distance which sums the squared differences of entries with the same indexes, DTW finds the optimal matching path such that the summed differences between matched entries are minimized under certain conditions (50). In addition, the Sakoe-Chiba band (51) was used to constrain the maximum temporal difference between matched entries to avoid pathological warping (e.g., matching activities in the morning to activities in the evening), and is denoted as constrained band DTW (CDTW).

The original CDTW was designed for 1-dimensional speech signals. To generalize CDTW to multidimensional time series such as the diet and PA time series, 2 commonly used methods (52), i.e., independent multivariate CDTW ($CDTW_I$) and dependent multivariate CDTW ($CDTW_D$), were adopted. $CDTW_I$ uses CDTW distances which were computed based on dietary data and PA data independently [i.e., to determine $CDTW_I$ for 1 pair of participants, 2 separate CDTW distances were computed: $CDTW_{diet} \sum_{(i,j)\in M} (EI_i^{(p)} - EI_j^{(q)})^2$ and $CDTW_{PA} = \sum_{(i,j\in M)} (PAC_i^{(p)} - PAC_j^{(q)})^2$ where M denotes the alignment (matching path) that is found by the DTW algorithm; it defines how entries/events (EI for diet) of participant p are matched to those in participant q. $EI_i^{(p)}$ and $PAC_i^{(p)}$ denote the EI and PACs in the ith minute of the day of participant p]; and the joint distance was determined from the equation: $CDTW_I = \alpha \times CDTW_{PA} + (1-\alpha) \times CDTW_{diet} (0 \le \alpha \le 1)$, where parameter α controls the emphasis on PA over diet. Note that $CDTW_I$ reduces to $CDTW_{PA}$ when $\alpha = 1$ and to $CDTW_{diet}$ when $\alpha = 0$, and larger values of α indicate more emphasis on PA than dietary information in the clustering. In contrast, $CDTW_D$ computes the joint distance following a similar procedure as 1-dimensional CDTW. First, the difference between 2 entries, (EI_i, PAC_i) and (EI_j, PAC_j), was defined as $(1-\alpha) \times (EI_i - EI_j)^2 + \alpha \times (PAC_i - PAC_j)^2 (0 \le \alpha \le 1)$. Next, the same dynamic programming algorithm that finds the optimal matching path in CDTW was used here using the newly defined difference. The joint distance $CDTW_D$ was determined as the summed differences along the optimal matching path. The parameter α in $CDTW_D$ has similar effects on the derived JTDPAPs as in $CDTW_I$. The discussion on multidimensional CDTW is kept necessarily brief in this article but more detail can be found in previous publications (50, 52).

Both $CDTW_I$ and $CDTW_D$ were coupled with 3 popular distance-based clustering algorithms including kernel k-means (53), spectral clustering (54), and hierarchical agglomerative clustering (55) to partition the participants into 4 mutually exclusive clusters based on internal criteria including Silhouette Index and Dunn Index and external criteria including the number of significant inferential analysis results. In addition, the density balanced hierarchical cluster agglomeration (DBHCA), which exploits the definition of local reachability density (56), was used to develop a density-based, distance-aided cluster agglomeration method. In this method, pairwise CDTW with Sakoe-Chiba band and kernel k-means were coupled to derive 4 clusters based on dietary data and PA data independently (9, 57). The cross product of diet and PA clusters resulted in 16 initial clusters. Next, DBHCA agglomerateed the 16 initial joint clusters into 4 final clusters by repeatedly merging the 2 most similar clusters. Unlike previous hierarchical agglomerative methods (58–60), DBHCA

follows a density-similarity-first strategy to avoid the chaining effect, and introduces a distance threshold to ensure diet and PA similarity between clusters. Python was used to perform all clustering.

Statistical analysis

The 3 aforementioned methods were evaluated using inferential analysis to determine the strength of the JTDPAP's relation with the health status indicators. For categorical disease status indicators for obesity (yes/no), T2DM (yes/no), and MetS (yes/no), the receiver operating characteristic curves were used to evaluate the models. The AUCs in all 3 categorical disease status models were >0.8. For continuous health status indicators including BMI, WC, fasting plasma glucose, HbA1c, triglycerides, HDL cholesterol, total cholesterol, and systolic and diastolic blood pressure, residual plots and outliers were checked, and triglycerides, HbA1c, total cholesterol, and fasting plasma glucose exhibited suspected outliers in the residuals. After rerunning the analysis without those points, the inferential analysis results did not change substantially. Further, the values that produced the extreme residuals were considered biologically possible and acceptable so they were retained. Ultimately, $CDTW_D$ with Sakoe-Chiba band = 240 and $\alpha = 0.0016$ produced the strongest relations with health status indicators based on inferential analysis results that included the most significant differences between the 6 pairwise comparisons among all health status indicators, the highest model R^2 values, or the lowest Akaike information criterion.

ANOVA and the Kruskal–Wallis test showed significant differences among the cluster means of HDL cholesterol and all other health status indicator models, respectively. Multiple linear regression models compared clusters of JTDPAPs on continuous health status indicators. Multiple logistic regression models compared clusters of JTDPAPs on categorical disease status indicators. Models using BMI, WC, and obesity as health status indicators were adjusted for survey year, age group, sex, race/ethnicity, PIR, total PACs per day, and energy misreporting, whereas models using other health and disease status indicators were in addition adjusted for BMI. The Tukey–Kramer adjustment was made for multiple comparisons. Adjusted $P < 0.05$ for comparisons among clusters was considered statistically significant. SAS version 9.4 (SAS Institute Inc) was used to complete the analysis.

Visualization

The visualization (**Figures 1** and **2**) used heat maps to reveal the distribution of nonzero eating occasions and nonzero PACs in 4 distinct JTDPAP clusters. The *x* axis indicated time ranging from 00:00 to 24:00, whereas the *y* axis was either absolute EI ranging from 0 kcal to 4000 kcal or PACs ranging from 0 to 1.2×10^5 (truncated) at a certain hour. Both EI and PAC were calculated from their minute records. The proportion of individuals in each cluster reporting eating occasions or PA was represented through shading and ranged from 0.0% to 27.7% or from 0.0% to 13.9% in the 4 JTDPAP clusters, respectively. The darker shading represented that a greater percentage of participants in the cluster reported the same amount of EI or PACs at that time. **Figures 3** and **4** added color to show the distribution of the largest

TABLE 4 Adjusted regression model results for mean WC (cm) with clusters representing joint temporal dietary and physical activity patterns of US adults aged 20–65 y as drawn from the NHANES, 2003–2006[1]

Adjusted models[2]	*n*, %	WC,[3] cm	$\beta^4 \pm$ SE compared with Cluster 2	95% CI	Adjusted *P* value	$\beta^4 \pm$ SE compared with Cluster 3	95% CI	Adjusted *P* value	$\beta^4 \pm$ SE compared with Cluster 4	95% CI	Adjusted *P* value
Cluster 1	256 (14.0)	93.4 ± 0.9	− 3.5 ± 1.9	−8.6, 1.7	0.28	1.0 ± 1.5	−3.0, 5.0	0.91	− 7.3 ± 1.4	−11.2, −3.4*	0.0001
Cluster 2	678 (36.9)	100.7 ± 0.6				4.5 ± 1.2	1.3, 7.6*	0.003	− 3.8 ± 1.4	−7.6, −0.1*	0.05
Cluster 3	472 (25.7)	94.8 ± 0.6							− 8.3 ± 1.3	−11.9, −4.6*	<0.0001
Cluster 4	430 (23.4)	100.4 ± 0.8									

[1]There were significant differences in mean WC between Clusters 1 and 2, Clusters 1 and 4, Clusters 2 and 3, and Clusters 3 and 4 in the unadjusted model at $P < 0.05$ (see Supplemental Table 2).
*Significant difference: adjusted $P < 0.05$. WC, waist circumference.
[2]Multiple linear regression models were used and were adjusted for survey year, age group, sex, race/ethnicity, poverty to income ratio, energy misreporting, and total physical activity counts per day.
[3]Values are mean ± SEM.
[4]β represents the difference of mean WC between 2 compared clusters. Least square means were used to calculate the differences in mean WC.

TABLE 5 Odds of obesity relative to normal weight status and covariate-adjusted regression model results for clusters representing joint temporal dietary and physical activity patterns of US adults aged 20–65 y as drawn from the NHANES, 2003–2006[1]

Adjusted models[2]	*n*, %	OR[3] compared with Cluster 2	95% CI	Adjusted *P* value	OR[3] compared with Cluster 3	95% CI	Adjusted *P* value	OR[3] compared with Cluster 4	95% CI	Adjusted *P* value
Cluster 1	256 (14.0)	0.6	0.3, 1.1	0.17	0.9	0.5, 1.6	0.96	0.2	0.1, 0.5*	<0.0001
Cluster 2	678 (36.9)				1.5	0.9, 2.5	0.15	0.4	0.2, 0.8*	0.004
Cluster 3	472 (25.7)							0.3	0.1, 0.5*	<0.0001
Cluster 4	430 (23.4)									

[1]There were significant differences in OR of obesity to normal weight among all clusters except Clusters 2 and 4 in the unadjusted model at $P < 0.05$ (see Supplemental Table 3). *Significant difference: adjusted $P < 0.05$.
[2]Multiple logistic regression models were used and were adjusted for survey year, age group, sex, race/ethnicity, poverty to income ratio, energy misreporting, and total physical activity counts per day.
[3]OR of obesity to normal weight between 2 compared clusters. Obesity was classified as BMI $\geq$ 30 kg/m^2 (95).

EIs (Figure 3) and PACs (Figure 4) throughout 24 h among the 4 clusters.

Results

Table 1 shows the demographic characteristics of participants in the 4 JTDPAP clusters. Cluster 2 had the largest proportion (36.9%) of participants, whereas Cluster 1 had the smallest proportion (14.0%); Clusters 3 and 4 had similar proportions of participants (25.7% and 23.4%, respectively). There were significant differences in sex ($P < 0.0001$), age group ($P < 0.0001$), PIR ($P = 0.007$), and BMI ($P < 0.0001$) among clusters. Men made up the majority in Cluster 1 (73.4%) and Cluster 4 (70.3%), whereas women made up the majority in Cluster 2 (68.0%) and Cluster 3 (60.2%). In addition, the age group 20–34 y was more heavily represented in Cluster 1 (44.9%), the age group 50–65 y was more heavily represented in Cluster 2 (45.2%), and the age group 35–49 y was more heavily represented in Clusters 3 (40.1%) and 4 (41.4%). Further, participants with the lowest household PIR (0–0.99) accounted for the largest percentage (13.2%) and those with the highest household PIR ($\geq$5.00) accounted for the smallest percentage (24.0%) in Cluster 2 compared with the 3 other clusters. Participants in Cluster 1 had a greater proportion (43.1%) of normal weight than the 3 other clusters; whereas Clusters 2 (41.8%) and 4 (39.4%) had greater proportions of participants with obesity than the 2 other clusters.

Characteristics of JTDPAPs

Characteristics of JTDPAPs are summarized in **Table 2** based on the cluster visualizations in Figures 1–4. In respect to dietary intake, the absolute EI in Cluster 4 was significantly higher than in the 3 other clusters. The absolute EIs in Clusters 2 and 3 were both less but more concentrated between 0 and 600 kcal around noon and in the evening than in Clusters 1 and 4, which were more concentrated between 0 and 800 kcal with a more dispersed distribution. Two main EI peaks from all 4 clusters occurred around 12:00 and 18:00. Clusters 1 and 4 displayed more EI around noon and in the evening, whereas Clusters 2 and 3 exhibited more energy-equivalent eating occasions with no distinct EI peaks.

With respect to PA, Cluster 1 demonstrated the highest PACs, Cluster 2 demonstrated the lowest PACs, and Clusters 3 and 4 demonstrated similar PACs in the middle among the 4 clusters. The intensity of activity in Cluster 3 tended to increase toward later hours from 16:00 to 20:00; however, Cluster 4 intensity tended to be greater toward the earlier hours from 09:00 to 12:00 and decrease toward later hours after 13:00. This suggested that Cluster 3 had more of an evening PA pattern, whereas Cluster 4 had more of an early morning PA pattern.

Associations of JTDPAPs with obesity

The primary result of this study is that JTDPAPs are associated with obesity-related health indicators. Participants in Cluster 1 had significantly lower mean BMI and smaller WC than those in Clusters 2 and 4 as well as those in Cluster 3 than those in Clusters 2 and 4 in the unadjusted model ($P < 0.05$) (**Supplemental Tables 1** and **2**). Participants in Cluster 4 had significantly higher mean BMI and larger WC than those in Clusters 1 ($P < 0.0001$,

$P = 0.0001$, respectively), 2 ($P = 0.01$, $P = 0.05$, respectively), and 3 ($P < 0.0001$, $P < 0.0001$, respectively), and participants in Cluster 3 also had significantly lower mean BMI and smaller WC than those in Cluster 2 ($P = 0.001$, $P = 0.003$, respectively) in the adjusted models (**Tables 3** and **4**). The greatest significant differences in mean BMI and mean WC were present between Clusters 3 and 4 (β: -3.7 ± 0.5 and β: -8.3 ± 1.3 cm, respectively) in the adjusted model (Tables 3 and 4).

There were significant differences among all comparisons of 2 clusters except for Clusters 2 and 4 in the odds of being obese to normal weight in the unadjusted model ($P < 0.05$) (**Supplemental Table 3**). The significant differences remained between Cluster 4 and Clusters 1 ($P < 0.0001$), 2 ($P = 0.004$), and 3 ($P < 0.0001$) in the adjusted models (**Table 5**). The greatest significant difference in odds of being obese was present between Clusters 1 and 4 in the adjusted model (OR: 0.2; 95% CI: 0.1, 0.5).

Association between JTDPAPs and other health status indicators

The secondary result of this study is that JTDPAPs are associated with other health indicators. **Supplemental Tables 4–12** present the association of JTDPAPs with other health status indicators, T2DM, and MetS in the unadjusted model. There were 3 significant differences in triglycerides between Clusters 1 and 2 or 3, and Clusters 2 and 4, and 3 significant differences in total cholesterol between Cluster 1 and the 3 other clusters, in the adjusted models (**Tables 6** and **7**). There were no significant differences in the adjusted models for all other examined health status indicators, T2DM, and MetS (**Supplemental Tables 13–19**).

Discussion

In this study, primarily, clusters representing JTDPAPs among US adults ages 20–65 y were created using a novel methodology. Even though previous studies investigated the potential role of timing of eating and PA for health (7–9, 61–65), to our knowledge, this is the first study to create JTDPAPs that integrated the amount/counts, frequency, and timing of dietary intake and PA throughout 24 h. JTDPAPs are associated with BMI, WC, triglycerides, total cholesterol, and odds of being obese among investigated health or disease status indicators. The circadian system has an important effect on the regulation of metabolism, physiology, and behavior and may help to explain why the timing of diet and PA exposures is important to health. Biological rhythms are coordinated in the circadian system through the involvement of clock genes (66–68). Diet and PA are behavioral factors that can have an impact on the circadian system. If these external behaviors are misaligned with the original circadian system, such as in eating late at night, metabolism may be impaired and could lead to dysfunction (69–74).

The significant mean differences in BMI, WC, triglycerides, but not total cholesterol, among JTDPAP clusters were both statistically significant and clinically meaningful (75–79), showing a potential for future clinical application. JTDPAPs could be an important health exposure that holds promise for early detection of lifestyle factors to promote health and prevent disease.

TABLE 6 Adjusted regression model results for mean triglycerides with clusters representing joint temporal dietary and physical activity patterns of US adults aged 20–65 y as drawn from the NHANES, 2003–2006[1]

Adjusted models[2]	*n*, %	Triglycerides,[3] mg/dL	$\beta^4 \pm$ SE compared with Cluster 2	95% CI	Adjusted *P* value	$\beta^4 \pm$ SE compared with Cluster 3	95% CI	Adjusted *P* value	$\beta^4 \pm$ SE compared with Cluster 4	95% CI	Adjusted *P* value
Cluster 1	256 (14.0)	121.3 ± 6.0	−40.6 ± 10.0	−67.8, −13.4*	0.002	−28.7 ± 9.1	−53.6, −3.8*	0.02	−13.5 ± 9.9	−40.3, 13.3	0.53
Cluster 2	678 (36.9)	155.5 ± 6.3				11.9 ± 7.6	−8.7, 32.5	0.41	27.1 ± 8.3	4.6, 49.6*	0.01
Cluster 3	472 (25.7)	136.8 ± 5.7							15.2 ± 10.3	−12.7, 43.1	0.46
Cluster 4	430 (23.4)	149.2 ± 6.8									

[1]There were significant differences in mean triglycerides between Clusters 1 and 2, Clusters 1 and 4, and Clusters 2 and 3 in the unadjusted model at $P < 0.05$ (see Supplemental Table 4). *Significant difference: adjusted $P < 0.05$.
[2]Multiple linear regression models were used and were adjusted for survey year, age group, sex, race/ethnicity, poverty to income ratio, BMI, energy misreporting, and total physical activity counts per day.
[3]Values are mean ± SEM.
[4]β represents the difference of mean triglycerides between 2 compared clusters. Least square means were used to calculate the differences in mean triglycerides.

TABLE 7 Adjusted regression model results for mean total cholesterol with clusters representing joint temporal dietary and physical activity patterns of US adults aged 20–65 y as drawn from the NHANES, 2003–2006[1]

Adjusted models[2]	*n*, %	Total cholesterol,[3] mg/dL	$\beta^4 \pm$ SE compared with Cluster 2	95% CI	Adjusted *P* value	$\beta^4 \pm$ SE compared with Cluster 3	95% CI	Adjusted *P* value	$\beta^4 \pm$ SE compared with Cluster 4	95% CI	Adjusted *P* value
Cluster 1	256 (14.0)	188.8 ± 2.3	− 16.0 ± 5.1	−30.0, −2.0*	0.02	− 11.6 ± 3.8	−21.9, −1.3*	0.02	− 14.9 ± 4.8	−27.8, −1.9*	0.02
Cluster 2	678 (36.9)	201.5 ± 1.9				4.4 ± 2.6	−2.7, 11.5	0.36	1.1 ± 2.8	−6.6, 8.9	0.98
Cluster 3	472 (25.7)	197.9 ± 1.7							−3.3 ± 3.5	−12.7, 6.2	0.79
Cluster 4	430 (23.4)	202.5 ± 1.9									

[1]There were significant differences in mean total cholesterol between Clusters 1 and 2, Clusters 1 and 3, and Clusters 1 and 4 in the unadjusted model at $P < 0.05$ (see Supplemental Table 5). *Significant difference: adjusted $P < 0.05$.
[2]Multiple linear regression models were used and were adjusted for survey year, age group, sex, race/ethnicity, poverty to income ratio, BMI, energy misreporting, and total physical activity counts per day.
[3]Values are mean ± SEM.
[4]β represents the difference of mean total cholesterol between 2 compared clusters. Least square means were used to calculate the differences in mean total cholesterol.

Participants in Cluster 1 had significantly lower BMI, total cholesterol concentration, odds of obesity, and smaller WC than those in Cluster 4. A pattern with 3 evenly spaced eating occasions with higher EI during 2 main eating occasions from 11:00 to 13:00 and 17:00 to 20:00 and higher PACs during the day, may bring more benefits to health than a pattern with higher overall EI and an energy peak from 17:00 to 21:00 and lower PACs throughout a day. These primary findings are in line with the previous finding that suggested lower EI and higher PA level are positively associated with a lower prevalence of obesity-related health outcomes (8, 9, 15, 80–83). Moreover, being in Cluster 1 was also associated with significantly lower total cholesterol than the 3 other clusters, a result that is also consistent with previous PA studies showing higher PA level is positively associated with a lower concentration of total cholesterol (84–86). Furthermore, Cluster 1 participants demonstrated peaks of PACs before corresponding eating occasions, which may indicate participants have a high level of PA before eating. Cluster 1 predominantly included men and the age group 20–34 y, which is consistent with previous studies showing young adults have higher PA intensities than older adults (87).

Cluster 2 had a significantly higher mean BMI and larger mean WC than Cluster 3. Because Clusters 2 and 3 had similar dietary patterns during the day, this result suggests that PA may have a main effect on modulating BMI and WC as supported by previous studies (15, 80–83). Cluster 2 with the lowest PACs among the 4 clusters had the highest number of participants (36.9%), corroborating evidence that US adults engage in high amounts of sedentary behavior (88). In addition, Cluster 2 predominantly included women, ages 50–65 y with low PIR and odds of obesity, which aligns with previous findings of lower PA and EI with advanced age (89, 90) and among women (82), especially those with low income (91, 92).

Results of no significant differences among JTDPAP clusters in terms of the other short-term health status indicators and disease statuses examined in this study were unexpected. A systematic review demonstrated that participants who exercised postmeal at any time of day had lower postprandial glycemia than those who exercised premeal (5). Further, a cross-sectional study showed that a temporal dietary pattern with "later lunch" (13:00–14:00) was associated with hypertension compared with that with "conventional lunch" (12:00–13:00) in women (62). Potential reasons for no significant differences in these health status indicators of this study may be due to the similar timing of dietary intake among the 4 clusters yet varying amounts of EI or individual variability in short-term serum biomarkers being larger than among long-term indicators like BMI and WC. If not, this finding may imply that JTDPAPs may be more closely related to long-term health status indicators like BMI and WC rather than short-term indicators such as blood pressure.

One of the strengths of the study was the comprehensive method to integrate temporal dietary and PA exposures together over a 24-h day. Using this method, the clusters were not generated from a predefined standard but data-driven methods based on the true nature of the behaviors. Even though this is the first attempt to integrate multiple behaviors, additional multidimensionality of dietary intake and PA such as diet quality and activity type, along with other factors such as comorbidity status, medication use, and other lifestyle behaviors such as smoking, should be incorporated in future studies. But because

of the cross-sectional study design, this study cannot be used to infer causation. In addition, the patterns generated integrate both EI and PA over time, but the influences of factors of behavior and timing are not distinguishable because the goal was to determine if their integration had a significant relation with health. Another limitation is that the dietary and PA data are from 1 weekday dietary recall and 1 weekday accelerometer record, respectively, likely representing different days because of NHANES protocol, yet their combination assumes the data represent participants' regular patterns. NHANES includes ≤2 dietary recalls and 7 d of PA accelerometer data, so the sample size would be further reduced if a second recall or another day of PA was also an inclusion criterion, even though two 24-h dietary recalls or multiple PA accelerometer data may better identify participants' usual temporal eating pattern and temporal PA pattern. In addition, because little is known about temporal dietary and PA behavior over multiple days, future studies should explore the integration of the amount/intensity and temporal sequence of dietary intake and PA over multiple days. A single 24-h dietary recall may be considered to be representative to estimate the general dietary pattern if days of the week of dietary recalls are evenly selected (93), and 1 valid random day of PA data is also considered to be sufficient at the population level (19). The dietary data in this study did not evenly distribute across the week, thus, weekend compared with weekday patterns should be further investigated and the conclusion of this study should be cautiously generalized because only weekday data were used. Accelerometers are not waterproof and only record uniaxial movement, so they did not record or accurately record all types of activity such as swimming or elliptical training (16), but main sources of PA for most people like walking were accounted for. Moreover, because total cholesterol may not be measured at fasting state, it may result in higher concentration than fasting total cholesterol (94), but compared with the fasting lipid profile, the diagnostic accuracy of the nonfasting lipid profile was significantly higher for the assessment of lipoprotein coronary risk (94). Finally, the study sample is only 8.97% of the original population in NHANES 2003–2006 because many participants in the original sample were outside of the age range 20–65 y and did not have valid fasting health status indicator information. Owing to the relatively small sample size, the unique JTDPAPs that may exist in the population, such as night shift patterns, may not be observed because these smaller patterns were combined with other patterns preventing observation of their unique temporal characteristics.

In conclusion, JTDPAPs are significantly associated with BMI, WC, triglycerides, total cholesterol, and obesity. A JTDPAP cluster with 2 energy-equivalent main eating occasions and higher PACs may be associated with more favorable health indicators including lower BMI, total cholesterol concentration, odds of obesity, and smaller WC in US adults than other JTDPAPs. The integration of weekday EI, PACs, and the timing of those exposures is possible in generating JTDPAPs that are associated with health status indicators and could contribute to early detection of lifestyle behavioral patterns prone to obesity.

The authors' responsibilities were as follows—LL and JG: analyzed the data; LL: wrote the paper; HAE-M, EJD, SBG, AB, EAR, EH, JG, and MMA: critically reviewed and edited the manuscript; HAE-M: had primary responsibility for the final content; and all authors: designed the research and read and approved the final manuscript. The authors report no conflicts of interest.

Data Availability

Data described in the article and code book are publicly and freely available without restriction at https://www.cdc.gov/nchs/nhanes/index.htm. Analytic code will be made available upon request pending application and approval.

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